Mechanisms of agricultural scale affecting greenhouse gas emissions

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Abstract

Agriculture is a significant contributor to anthropogenic global warming. In recent years, agricultural greenhouse gases (GHG) emissions in China, which is the largest emitter of agricultural GHG, had been decreasing. In order to identify whether or not Chinese agricultural development had affected the GHG emission, we used logarithmic mean Divisia index (LMDI) factor decomposition model to investigate the effect of productivity factors on GHG emission and their characteristics in the four phases of Chinese agricultural development. Our results indicated that land productivity as the most significantly promotion faction factor contributes to 1.12 Gt CO_2e GHG emission growth. On the contrary, technological input intensity exerts an obvious mitigating effect with 1.57 Gt CO_2e GHG emission reduction. The effects of productivity factors on GHG emission indicated that there were important differences of productivity factors influential direction between in household-based farming system and in large-scale management system. A more nuanced perspective on the significant role of agricultural large-scale management in GHG emission could aid climate change mitigation.

Keywords: agricultural scale, LMDI, productivity, agricultural development phases

1 Introduction

Agriculture is a significant contributor to anthropogenic global warming which is responsible for 21%-37% of annual greenhouse gases (GHG) emission (Mbow et al., 2019). Direct agricultural emission is unusual in being dominated by CH_4 and N_2O, with agricultural activity generating around half of all anthropogenic methane emissions and around three-quarters of anthropogenic N_2O emissions (Lynch et al., 2021). Therefore, agriculture is facing new challenges on how to coordinate the production increases with the greenhouse gas emissions reduction.

China is an important agricultural country and also the largest emitter of agricultural GHG emission (Zhu et al., 2018). China is also a typical region, still dominated by agricultural evolution since 1978. With 1999 as demarcation point, household contract system (HCS) and moderate scale management (MSM) were implemented in succession. In the course of HCS, it was executed based on the responsibility system of contract for production and work to households before 1984, and by means of reform of rural economic system and legislation hereafter. During 1999-2008, MSM had been realized by means of socialized service, and land transfer and cooperation. After 2009, the agricultural management scale is further expanded in various forms including innovative agricultural management units (e.g. family farm, professional household, peasant cooperative, agricultural industrialization leading enterprises, etc.) and innovative agricultural service units who provide professional and large-scale service such as replaced plough and sow, combined tillage and land trust for continuous tillage. The latest agricultural census data show that number of large-scale agricultural operators is 3.98 million households accounting for 2% of national agricultural operators (NBS, 2017).

Research showed that agricultural scale management characterized by centralized use and effective management of land and concentrated input of production factors to land could affect the greenhouse gases emissions (Ma & Guo, 2012; DRC, 2018). The aim of this study is to uncover the relationship between agricultural development and GHG emission. Firstly, we estimated agricultural GHG emission from 1979 to 2015. Secondly, we divided agricultural development into four stages according to the characteristics of agricultural management. Thirdly, using the Logarithmic Mean Divisia Index (LMDI) factor decomposition model, we highlight the main role of agricultural management scale and quantify various relevant productivity factors of GHG emission and their characteristics in the four phases of

Chinese agricultural development.

2 Materials and Methods

2.1 GHG emission calculation

The accounting system boundary was established according to life cycle assessment to estimate agricultural GHG emission. Firstly, the GHG emission from agricultural inputs production were calculated including the production emission of fertilizer, pesticide and agri-film and collection, storage and use emission of irrigation water. Secondly, the GHG emissions from draft stock management were computed including enteric fermentation and manure management. Thirdly, the GHG emissions from fuel consumption were obtained from machinery diesel oil consumption for tillage, seeding, fertilization, etc. Fourthly, the GHG emissions of soil management were reckoned from soil organic carbon decomposition, anaerobic decomposition of organic material in flooded rice fields, background and fertilizer-induced N_2O emission and urea fertilization emission. In the accounting system, we also estimated the GHG emission of crop residue open burning and GHG sink of crop residue returned to soil and used as alternative energy. The accounting data were obtained from statistical yearbook and relational database (EBCAY, 1980-2016; NBS, 1980-2016, 2015; ISSCAS, 1985).

We calculated CO_2 emission from agricultural inputs production, including CO_2 emission from fertilizer production, pesticide production, agricultural film production and collection, storage and use of irrigation water. Formulas and emission factors for calculating agricultural inputs production were obtained according to Chen et al. (2015) and West and Marland (2002). In this method, the consumptions of fertilizer, pesticide and agricultural film and the areas of electromechnical irrigation and drainage were obtained from China Rural Statistics Yearbook and China Agriculture Yearbook

(EBCAY, 1980-2016; NBS, 1980-2016).

$$E_{ap} = \sum_i A_i \times f_{ap_i}$$

where E_{ap} is CO_2 emission from agricultural inputs production, including fertilizer, pesticide, agri-film and irrigation water, A_i is application of fertilizer, pesticide, agri-film, and electromechanical irrigation and drainage area, f_{ap_i} is emission factor for fertilizer, pesticide, agri-film and irrigation water.

We calculated GHG emission from draft stock management, including CH_4 emission from enteric fermentation and CH_4 and N_2O emission from manure management. Formulas for computing draft stock management and the values of emission factors for CH_4 from enteric fermentation, N_2O from manure management and CH_4 from manure management were acquired according to IPCC (2006). In this method, the number of draft stocks was from China Rural Statistics Yearbook (NBS, 1980-2016).

$$E_{ds} = \sum_i N \times f_{ds_i}$$

where E_{ds} is GHG emission from draft stock management, including enteric fermentation and manure management, N is the number of draft stock, f_{ds_i} is emission factor for enteric fermentation and manure management.

We calculated CO_2 emission from fuel consumption, mainly the diesel consumption. Formulas for obtaining fuel consumption were got according to West and Marland (2002) and IPCC (2006). In this method, the consumptions of diesel were from China Rural Statistics Yearbook (NBS, 1980-2016). The emission factor for diesel was obtained according to Chen et al. (2015).

$$E_{fu} = A_{fu} \times f_{fu}$$

where E_{fu} is CO_2 emission from fuel consumption, A_{fu} is consumption of fuel, f_{fu} is emission factor for fuel consumption.

CO_2 emission changes for soil management can be calculated by quantifying the decomposition of soil organic matter, the CH_4 emissions from rice cultivation, the background emission plus the fertilizer-induced emission and the CO_2 emission from urea fertilization. Formulas and emission factors for reckoning soil management were obtained according to Aguilera et al. (2018), Zhang et al. (2013), Berdanier and Conant (2012) and IPCC (2006). In the method, we summarized the decomposition rate of soil organic carbon in different spatial and temporal scales. C input to the method was the amount of soil organic carbon from 0 to 20 cm in China. In the method, data of cultivated areas, N and urea fertilizer amounts from 1979 to 2015 were obtained from China Rural Statistics Yearbook (NBS, 1980-2016).

$$E_{od} = C \times r_d$$

$$E_r = A_r \times f_r$$

$$E_N = A \times f_b + f_{N_2O} \times AM_N$$

$$E_u = AM_N \times r_u \times f_u$$

where E_{od} is CO_2 emission from organic matter decomposition, C is the amount of soil organic carbon, r_d is annual decomposition rate of soil organic carbon, E_r is CH_4 emission from rice cultivation, A_r is cultivated area of rice, f_r is emission factor for rice, E_N is N_2O emission from cultivated soil, A is cropland area, f_b is background emission rate, f_{N_2O} is fertilizer-induced N_2O emission rate, AM_N is N fertilizer application, E_u is CO_2 emission from urea, r_u is the fraction urea in N fertilizer, f_u is emission factor for urea.

We calculated the CO_2 emission changes by quantifying the organic carbon amount of crop residue returned to soil as addition of organic matter to the soil, the emissions from crop residue burning based on the amounts of crop residue burnt, combustion factor and emission factors and CO_2 abatement of alternative energy from crop residue based on the amounts of alternative energy and power consumption of alternative energy production. Formulas and factors for estimating crop residue treatment were achieved according to Aguilera et al. (2018), Li et al. (2017), Lucian and Fiori (2017), Hong et al. (2016), Zeng et al. (2007), Zhang et al. (2007), IPCC (2006) and Leung et al. (2004). In the method, the amounts of crop residue returned, and soil organic matter are expressed as dry matter. Data of crop yield from 1979 to 2015 are obtained from China Rural Statistics Yearbook (NBS, 1980-2016). In addition, calorific values and efficiency of alternative energy and fossil energy are taken into consideration. Amounts of alternative energy from crop residue were also obtained from China Rural Statistics Yearbook (NBS, 1980-2016), including pyrolysitic gasification, anaerobic digestion, carbonization and briquetting.

$$E_{cb} = AM_{cb} \times C_f \times f_{\mathrm{cb}}$$

$$AE_{cr} = 0.58 \times \sum_i h_{c_i} \times Y_i \times r_{dr_i} \times r_{sg_i} \times r_{s_i}$$

$$AE_{ce} = A_e \times \frac{CV_e \times \eta_e - r_{cost}}{CV_f \times \eta_f} \times f_f$$

where E_{cb} is GHG emission from crop residue burning, AM_{cb} is amount of burning crop residue (dry), C_f is combustion factor, f_{cb} is emission factor for crop residue burning, AE_{cr} is CO_2 abatement of crop residue returned to soil, h_c is humification coefficient of the crop residues, Y is crop yield, r_{dr} is dry matter fraction, r_{sg} is ratio of crop straw to grain, r_s is ratio of crop residue returned to soil, i represents different crops, AE_{ce} is carbon abatement of alternative energy, A_e is amount of alternative energy, including gas, carbonization and briquetting, CV_e is calorific values of alternative energy, CV_f is calorific values of fossil energy, η_e is efficiency of alternative energy, η_f is efficiency of fossil energy, r_{cost} is power consumption of alternative energy production, f_f is emission factor of fossil energy.

2.2 LMDI factor decomposition model

LMDI method is used to analyze the relationships and driving effects between agricultural management and carbon emissions efficiency. To better investigate the driving factors on GHG emissions change, this paper makes contribution to three aspects. First, based on data availability, the time span (1979-2015) of data samples is longer than those of existing studies on Chinese cropland GHG emissions, presenting more detailed information on historical trend of cropland GHGs emission changes in China. Second, based on the characteristics of agricultural management in China, the time span is divided into four phases. From 1978, China's agricultural development has gone through four phases. The phases of popularizing the household contract system (1978-1984), improving the household contract system (1985-1998), exploring the moderate scale management of agriculture (1999-2008) and promoting scale management in various forms (since 2009) were implemented in succession. Thus, the four phases are 1979-1984 (phase I), 1985-1998(phase II), 1999-2008(phase III) and 2009-2015 (phase IV). Third, existing LMDI decomposition analysis model (Ang, 2005; Shao et al., 2016; Yu & Kong, 2017) is extended not only considering the conventional driving factors of cropland GHG emission changes, such as cropland energy related input structure and output scale, but also including the productivity factors specially adapted to reflect effect of agricultural management mode on cropland GHG emission changes. It provides better understanding on the real roots of cropland GHG emission changes so that the decision-makers can make more appropriate agricultural management and emission-reduction policies. We adopted the LMDI approach to decompose the cropland GHG emission changes into the following eight productivity factors.

$$E_c = \frac{E_c}{A_l} \cdot \frac{A_l}{A_t} \cdot \frac{A_t}{I_m} \cdot \frac{I_m}{Y_c} \cdot \frac{Y_c}{A_c} \cdot \frac{A_c}{A_l} \cdot \frac{A_l}{P} \cdot P = I_{ce} \cdot I_t \cdot A_{tf} \cdot R_{io} \cdot P_l \cdot I_{mc} \cdot L_p \cdot P$$

where E_c is CO_2-equivalent emissions, A_l is cropland area, A_t is agro-technician number, I_m is material consumption input, Y_c is crop yield, A_c is cultivated area, P is agri-population, I_{ce} is GHG emission intensity, I_t is technological input intensity, A_{tf} is tech-fund allocation ratio, R_{io} is input-output ratio, P_l is land productivity, I_{mc} is multi-cropping index, L_p is cultivable land per agri-labor.

2.3 Productivity factors

We formulated productivities and associated effect dynamics for different agricultural management mode using LMDI approach (Ang, 2005). Productivities used in LMDI approach, including GHGs emission intensity (I_{ce}), technological input intensity (I_t), tech-fund allocation ratio (A_{tf}), input-output ratio (R_{io}), land productivity (P_l), multi-cropping index (I_{mc}) and cultivable land per agri-person (L_p), are derived from agricultural management characteristic and accounting methodology. The productivities are calculated using equation (1). The data used in the formulas are obtained from China Rural Statistics Yearbook. It is worth mentioning that the material consumption input (I_m) is estimated using energy value as standard.

3 Results

3.1 Greenhouse gas emission and intensity

The amounts and intensity of cropland GHG emission are given in Fig.1. The Chinese GHGs emissions of cropland from 1979 to 2015 is estimated at 1.28 Gt CO_2e yr^{-1}, with a range between 1.02-1.52 Gt CO_2e yr^{-1}. There was an upward trend for both GHG emission and intensity during phase I

(1979-1984) with average annual growth rates of 1.87% and 1.21%, respectively. During phase II (1985-1998), the similar trend with lower average annual growth rates of 0.97% and 0.79% was observed. During phase III (1999-2008), the GHG emission reached the peak at 1.52 Gt CO_2e yr^{-1} by 2006. In this phase, the average annual growth rate of emission intensity was -1.34%. During phase IV (2009-2015), the opposite trend was observed with average annual growth rates of -1.06% and -2.61%.

3.2 Contributions of productivity factors

The decomposition results of GHG emission changes are given in Fig.2 and Fig.3. The contributions of productivity factors to GHG emissions changes were discussed, which refer to the proportion of GHG emissions changes caused by each factor in the entire period and in the specific period. The contributions of each factor were calculated through the multiplicative and additive decomposition. With contributions from high to low orders during 1979-2015, the promotion factors of GHG emissions are P_l (110.73%), R_{io} (65.01%), A_{tf} (54.90%) and L_P (45.84%), while the mitigating factors are I_t (-154.76%), I_{mc} (-75.88%), I_{ce} (-13.20%) and agri-population (-2.37%). The results show that total promotion effects (276.48%) are much greater than total mitigating effects (-246.22%), causing a remarkable increase of 30.26% in GHG emissions over 1979-2015. Particularly, the multiplicative and additive decomposition results of land productivity are 2.63 and 1.12 Gt CO_2e, respectively, resulting in that P_l is the largest driver of GHG emissions growth. Correspondingly, I_t is the largest driver of GHG emissions mitigation with the results of 0.26 and -1.57 Gt CO_2e.

3.3 Influential direction of productivity factors at different stages

To further explore the characteristics and reasons of GHG emissions changes, we regard four stages according to China's agricultural development and compare the decomposition results at each stage.

Since 1978, the Chinese government have proposed a plan for comprehensive implementation of agricultural household management for agriculture industrialization. During the first two phases (popularizing the household contract system and improving the household contract system), A_{tf}, R_{io}, P_l and agri-population remain positive effects on GHG emissions revealing the dominant effects of high input for high output management on GHG emissions growth. However, during the last two phases (exploring the moderate scale management of agriculture and promoting scale management in various forms), A_{tf} and agri-population show the mitigating effects on GHG emissions and R_{io} and P_l show weaker positive effects, attributed to the implementation of moderate large-scale management. While I_t and L_P took negative effects in the first two phases and positive effects in the last two phases indicating that agricultural scale expansion has the strong effects on GHG emissions growth.

4 Discussion

In order to ensure the continuity and comparability of the data, the effects of certain factors on the GHG emission were ignored. A_{tf}, P_l and R_{io} are the prominent factors for GHG emission in the first phase. These three factors experienced upward trends by average annual growth rates between 8.6% and 3.4% (Fig.2). The increases in GHG emission resulting from the three factors are 0.38, 0.28 and 0.17 Gt CO_2 equiv. (Fig.3) with the contributions of 37.6%, 27.1% and 16.5%, respectively. In this phase, the agricultural management system represented household-based farming system was implemented (Gong, 2018; Ren et al., 2019). Agriculture development characterized by decollectivization and decentralization induced material consumption and GHG emission. In this study, we find that P_l increased significantly in 1979-1984 which was the target of household contract system. Therefore, agricultural material consumption rise was the concomitant outcome of increasing P_l and agriculture development. Land fragmentation resulted from household-based farming system brought excess agricultural inputs which mismatched the demands of production increase and input of science and technology. It was the reason for GHG emission increase caused by the increases of A_{tf} and R_{io}.

Economic system and subsidy system were reformed in the second phase. On the one hand, market driven economic system made agricultural production grow slowly due to the diminishing returns from the implementation of household contract system (Ren et al., 2019). The average annual increase in GHG emission resulting from P_l was 0.06 Gt CO_2 equiv. (Fig.3) with the contributions of 77.1% indicating that agricultural production demand was still a powerful drive for GHG emission. On the other hand, to meet food security objective, fertilizer related subsidies increased the affordability of fertilizers to farmers at all levels (Ren et al., 2019). It also resulted in a drop in agricultural inputs efficiency (Fan et al., 2011) that led to the deeper mismatch. Conversely, I_t had a mitigating effect on GHG emission in the first two phases, causing the average annual GHG emission reductions of 0.15 and 0.17 Gt CO_2 equiv. (Fig.3), respectively.

In the third phase, moderate scale management of agriculture has been realized by means of socialized service, and land transfer and cooperation. Land contiguous planting were growing up. We found that there were decrease trends in the material consumption per cropland area, such as fertilizer, pesticide, and agricultural film. As a result, the relationships between material consumption and the demands of production increase and input of science and technology were more fitting. Moreover, the increases in GHG emission resulting from R_{io} and A_{tf} are 0.025 and -0.111 Gt CO_2 equiv. (Fig.3) with the contributions of 2.5% and -11.0%, respectively.

It is worth mentioning that the values of I_t decreased in phase I and phase II and increased in phase

III and phase IV. In the first two phases, small size and fragmented plots limited the introduction of technological input which concentrated on some new technologies such as hybrid rice (Ren et al., 2019; Gong, 2018). From the third phase, modern agricultural techniques began to spread. Agricultural machines moved frequently between small and scattered plots resulting in higher GHG emission sourced from fuel consumption for different agricultural operations (Zhu et al., 2018). Similar to I_t, the effects of labor related factors displayed distinct instability owing to machinery as a substitute for labor.

In the last phase, the Chinese government had encouraged the large-scale farming operation by means of joint-household management, professional large family and family farm (State Council, 2012). Agricultural factors, such as productivity, efficiency, etc. may be closely related to farm size (Ren et al., 2019). Previous studies had found that increasing the scale of farming operations may improve resource use efficiency and significantly reduce GHG emission (Zhu et al., 2018; Huang et al., 2011; Pishgar-Komleh et al., 2012; Yan et al., 2015; Ju et al., 2016). Therefore, the effects of productivity factors on GHG emission were similar to that in the third phase (Fig.2 and Fig.3). Overall, I_t, A_{tf}, R_{io}, L_P and agri-labor exert the significantly opposite effects on GHG emission in order to contrast the first and last two phases. Among the inconsistent effects of productivity factors on GHG emission, scattered land structure due to household management makes agricultural technology extension and agricultural productivity improvements less effective, indicating that it is very critical to take into account how to carry out large-scale management on the basis of household contract system. In the future, to better explore the carbon mitigation in agricultural large-scale management, we can focus on biomass carbon sequestration, product decision-making information systems and energy combustion efficiency.

5 Conclusion

37-year historical GHG emissions show that there are rising trends of GHG emission and intensity during 1979-1998 and contrary trends of those are observed from 2006 during 1999-2015. Using LMDI model, we decompose GHG emission of cropland over 1979-2015 into 8 productivity factors reflecting the policy cause of GHG emission changes and examining the effects of agricultural management on efficiencies and GHG emission. Our results indicate that land productivity is the most significantly promotion faction factor of GHG emissions and that technological input intensity exerts an obvious mitigating effect on GHG emission.

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Figure legends

Figure 1 Cropland greenhouse gas (GHG) emission and GHG emission intensity

The histogram charts show the amounts of GHG in Chinese Mainland from 1979 to 2015. The line chart shows the emission intensity represented by GHG emission per area of cropland.

Figure 2 Multiplicative decomposition results of GHG emission changes in the entire period (1979-2015) and four phases

Part a shows the multiplicative decomposition results of GHG emission changes in the entire period (1979-2015). Part b shows the multiplicative decomposition results of GHG emission changes in the four phases. The line charts show the different phases. DI_{ce}, DI_t, DA_{tf}, DR_{io}, DP_l, DI_{mc}, DL_p and DP denote the effects of GHGs emission intensity, technological input intensity, tech-fund allocation ratio, input-output ratio, land productivity, multi-cropping index, cultivable land per agri-person and agricultural population, respectively.

Figure 3 Additive decomposition results of GHG emission changes in the entire period (1979-2015) and four phases

The histogram charts show the different phases. ΔCI_{ce}, ΔCI_t, ΔCA_{tf}, ΔCR_{io}, ΔCP_l, ΔCI_{mc}, ΔCL_p and ΔCP denote the effects of GHGs emission intensity, technological input intensity, tech-fund allocation ratio, input-output ratio, land productivity, multi-cropping index, cultivable land per agri-person and agricultural population, respectively.

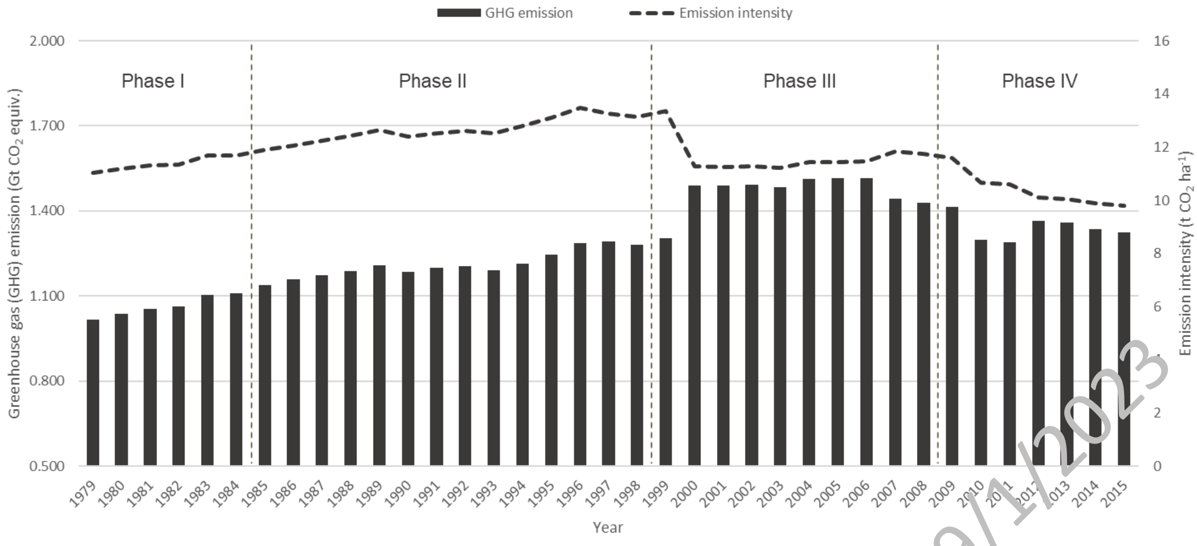

Figure 1 Cropland greenhouse gas (GHG) emission and GHG emission intensity

The histogram charts show the amounts of GHG in Chinese Mainland from 1979 to 2015. The line chart shows the emission intensity represented by GHG emission per area of cropland.

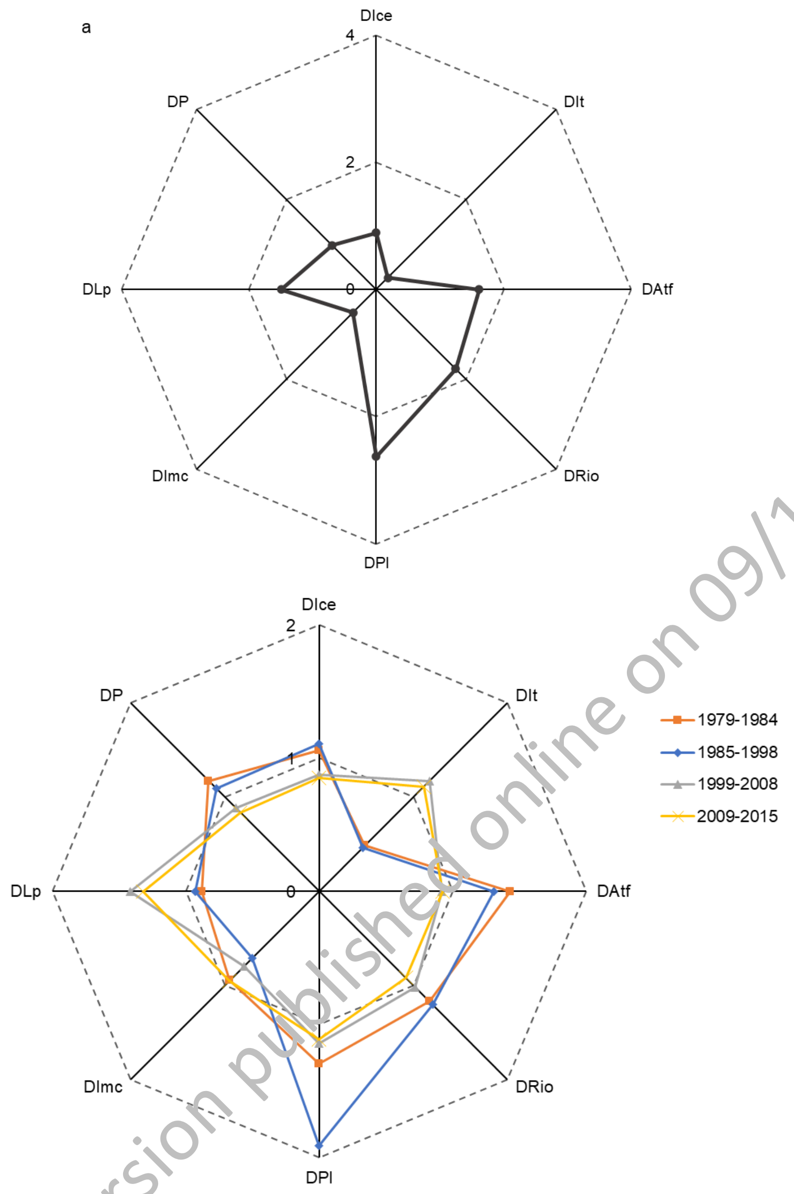

Figure 2 Multiplicative decomposition results of GHG emission changes in the entire period (1979-2015) and four phases

Part a shows the multiplicative decomposition results of GHG emission changes in the entire period (1979-2015). Part b shows the multiplicative decomposition results of GHG emission changes in the four phases. The line charts show the different phases. DI_{ce}, DI_t, DA_{tf}, DR_{io}, DP_l, DI_{mc}, DL_p and DP denote the effects of GHGs emission intensity, technological input intensity, tech-fund allocation ratio, input-output ratio, land productivity, multi-cropping index, cultivable land per agri-person and agricultural population, respectively.

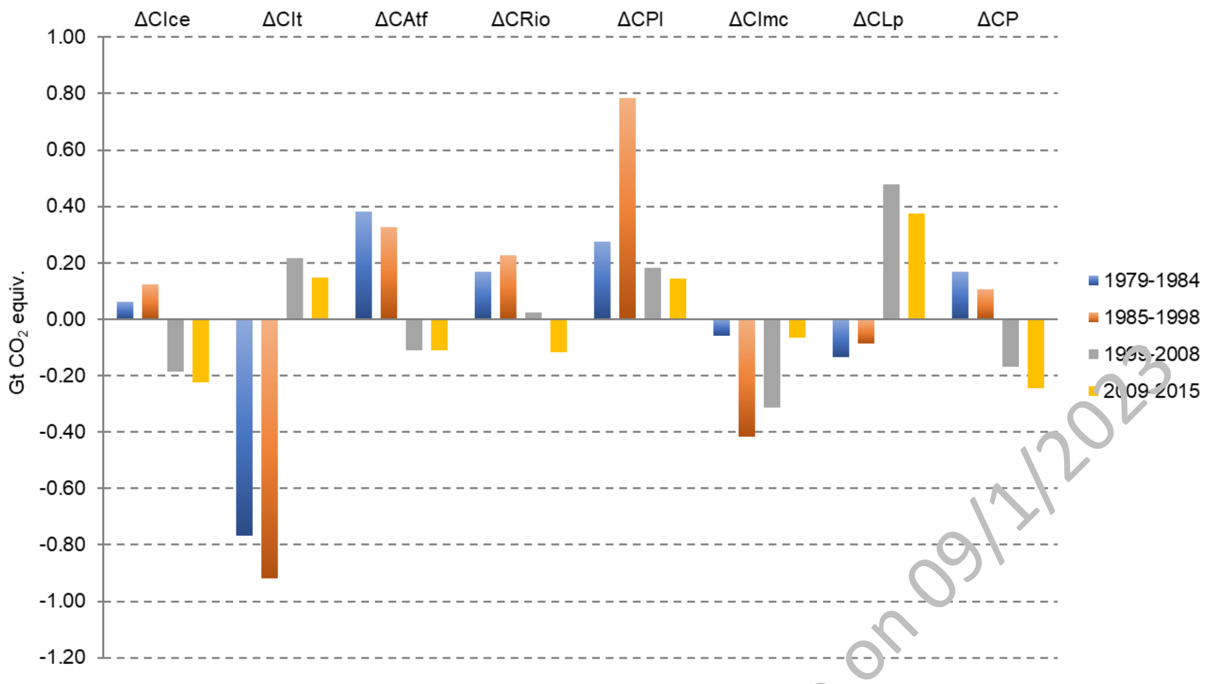

Figure 3 Additive decomposition results of GHG emission changes in the entire period (1979-2015) and four phases

The histogram charts show the different phases. ΔCI_{ce}, ΔCI_{t}, ΔCA_{tf}, ΔCR_{io}, ΔCP_{l}, ΔCI_{mc}, ΔCL_{p} and ΔCP denote the effects of GHGs emission intensity, technological input intensity, tech-fund allocation ratio, input-output ratio, land productivity, multi-cropping index, cultivable land per agri-person and agricultural population, respectively.