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The Decarbonization of China's Agriculture

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Abstract

Agriculture is one of the major greenhouse gas (GHG) emission sources in China. This paper aims to identify the key factors that have led to rising GHG emissions in China's agricultural sector in recent decades. This research allows for spatial dependence across provinces, making use of regional data from 31 provinces in mainland China. It investigates the effects of agricultural machinery, different energy types, fertilizer consumption, pesticide employment and agricultural investment on carbon emissions. The findings of this research contain significant policy recommendations for Chinese policy makers in terms of how to decarbonize China's agricultural sector, based on diverging circumstances of each region's agricultural system. It also has important implications for emission abatement policies in other developing countries sharing a similar emissions profile and regional characteristics.

Keywords: agriculture, emission reductions, spatial dependence, China
JEL classification: Q11, Q18, Q54, Q55, Q58

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Figures and Tables appear at the end of the paper.

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1 Introduction

As the world's largest developing country, China's huge population exerts heavy demand on its agricultural sector. China suffers a relatively high occurrence of natural disasters, and is characterized with low per capita cultivated land, a less developed agricultural system and therefore a low adaptation capacity to deal with the negative impacts of climate change. For governments at central and provincial levels in China, the major challenge has been how to meet the increasing demand for food while at the same time reducing greenhouse gas (GHG) emissions from its agricultural sector.[1] This highlights the importance and urgency of decarbonizing this sector, or embarking on a low-carbon agricultural development path, before it is too late.

Roughly speaking, China has a continental monsoon climate with four clear seasons throughout the year. Owing to vast land area and varying natural conditions across regions, diverging patterns of climate situations exist for the agricultural sector in different provinces in China, as shown in Figure 1. Basically, the northern part of China suffers most from the disasters while the southern part enjoys higher temperature and a comparatively good level of precipitation.[2] All these features of natural climate conditions across China's different regions tend to impact the employment of energy, fertilizers and pesticides and call for more agricultural investment in different provinces.[3]

The low-carbon agriculture requires certain measures used to reduce GHG emissions from the origins in this sector. As suggested by the literature, main contributors to this sector's GHG emissions are energy consumption, fertilizer consumption, and employment of pesticides. Energy is an essential but carbon-intensive input for agricultural production, including direct energy use and indirect energy use.[4] Fertilizer, nitrogen fertilizer in particular, and pesticides are two large GHG-emission-contributing factors in the agriculture sector, although they might be contributing factors for the high agricultural productivity as well.

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1 The GHG emissions from its agricultural sector have been on an increase for the past 25 years, representing 20 per cent of China's total emissions in recent years (SAIN 2011). Of the total GHG emissions from the agricultural sector, for the years 1995, 2000 and 2005 the methane (CH4) emissions from agricultural activities amounted for 48.1 per cent, 47.3 per cent and 38.8 per cent of China's total CH4 emissions, respectively, and the nitrous oxide (N_2O) emissions accounted for 79 per cent, 77.4 per cent and 74.3 per cent of China's total N_2O emissions, respectively (World Bank's World Development Indicators 2012).

2 China's precipitation not only unevenly distributes across regions but also demonstrates seasonal variations with the summer witnessing most of the precipitation.

3 In fact, climate change has already exerted harmful effects on China's agricultural sector. There can be increased risks of farm land desertification, reduced land fertility, more pest outbreaks, higher production costs and more investment need due to climate change-induced changes in the agricultural production process. If no immediate action has been taken to tackle these problems, more damages can be expected.

4 The main direct energy use comes from the operation of machinery and equipment, the heating and cooling of buildings, and lighting on the farms while the indirect energy consumption is from fertilizers and chemicals produced off the farm (Schnepf 2004). Direct energy use has been found relatively low as compared to indirect energy inputs, especially for the energy used in the production of synthetic nitrogen fertilizers (Norse 2012).

Despite the importance of China's agricultural sector in the light of GHG emission reductions, there exists very limited evidence in terms of what drives GHG emissions in this sector. Hu and McAleer (2005) and Zhang et al. (2012) are among the few examples.[5] Most of the existing research does not incorporate any of the key factors of energy, fertilizer or pesticide in the analysis. Other studies are largely descriptive based on either desktop research or case studies, which shed light on the issue but failing to generate convincing empirical evidence to guide further research and practice.

The regional differences in terms of agricultural production and GHG emissions across China's regions underlie the importance of employing a regional approach in the analysis. Given the data availability of 31 provinces in mainland China over 1995-2007, this paper aims to bridge this research gap by employing spatial panel data methods to investigate the impacts of some key factors on GHG abatement, namely, machinery, energy use, fertilizer use, pesticide use and agricultural investment, controlling for disaster measures.

The remainder of the paper proceeds as follows. Section 2 describes the data and shows some stylized facts. Section 3 contains a description of econometric methods, followed by the empirical results in Section 4. Section 5 discusses China's policies and Section 6 concludes.

2 Sample and variables

This section is about the sample used and describes the dependent variable, key independent variables and control variables. Our sample includes 31 provinces in mainland China.[6] The time period we consider is from 1995 to 2007.[7]

The dependent variable is CO_2 emissions from the agricultural sector (ton CO_2 per hectare of sown area) in each province, simply denoted by CO_2.[8] It is the total CO_2 emissions from China's agriculture, multiplied by the shares of regional agricultural output over China's total agricultural output, divided by the total sown areas of each province.[9] Annual data on total CO_2 emissions (Mtons) from China's agriculture,

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5 With a panel dataset made up of 30 provinces over the period of 1991-97, Hu and McAleer (2005) estimate the production efficiency in China's agricultural sector based on Cobb-Douglas production function. Zhang et al. (2012) employs a DeNitrification-DeComposition (DNDC) model to quantify the regional CH4 emissions from the entire rice paddies in China's northeast region.

6 The sample consists of four municipalities (Beijing, Tianjin, Chongqing, and Shanghai), five autonomous regions (Xinjiang, Xizang or Tibet, Ningxia, Inner Mongolia and Guangxi) and 22 provinces.

7 The China's Sustainable Development Database developed by the Chinese Academy of Sciences (2012) has data up to 2007 (some variables to 2008). Effort is being made to find up-to-date data to revisit this topic.

8 CH4 and N_2O are also the main forms of GHG emissions in the agriculture sector, which are actually 21 and 310 times more harmful than CO_2 in terms of greenhouse warming effect, respectively (IPCC 2007). Due to the lack of data for CH4 and N_2O, this analysis focuses on CO_2 emissions. A good direction to revisit this topic is to use provincial data for CH4 and N_2O emissions in the future.

9 We assume that one unit of agricultural output produces one unit of CO_2 emissions in different provinces.

including both direct and indirect emissions, are taken from the Enerdata's Global Energy Market Data (2012). Annual data on total agricultural output (in billion Yuan) and total sown area of crop (in 1000 hectares) of each province are taken from China's Sustainable Development Database developed by the Chinese Academy of Sciences (2012). The regression uses the natural logarithm of 1000 times CO_2.

We consider five key independent variables, which are closely related to CO_2 emissions: agricultural machinery, energy use, fertilizer use, pesticide use and agricultural investment. The variable of agricultural machinery (MACH) is to measure the extent of technological progress. There are two variables for energy use: electricity use denoted by ELECTRICITY and diesel use denoted by DIESEL. The fertilizer use, denoted by FERTILIZERS, and pesticide use, denoted by PESTICIDES, could contribute to both the agricultural output and environmental pollution. Agricultural investment (INVESTMENT) to some extent determines agricultural productivity and reflects the government's agricultural investment policies and the potential of emission reductions from this sector. Annual data on total agricultural machinery per hectare of sown area (kw per hectare), total electricity use per hectare of sown area (kWh per hectare), total diesel use per hectare of sown area (kg per hectare), total fertilizer use per hectare of sown area (kg per hectare), total pesticide use per hectare of sown area (kg per hectare), and total agricultural financial expenditure per hectare of sown area (Yuan per hectare) of each province are taken from China's Sustainable Development Database developed by the Chinese Academy of Sciences (2012). All variables are taken in log.

Control variables included in this analysis are natural disaster (DISASTER) and drought (DROUGHT). Following the definition used by the US National Climatic Data Center, we use the standardized precipitation index as a way of measuring drought. Both DISASTER and DROUGHT are used to control for the adverse natural environment for China's agriculture. Annual data on the ratio of the area affected by disasters over total sown area and the annual average precipitation (mm) are from the China's Sustainable Development Database developed by Chinese Academy of Sciences (2012). DISASTER is taken in log.

Agricultural investment and machinery, energy consumption, fertilizer and pesticide use exhibits varying characteristics in different parts of China, as shown in Figures 2-4, respectively. This highlights the importance of adopting a regional approach to explore the impacts of these factors on carbon emissions in China's agriculture. More specifically, in terms of investment in agricultural sector as depicted in Picture A of Figure 2, China's western areas such as Xizang (Tibet) and Qinghai have carried out considerable investment in agricultural sector, which to some extent reflects the adverse natural conditions for agricultural production as well as financial support provided by the central government and local governments because those regions are typically under-developed. The picture also demonstrates the substantial investment undertaken in some eastern regions like Liaoning, Jiangsu, Zhejiang and Guangdong. This seems to be somewhat related to higher levels of economic development across regions. The pattern of the agricultural machinery as shown in Picture B of Figure 2 is similar to that of agricultural investment—more agricultural machinery corresponds to more agricultural investment. Regions around Beijing witness the wider use of machinery, which might be related to the better technological progress. When it comes to the energy use as shown in Figure 3, both electricity and diesel are heavily consumed in the eastern coastal areas, followed by the western region like Xinjiang. In comparison to diesel consumption, it is interesting to note that electricity consumption is very popular in the central regions. This trend is somewhat related to the degree of infrastructure development, income level and industrialization. For the fertilizer use and pesticide use as shown in Figure 4, the eastern coastal regions, some central regions and western regions like Xinjiang are the areas where fertilizers and pesticides have been heavily used, in contrast to other regions.

Descriptive statistics of all the variables can be found in Appendix Table 1 while correlations among them are presented in Appendix Table 2.

3 Econometric method

We assume that CO_2 emissions observed in province *i*th at time *t*, namely y_{it}, is generated by the following linear regression panel data model:

$$y_{it} = \alpha_i + x'_{it}\beta + \mu_{it} \tag{1}$$

$i = 1,2...31$; t=1,2...13

where α_i are the spatial specific effects or individual effects, which capture time invariant unobserved spatial heterogeneity whose omission can potentially lead to estimation bias. x_{it} is a k×1 vector of observations of independent variables including key independent variables and control variables introduced in Section 2 (k is the number of independent variables). β is a k×1 vector of fixed but unknown parameters. The error term, μ_{it}, is a N×1 (N is the number of cross-section units) idiosyncratic error term, assumed to be independently and identically distributed across the cross-sectional dimension with zero mean and constant variances σ_ε^2.

We assume that the current values of independent variables are less likely to be affected by the past errors, but they may be related to some individual fixed effects. The error term, μ_{it}, and spatial specific effects, α_i, are assumed to be independent from each other. α_i can be removed via within group transformation or first-differencing.

When the spatial dependence exists in the error term due to unobserved effects of common shocks (for example, macroeconomic shocks, political shocks or environmental shocks), the spatially autocorrelated error term can be expressed as follows,

$$\begin{aligned} y_{it} &= \alpha_i + x'_{it}\beta + \mu_{it} \\ \mu_{it} &= \rho \sum_{j=1}^{N} w_{ij}\mu_{it} + \varepsilon_{it} \end{aligned} \tag{2}$$

where the regression disturbances, μ_{it}, are assumed to be corrected across space and independent of regressors x_{it} . ρ is the spatial autocorrelation coefficient, measuring the amount of spatial correlation in the errors. ρ is also subject to the interval ($1/\omega_{min}$,

$1/\omega_{max}$). w_{ij} is the N×N spatial weighting matrix of known constants, reflecting the neighbouring relationships with zero across diagonals and in row-standardized form. $\rho \sum_{j=1}^{N} w_{ij}\mu_{it}$ is known as a spatially autocorrected error or spatial lag of μ_{it}, to capture the spatial error dependence in the sense that a shock in any province *i* at time *t* will be simultaneously transmitted to all the other provinces. ε_{it} are the independent and identically distributed disturbances with zero mean and constant variances σ_{ε}^{2}.

The above model (2) can be rewritten as:

$$y= (\iota_{T} \otimes I_N)\, \alpha + x\beta + [I_T \otimes (I_N - \rho w_N)^{-1}]\mu \tag{3}$$

When the above regression model is extended to include a spatially lagged dependent variable, we have the following comprehensive spatial model:

$$\begin{aligned} y_{it} &= \alpha_i + \lambda \sum_{j=1}^{N} w_{ij} y_{it} + x'_{it}\beta + \mu_{it} \\ \mu_{it} &= \rho \sum_{j=1}^{N} w_{ij}\mu_{it} + \varepsilon_{it} \end{aligned} \tag{4}$$

where λ is the spatial autoregressive coefficient or spatial interdependence coefficient, measuring the extent of endogenous interaction effects. Like ρ, λ falls into the interval ($1/\omega_{min}$, $1/\omega_{max}$), where ω_{min} and ω_{max} are the smallest and largest characteristic roots of the matrix w_{ij} (Elhorst 2010: 377-407). The added variable, $\lambda \sum_{j=1}^{N} w_{ij} y_{it}$, is referred to as a spatially lagged dependent variable, or a spatial lag of y_{it}. The added spatial lag of y_{it} captures the potential spatial lag dependence due to the presence of social and spatial interactions, in which CO_2 emissions in one province is simultaneously determined by that of its neighbouring provinces. In this analysis we assume that ρ and λ are the same spatial weighting matrix. In what follows, ρ is used.

For the sake of simplicity, we rewrite the above model (4) as follows,

$$y= (\iota_{T} \otimes I_N)\, \alpha + [I_T \otimes (I_N - \rho w_N)^{-1}]x\beta + [I_T \otimes (I_N - \rho w_N)^{-1}]\mu \tag{5}$$

Kapoor et al. (2007) propose a method to estimate the spatial panel model with spatially autocorrected error components (2), by extending the generalized moments estimators of Kelejian and Prucha (1999) to the context of panel data model. Kapoor et al. (2007) consider a spatial panel model with exogenous regressors.[10] Fingleton (2009) suggests adapting the method of Kapoor et al. (2007) to allow for endogenous variables, lagged dependent variable and some endogenous variables, to be added to the regressor matrix. It proceeds to use the instrumental variable approach, but also takes account of the non-sphericity of variance-covariance matrix.

10 Fingleton (2008) extends the method of Kapoor et al. (2007) to allow for an endogenous spatial lag and a moving average error process.

Following Kapoor et al. (2007) and Fingleton (2009), this analysis estimates the spatial error model (2) as well as the comprehensive spatial panel model (4) with both the spatially lagged dependent variable and spatially autocorrected error components.

The estimation strategy due to Kapoor et al. (2007) involves a three-stage procedure. In the FIRST step, the model is estimated by the ordinary least squares (OLS) to obtain the residuals. In the SECOND step, the spatial autocorrelation parameter, ρ, and the variance of the innovation term ε_n, $\sigma^2_{\varepsilon,t}$, are estimated by applying the Generalized Method of Moment (GMM), which uses nonlinear least squares based on the residuals $\widehat{\mu_{\iota t}}$obtained from Step One. In the THIRD step, a feasible GLS is applied to the transformed regression model, which is yielded via a spatial Cochrane-Orcutt type transformation, after replacing ρ with $\widehat{\rho_t}$, obtained in Step Two.[11]

4 Empirical results

This section presents the empirical evidence for the impacts of various factors on regional CO_2 emissions in China's agricultural sector. Two different spatial weighting matrices, an inverse-distance spatial weighting matrix and a binary spatial weighting matrix, are used in this analysis. The inverse-distance spatial weighting matrix gives the inverse of the distance to each sample point within a 1200km neighbourhood, and zero otherwise, while the binary spatial weighting matrix gives a weight of 1 to all sample points within a 1200km neighbourhood, and zero otherwise.[12] Both matrices are row-standardized of one.

Tables 1 and 2 compare fixed effect estimates (for the fixed effect model) with spatial feasible GLS estimates (for both spatial error models and spatial SARAR models), by using the inverse-distance spatial weighting matrix and the binary spatial weighting matrix, respectively. Both tables examine the effects of agricultural machinery, energy use, fertilizer use, pesticide use and agricultural investment on CO_2 emissions, controlling for natural disaster and drought. There are two spatial error models and two spatial SARAR models in each table, which study the situation where the interaction terms between MACH and ELETRICITY and between MACH and DIESEL are included into the model. For spatial SARAR models, the spatial autoregressive coefficients, ρ, are reported.

The feasible GLS estimates suggest that the spatial autoregressive coefficients, ρ, are significantly negative in two spatial SARAR models, indicating the existence of negative spatial lag dependence associated with neighbourhood effects and social interactions among observations in this context.

The employment of agricultural machinery is among the most important factors determining the agricultural productivity. The agricultural machinery (MACH) has been found significantly positively associated with CO_2 emissions in China's agricultural sector in two spatial models without interaction terms. This is very likely—the more

11 The transformed regression model is generated by pre-multiplying the regression model (2) by $I_N - \rho w_N$.

12 The information on the spatial distance between different provinces in China is taken from Yu (2009).

agricultural machinery is adopted, the higher yields and the more associated CO_2 emissions can be expected from the agricultural sector. It is worth noting that the coefficients in spatial SARAR models are larger than their counterparts in spatial error models.

Since agricultural machinery is a major energy consumer, it is sensible for MACH to interact with ELETRICITY and DIESEL. It is interesting to note that the interaction term, MACH×ELETRICITY, has been found significantly negative in two spatial models, while MACH×DIESEL is significantly positive in two spatial models. Like many other developing countries, China has adopted an energy-intensive agricultural system, which is highly effective in terms of production. However, this system has detrimental impacts on the climate change due to the large amount of GHG emissions from employing fossil resources to provide energy for machine operation and some other activities like irrigation, fertilizer use and pesticide use. In comparison to other energy sources such as diesel, electricity has higher energy content but lower carbon content. The evidence clearly implies that electricity consumption could be an effective option for China's low-carbon agriculture, before any renewable energy options become available.

Both fertilizer consumption (FERTILIZERS) and pesticide consumption (PESTICIDES) have been found positively and significantly associated with CO_2 emissions in the agricultural production in China, in all models. Due to China's high intensive cropping systems with the high use of nitrogen fertilizers inefficiently and inappropriate employment of pesticides, the agricultural sector no doubt produces considerable GHG emissions associated with fertilizer uses and pesticide uses. This area, however, offers a great potential for GHG abatement.

In terms of agricultural investment (INVESTMENT), the estimates in all models suggest a significantly positive impact on carbon emissions. Agricultural investment being a contributing factor for CO_2 emissions in China's agriculture might be surprising at first glance, but makes good sense on second thoughts. The increased agricultural investment will no doubt enhance output productivity, which requires an increased level of energy use for such agricultural activities as machine operation, and calls for demand for more employment of pesticides and fertilizers. All these can lead to a higher level of GHG emissions.

For control variables, drought (DROUGHT) has been observed significantly positive in the model, but not necessarily for the natural disaster (DISASTER). This shows that, among other natural disasters, drought could effectively cause considerable increase in CO_2 emissions in China's agriculture.

In Table 2, the binary spatial weighting matrix is used. The spatial autoregressive coefficients, ρ, are smaller than those in Table 1. This is likely due to the fact that the inverse-distance spatial weighting matrix contains much rich information than the binary spatial weighting matrix. The significance of the positive effect of fertilizer use on CO_2 emissions is close to the 10 per cent level. In general, the findings of Table 2 confirm those of Table 1.

In sum, this research produces the following significant findings. First, it provides evidence for the presence of spatial dependence across provinces in this context, especially for the spatial lag dependence associated with neighbourhood effects and social interactions. Second, when the spatial lag dependence is allowed, the feasible GLS estimates in spatial SARAR models in general indicate larger effects than their counterparts in spatial error models. Third, by allowing for spatial dependence, this research finds that agricultural machinery, fertilizer consumption, pesticide employment and agricultural investment contribute to recent increases in CO_2 emissions in China's agriculture, so does adverse natural drought. In terms of energy consumption, electricity consumption could lead to emission reductions, but not necessarily for the diesel consumption.

5 Policy discussion

The above analysis finds that agricultural machinery, fertilizer consumption, pesticide employment, agricultural investment and drought are important driving factors for CO_2 emissions in China's agriculture. To embark on a low-carbon agricultural development path is never an easy job, which requires considerable determination and efforts, including both technological innovation and policy interventions for the establishment of an enabling and incentive environment. In its 12th Five-Year Plan, Chinese central government has put it as an important action plan to 'enhance public service capacity-building for agricultural development; accelerate the improvement in public service agencies for rural or regional agricultural technology dissemination, animal and plant disease prevention and control, and agricultural products quality supervision' (Ministry of Agriculture 2012).

To transit from the traditional fossil-resource-based energy to renewable energy in the agricultural sector, Chinese Ministry of Agriculture has implemented a series of sustainable agriculture laws and regulations to promote the development of fuelwood-saving stoves, biogas and solar energy; accordingly, the proportion of biomass energy usage has decreased a lot in the rural areas. The positive effects of these policy interventions are starting to show.[13]

Chinese governments have long provided perverse subsidies for nitrogen fertilizer production, which used to play a positive role in boosting China's fertilizer industry and in enhancing crop yields. However, such a subsidy has become an obstacle to the fight against the overuse of nitrogen fertilizers, held responsible for considerable N_2O emissions into the air. In recent years, the battle in China against the overuse of nitrogen fertilizers has resulted in the removal of these perverse subsidies. To mitigate emissions from fertilizers, organic fertilizers, produced from animal manure, have been developed and promoted in China.[14]

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[13] For example, owing to government support for biogas development through making use of animal and poultry wastes, 'completed are 3,556 biogas projects with annual processing capability of over 80 million tons of animal and poultry wastes, 146,000 digesters for making use of effluents from daily life to generate biogas, more than 500 projects for central biogas supply by making use of straw and stalk, 189 million fuelwood-saving stoves, and 28.46 million square metres of solar-energy water heaters' (Ministry of Agriculture of the People's Republic of China 2009).

[14] Norse (2012) summarizes that there are at least two types of measures suggested so far to mitigate emissions from fertilizers. One is to improve the timing and placement of synthetic nitrogen fertilizers and integrated nutrient management, which is one of the most effective emission abatement measures at negative costs of between US$30 and US$60, thanks to the generated production cost savings. The

The overuse of pesticides is another serious problem in China, which jeopardizes both the environment and public health. In response to the concern of the damaging impacts of pesticides on GHG emissions, China has set up strict regulations on pesticide uses. The revised regulation improves the existing one in such areas as 'production register, quality control, marketing, and the use and administrative management of pesticides', and requires local governments to review the registered pesticides and to ban the employment of those pesticide products which are found risky to public health and the environment (*China Daily* 2011).

However, more policy regulations or efforts are still needed to encourage the production and wider application of low-carbon-content energy (such as hydropower, biogas, solar, geothermal and wind power), organic fertilizers, and low-carbon pesticides. On top of policy regulations, capacity-building and financial measures are crucial to resolving the problem.

At present, most farmers do not have sufficient knowledge of energy-saving and climate-friendly machinery as well as low-carbon fertilizers and pesticides. They apply fertilizers and pesticides merely based on their limited experience, which leads to the overuse and even misuse of them. More efforts are needed to raise the farmers' awareness of the necessity and benefits of using sustainable energy in the farm production and the fact that the overuse of fertilizers and pesticides not only increases carbon emissions but also brings about unnecessary expenditure on the part of farmers. Public service organizations should disseminate related information and technology to farmers and train them regarding how to adopt the recently developed clean-energy-powered or energy-saving farming machinery, how to better the timing and placement of nitrogen fertilizers, and how to use slow release fertilizers and low-carbon fertilizers and pesticides in the agriculture sector.

More financial incentives especially subsidies and tax reductions should be granted to farmers to cover their extra cost of employing renewable energy and applying less polluting nitrogen fertilizers and pesticides. More investment should be directed to renewable energy development and R&D on the production of environmental friendly fertilizers and pesticides, which will help reduce the level of carbon intensity and pave the way for a sustainable agriculture. It is worth pointing out that, apart from governmental investment, economic incentives and policy interventions are also needed to attract private sectors to get involved in the process of sustainable agriculture development.

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other is through employment of slow release fertilizers and nitrification inhibitors, which are only 5-10 per cent more expensive than the conventional ones but can reduce N_2O emissions by half.

6 Conclusion

The alarming fact that the level of GHG emissions from China's agricultural sector has been increasing over the past decades once again underlies the necessity and urgency for China to adopt a low-carbon agricultural development path. Based on the spatial panel econometric analysis of 31 provinces in mainland China over 1995-2007, this research provides evidence for the existence of spatial lag dependence associated with neighbourhood effects and social interactions among provinces in this context. Given China's regional variations in the light of the use of energy, fertilizers, pesticides, it is important for the Chinese government to bear regional differences in mind when setting emission reduction targets for different provinces (Huang and He 2011). It can be inferred that only by setting targeted emission reduction measures which reflect the regional characteristics of different provinces and their specific adaptation needs can China's low-carbon agricultural development strategy be truly effective.

This research also identifies some important contributing factors for CO_2 emissions in China's agriculture, including agricultural machinery, fertilizer consumption, pesticide employment, agricultural investment and drought. In terms of energy consumption, electricity consumption can contribute to emission reductions, but not necessarily for the diesel consumption. China's actions towards low-carbon agriculture and further actions have been discussed. This paper offers some much-needed advice for China's central and local governments to embark on this highly challenging but also enormously rewarding sustainable agricultural development trajectory. The advice might be worthwhile for emission abatement policies in other developing countries sharing a similar emissions profile and regional characteristics.

References

China Daily (2011). 'China to Tighten Rules on Pesticide Use'. China Daily website.

Chinese Academy of Sciences (2012). *China's Sustainable Development Database*. Available at: http://www.chinasd.csdb.cn/tree.jsp.

Elhorst, J.P. (2010). 'Spatial Panel Data Models'. In M. Fischer and A. Getis (eds), *Handbook of Applied Spatial Analysis*. Springer Berlin Heidelberg, pp. 377-407.

Enerdata (2012). *Global Energy Intelligence's Global Energy Market Data* (emission data updated on 1 March 2012).

Fingleton, B. (2008). 'A Generalized Method of Moments Estimator for a Spatial Panel Model with an Endogenous Spatial Lag and Spatial Moving Average Errors'. *Spatial Economic Analysis*, 3(1): 27-44.

Fingleton, B. (2009). 'Prediction using Panel Data Regression with Spatial Random Effects'. *International Regional Science Review*, 32(2): 195-220.

Hu, B., and M. McAleer (2005). 'Estimation of Chinese Agricultural Production Efficiencies with Panel Data'. *Mathematics and Computers in Simulation*, 68(5-6): 474-83.

Huang, Y., and J. He (2011). 'China's Regional Emissions'. *Nature Climate Change*, 1(7): 347-49.

IPCC (2007). *Climate Change 2007: Mitigation: Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge: Cambridge University Press.

Kapoor, M., H.H. Kelejian, and I.R. Prucha (2007). 'Panel Data Models with Spatially Correlated Error Components'. *Journal of Econometrics*, 140(1): 97-130.

Kelejian, H.H. and I.R. Prucha (1999). 'A Generalized Moments Estimator for the Autoregressive Parameter in a Spatial Model'. *International Economic Review*, 40(2): 509-33.

Ministry of Agriculture The People's Republic of China (2012). *Excerpt of China's 12th Five-Year Plan: Agriculture Part*. Ministry of Agriculture website. Available at: http://english.agri.gov.cn/Topics/12th/201204/t20120428_4365.htm.

Ministry of Agriculture of the People's Republic of China (2009). *Sustainable Development of Agriculture*. Ministry of Agriculture website. Available at: http://english.agri.gov.cn/sa/ca/200906/t20090624_1148.htm.

Norse, D. (2012). 'Low Carbon Agriculture: Objectives and Policy Pathways. *Environmental Development*, 1(1): 25-39.

SAIN (2011). 'Improved Nutrient Management in Agriculture – A Neglected Opportunity for China's Low Carbon Growth Path. Policy Brief 1.

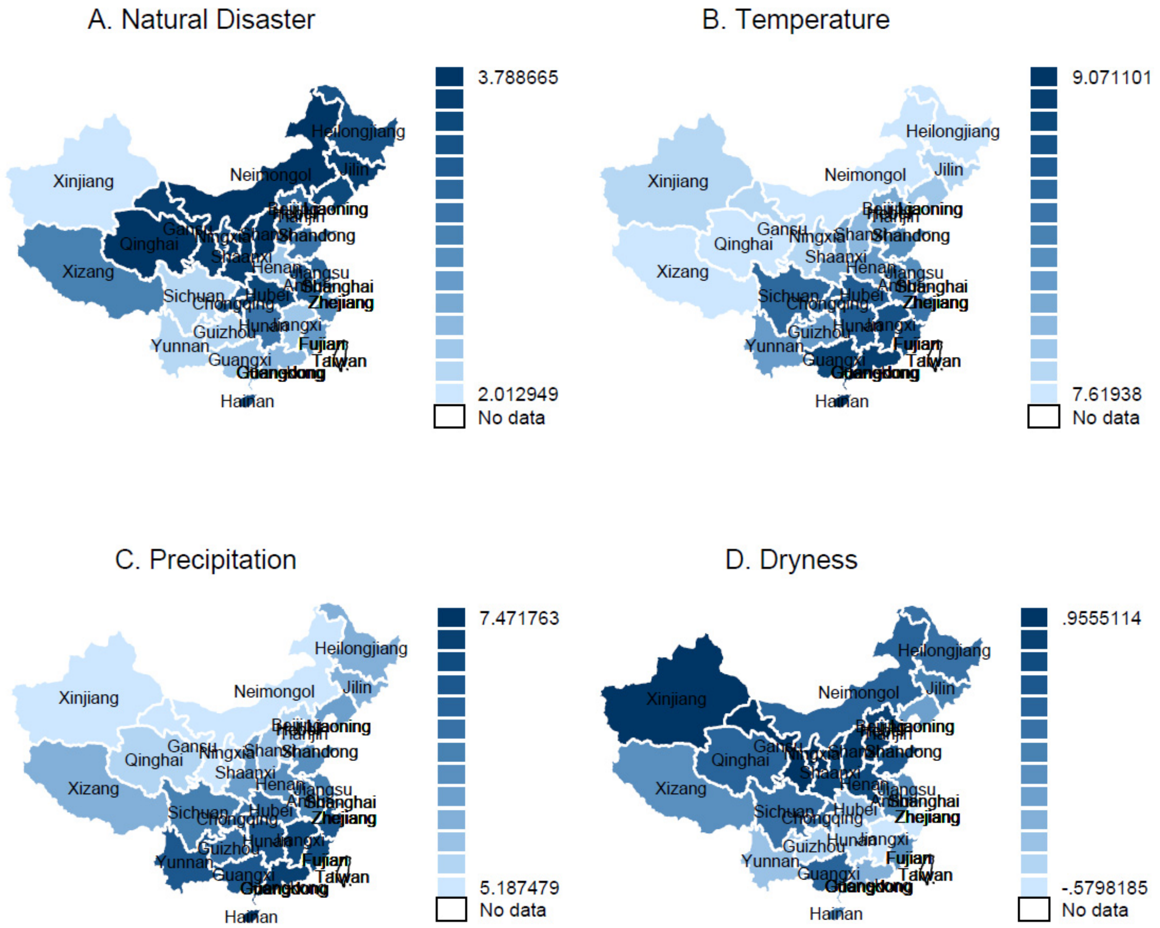
Schnepf, R. (2004). 'Energy use in Agriculture Background and Issues'. UNT Digital Library.

World Bank (2012). World Development Indicators (edition April 2012).

Yu, Y. (2009). CHINA_SPATDWM: Stata Module to Provide Spatial Distance Matrices for Chinese Provinces and Cities. Statistical Software Components S457059, Boston College Department of Economics.

Zhang, Y. et al. (2012). 'Characterizing Spatiotemporal Dynamics of Methane Emissions from Rice Paddies in Northeast China from 1990 to 2010'. *PLoS ONE*, 7(1): e29156.

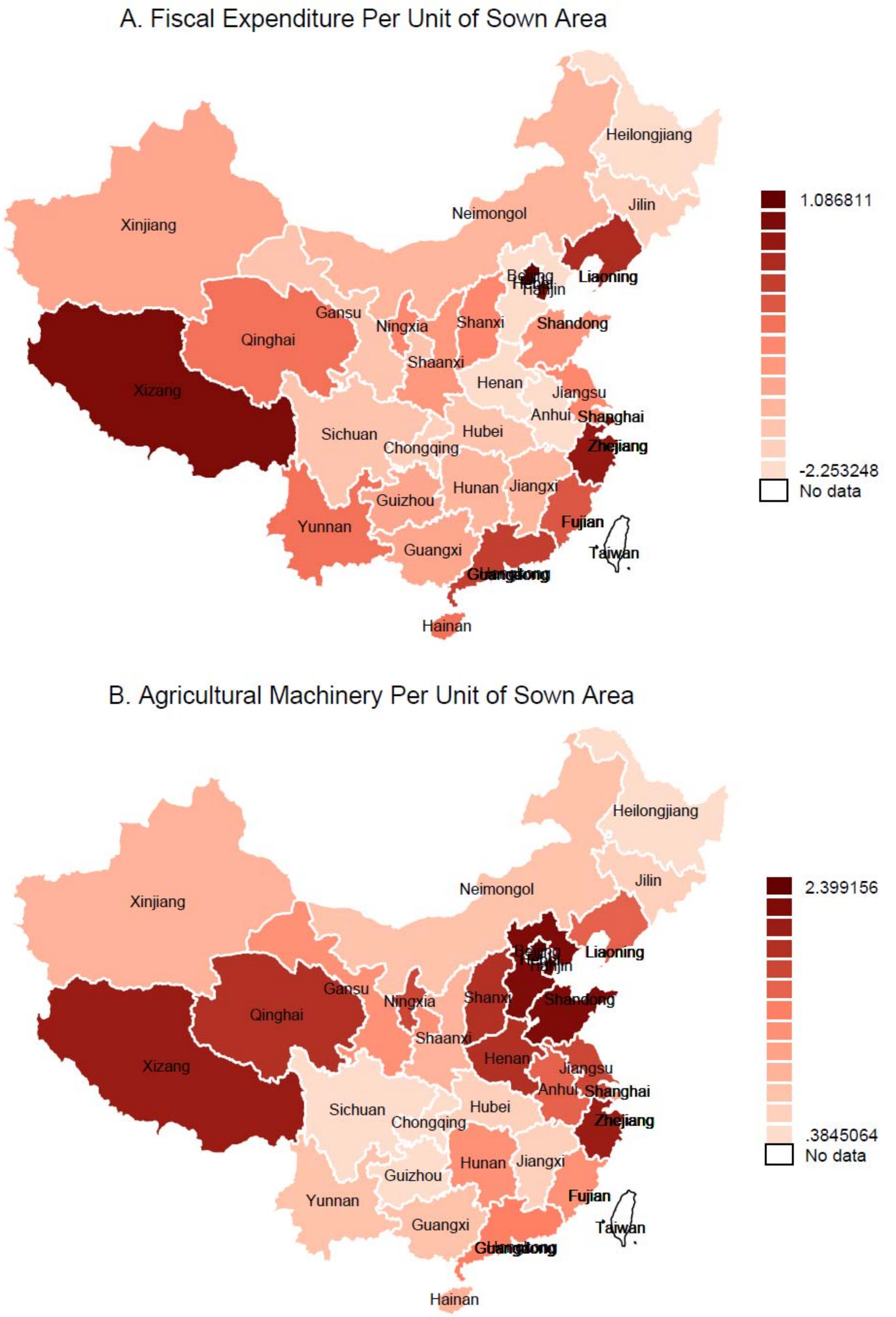
Figure 1: Climate situations for China's agriculture: 31 provinces, 1995-2007



Note: Picture A depicts the averaged ratio of the area affected by natural disaster over total sown area (%). Picture B is about the averaged sum of daily temperature greater than 10 degrees celsius. The average precipitation and dryness are presented in Pictures C and D. Data are from the China's Sustainable Development Database (2012). Variables are in log.

Source: Authors' calculations.

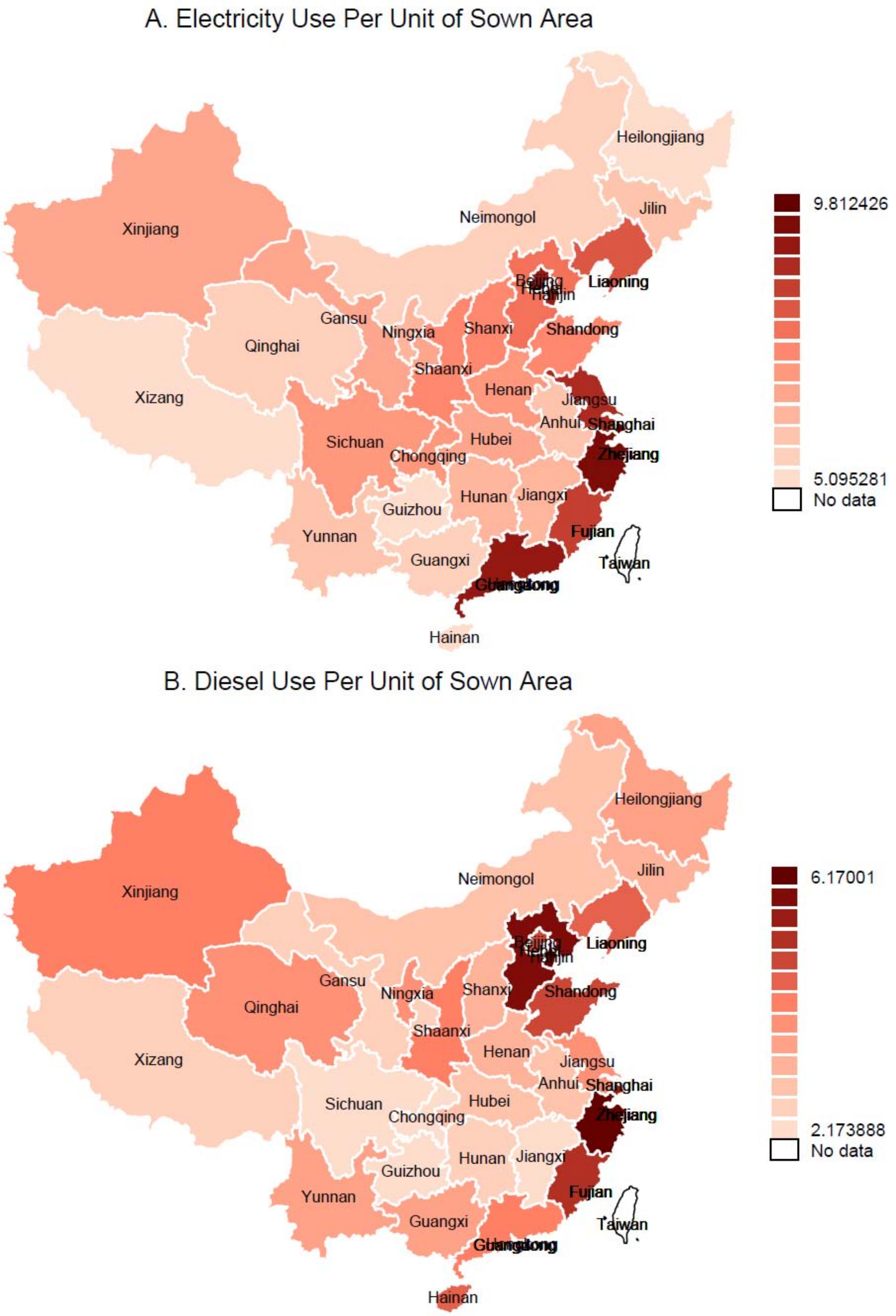
Figure 2: Investment and machinery in China's agriculture: 31 provinces, 1995-2007



Note: See the main text for the description of variables and data source.

Source: Authors' calculations.

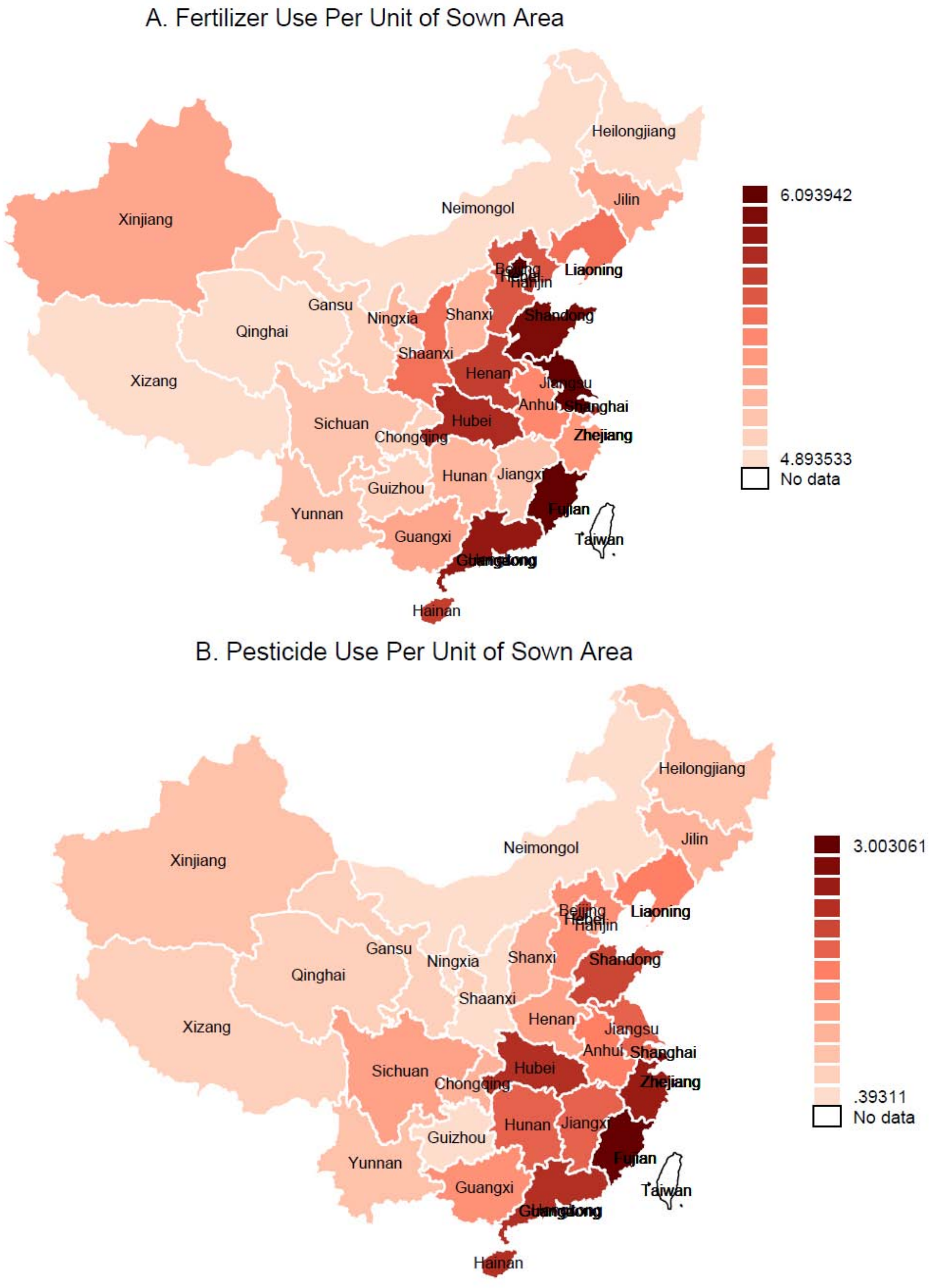
Figure 3: Energy use in China's agriculture: 31 provinces, 1995-2007



Note: See the main text for the description of variables and data source.

Source: Authors' calculations.

Figure 4: Fertilizers and Pesticides in China's Agriculture: 31 provinces, 1995-2007



Note: See the main text for the description of variables and data source.

Source: Authors' calculations.

Table 1: The drivers of China's regional CO_2 emissions in agricultural sector: inverse-distance spatial weighting matrix

Dept variable: CO_2	Fixed effect model	Spatial error model		Spatial SARAR model	
ρ				-0.314***	-0.556***
				(0.003)	(0.000)
MACH	0.008	0.096***	0.010	0.126***	-0.083
	(0.796)	(0.004)	(0.924)	(0.000)	(0.437)
MACH × ELECTRICITY			-0.042***		-0.046***
			(0.001)		(0.000)
MACH × DIESEL			0.081***		0.116***
			(0.000)		(0.000)
FERTILIZERS	0.281***	0.110*	0.108*	0.132**	0.122**
	(0.008)	(0.061)	(0.062)	(0.019)	(0.030)
PESTICIDES	0.108***	0.325***	0.309***	0.341***	0.328***
	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
INVESTMENT	0.083***	0.115***	0.129***	0.115***	0.129***
	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
DROUGHT	0.011	0.106***	0.105***	0.128***	0.147***
	(0.468)	(0.000)	(0.000)	(0.000)	(0.000)
DISASTER	0.054**	0.056	0.037	0.033	-0.012
	(0.039)	(0.178)	(0.367)	(0.429)	(0.779)
Constant	-1.843***	-1.317***	-1.176***	-1.390***	-1.108***
	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	403	403	403	403	403
Number of Provinces	31	31	31	31	31
Adjusted R2	0.65	0.73	0.74	0.74	0.76

Note: This Table compares the fixed effect estimates for the fixed effect model and spatial GLS estimates for the spatial error models and spatial SARAR models. An inverse-distance spatial weighting matrix is used for the spatial error models and spatial SARAR models. The matrix is row-standardized of one. Variables and data sources are described in the text. All equations include year dummies. Robust p-values are in parentheses. *, **, *** significant at 10%, 5%, 1%, respectively.

Source: Authors' calculations.

Table 2: The Drivers of China's Regional CO_2 Emissions in Agricultural Sector: Binary Spatial Weighting Matrix

Dept variable: CO_2	Fixed effect model	Spatial error model		Spatial SARAR model	
ρ				-0.046***	-0.048***
				(0.000)	(0.000)
MACH	0.008	0.107***	0.047	0.145***	0.049
	(0.796)	(0.001)	(0.656)	(0.000)	(0.623)
MACH × ELECTRICITY			-0.038***		-0.036***
			(0.004)		(0.003)
MACH × DIESEL			0.069***		0.075***
			(0.000)		(0.000)
FERTILIZERS	0.281***	0.093	0.097	0.093	0.089
	(0.008)	(0.126)	(0.102)	(0.120)	(0.127)
PESTICIDES	0.108***	0.326***	0.312***	0.346***	0.330***
	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
INVESTMENT	0.083***	0.113***	0.125***	0.124***	0.134***
	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
DROUGHT	0.011	0.105***	0.104***	0.152***	0.154***
	(0.468)	(0.000)	(0.000)	(0.000)	(0.000)
DISASTER	0.054**	0.053	0.035	0.031	0.011
	(0.039)	(0.182)	(0.385)	(0.411)	(0.778)
Constant	-1.843***	-1.210***	-1.115***	-1.138***	-0.989***
	(0.004)	(0.001)	(0.001)	(0.001)	(0.003)
Observations	403	403	403	403	403
Number of Provinces	31	31	31	31	31
Adjusted R2	0.65	0.73	0.74	0.75	0.75

Note: A binary spatial weighting matrix giving a weight of 1 to all sample points within a 1200km neighbourhood and zero otherwise is used for the spatial error models and spatial SARAR models. See Table 1 for more notes.

Source: Authors' calculations.

Appendix Table 1: Descriptive statistics

Variable		Mean	Std. Dev.	Min	Max	Observations	
co2	overall	0.048	0.469	-0.978	1.158	N =	403
	between		0.455	-0.721	0.869	n =	31
	within		0.139	-0.347	0.421	T =	13
MACH	overall	1.211	0.572	-0.105	3.447	N =	403
	between		0.510	0.385	2.399	n =	31
	within		0.273	0.451	3.193	T =	13
ELECTRICITY	overall	7.115	1.243	4.468	10.691	N =	403
	between		1.209	5.095	9.812	n =	31
	within		0.359	5.739	8.152	T =	13
DIESEL	overall	4.422	0.849	1.825	6.667	N =	403
	between		0.821	2.174	6.170	n =	31
	within		0.257	3.484	6.175	T =	13
FERTILIZERS	overall	5.557	0.377	4.225	6.389	N =	403
	between		0.351	4.894	6.094	n =	31
	within		0.149	4.841	6.129	T =	13
PESTICIDES	overall	1.897	0.778	0.182	3.500	N =	403
	between		0.763	0.393	3.003	n =	31
	within		0.200	1.356	2.855	T =	13
INVESTMENT	overall	-1.266	1.185	-3.669	3.155	N =	403
	between		0.824	-2.253	1.087	n =	31
	within		0.864	-4.063	0.968	T =	13
DISASTER	overall	3.248	0.468	0.788	4.072	N =	403
	between		0.345	2.013	3.789	n =	31
	within		0.323	2.023	4.026	T =	13
DROUGHT	overall	0.000	1.000	-1.499	2.534	N =	403
	between		0.977	-1.372	1.664	n =	31
	within		0.271	-1.061	0.888	T =	13
	between		0.977	-1.372	1.664	n =	31
	within		0.271	-1.061	0.888	T =	13

Note: See the main text for the description of each variable.

Source: Authors's calculations.

Appendix Table 2: Correlations among variables

	CO_2	MACH	ELECTRICITY	DIESEL	FERTILIZERS	PESTICIDES	INVESTMENT	DISASTER	DROUGHT
CO_2	1.000								
MACH	0.390	1.000							
ELECTRICITY	0.534	0.507	1.000						
DIESEL	0.515	0.607	0.673	1.000					
FERTILIZERS	0.611	0.421	0.696	0.566	1.000				
PESTICIDES	0.760	0.290	0.591	0.467	0.717	1.000			
INVESTMENT	0.525	0.542	0.536	0.445	0.370	0.319	1.000		
DISASTER	-0.230	0.136	-0.191	-0.053	-0.137	-0.252	-0.092	1.000	
DROUGHT	0.465	-0.267	0.115	-0.047	0.284	0.584	0.011	-0.287	1.000

Note: See the main text for the description of each variable.

Source: Authors' calculations.