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Impact of carbon pricing on mitigation potential in Chinese agriculture: A model-based multi-scenario analysis at provincial scale

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ABSTRACT

China's 'dual carbon' goals seek to achieve peak CO_2 emissions before 2030 and carbon neutrality before 2060. China is one of the world's largest emitters of agricultural greenhouse gases. Although existing studies have evaluated GHG mitigation potential in Chinese agriculture, few built models by incorporating socioeconomic conditions, technology diffusion, and carbon pricing policies. This study developed a bottom-up Agricultural Technology Optimisation Model (ATOM) for GHG mitigation, which selected optimal mitigation measure portfolios by minimising costs based on inventories of agricultural GHG and mitigation measures. It was employed to quantify long-term mitigation potential in Chinese agriculture under a range of socioeconomic and carbon pricing scenarios. GHG emissions in Chinese agriculture totalled 720.3 $MtCO_2e$ in 2017. Assuming an SSP2 scenario, the maximum technical mitigation potential of the evaluated measures in 2060 will be 554.1 $MtCO_2e$, with 78.2% contributed by mitigation measures for crop production. 38.9% of this potential is possibly achievable with negative cost mitigation measures, and carbon pricing can help achieve greater emission reductions. Chinese agriculture theoretically possesses significant mitigation potential, but the implementation of mitigation measures may be hindered by multiple obstacles. The government should adopt counterstrategies to ensure that the agricultural sector remains on track to meet China's carbon neutrality goal.

1. Introduction

Greenhouse gas (GHG) emissions from human activities are the main cause of global warming (Montzka et al., 2011). During the 2010s, the agriculture, forestry, and other land use (AFOLU) sectors contributed an average of 13–21% of global total anthropogenic GHG emissions. Major sources of agricultural GHG emissions include rice cultivation, synthetic fertiliser application, enteric fermentation, manure management, managed soils and pasture, and biomass burning (IPCC, 2022). The GHGs released by these activities include CO_2 and non-CO_2 GHGs (mostly methane [CH_4] and nitrous oxide [N_2O]) (Nayak et al., 2015). Non-CO_2 GHGs are more potent than CO_2 in terms of warming the planet (Lynch, 2019; Ragnauth et al., 2015). The 100-year global warming potentials (GWP100) of CH_4 and N_2O are 27.9 and 273 CO_2 equivalents (CO_2e), respectively, according to the IPCC AR6 (IPCC, 2022). Agriculture is the largest source of anthropogenic non-CO_2 GHG emissions (Beach et al., 2015; Frank et al., 2018; Wang et al., 2023), contributing to 40% of total CH_4 emissions and 60% of total N_2O emissions (Frank et al., 2019). China has a large agricultural sector (Cui et al., 2022). In 2014, China's agricultural activities contributed 6.7% (830 $MtCO_2e$) of the nation's total GHG emissions (MEE, 2018a). In 2007, the Chinese government identified 'reducing GHG emissions from agricultural sources by altering land use patterns and regulating agricultural production methods' as a key task. However, limited progress has been

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made in this area (Hu et al., 2020). Recently, with the announcement of China's 'dual carbon' goal (EF, 2020), research has focused on measures compatible with decreasing agricultural GHG emissions and achieving sustainable agriculture while ensuring food security.

Agricultural GHG mitigation measures can be classified into three categories according to the mechanism: reducing emissions, enhancing removal, and displacing emissions (Pellerin et al., 2017); the first two categories are more common (Northrup et al., 2021). Reducing emissions involves restricting GHG fluxes through the implementation of more efficient management of carbon and nitrogen flows in agro-ecosystems. CH_4 emissions can be reduced by improving irrigation practices and increasing the feed utilisation efficiency of ruminants, whereas N_2O emissions can be reduced by decreasing nitrogen fertiliser application and improving the nitrogen use efficiency of crops; both CH_4 and N_2O emissions can be reduced by more effective livestock manure management (Herrero et al., 2016; Reay et al., 2012; Rees et al., 2013; Shang et al., 2021; Xu et al., 2019). CO_2 removal measures provide the largest land-based mitigation potential (Roe et al., 2019). Straw return to the field is a common carbon sequestration measure; an even greater GHG mitigation potential are achieveable by returning crop straw after it has been converted to biochar via pyrolysis than by direct return (Xia et al., 2023). Researchers have studied agricultural GHG mitigation measures from the perspective of abatement effects and cost-effectiveness. A comparative analysis based on field experiments showed that intermittent irrigation in rice cultivation can reduce both GHG emission intensity and production costs (Zhou et al., 2017). A meta-analysis showed that in biochar amendment, an application rate of <30 t ha^{-1} was most effective in mitigating GHGs while retaining a high crop yield potential (Shakoor et al., 2021). In manure management, anaerobic fermentation coupled with biogas engineering can significantly reduce non-CO_2 GHG emissions, including a $>90\%$ reduction in N_2O emissions compared with conventional manure disposal methods (Liu and Yong, 2019; Yang et al., 2016). In addition, the use of silage instead of conventional feed can reduce the cost while reducing CH_4 emissions from enteric fermentation (Han et al., 2018).

The assessment of agricultural GHG mitigation potential can help guide decision-making. Several country-level studies screened feasible GHG mitigation measures and then estimated the technical and economic potentials of agricultural GHG mitigation. Technical potential refers to the maximum mitigation potential that can be achieved using existing measures without considering constraints. Economic potential is the mitigation potential constrained by costs (usually a specific carbon price) (IPCC, 2022). A study used deliberative methods to identify 10 technical measures, including 26 submeasures, and calculated that the total mitigation potential of France agriculture would be 32.3 $MtCO_2e$ in 2030, with the mitigation potential of negative, low and high costs accounting for 1/3 each (Pellerin et al., 2017). A marginal abatement cost curve (MACC) developed via meta-analysis of published data showed that the maximum technical mitigation potential in Chinese agriculture would be 402 $MtCO_2e$ in 2020 (Wang et al., 2014). Several studies have used sector-specific bottom-up models to assess agricultural GHG mitigation potential (Beach et al., 2015; Chen et al., 2022; Hasegawa and Matsuoka, 2012). This type of model usually contains details of mitigation measures and uses a bottom-up approach to estimate GHG emissions in the future under different scenarios. The AFOLU bottom-up (AFOLU-B) model has been used to quantitatively analyse agricultural GHG mitigation potentials in Southeast Asian countries, and studies in Nepal and Thailand further explored the mitigation pathways under different carbon prices (Hasegawa and Matsuoka, 2015; Hoa et al., 2014; Jilani et al., 2015; Pradhan et al., 2019; Pradhan et al., 2017). In contrast, another commonly used sort of model for assessing agricultural GHG mitigation potential, the top-down equilibrium model, incorporates multiple representative economic agents (Frank et al., 2018; Frank et al., 2019; Gernaat et al., 2015). The mitigation potential calculated by this type of model is usually higher than the former since it allows for more flexible allocation of resources and thus lower abatement costs (Vermont and De Cara, 2010). Additionally, a multi-model assessment approach was employed to quantify the potential contributions of GHG mitigation in the agricultural sector compatible with the 1.5 °C target (Frank et al., 2019). Although some previous studies have evaluated GHG mitigation potential in Chinese agriculture, few modelled mitigation pathways by incorporating socioeconomic conditions, technology diffusion, and carbon pricing policies, which are comprehensively considered in our bottom-up agricultural technology optimisation model (ATOM) for GHG mitigation. Furthermore, our study innovatively disaggregates China's agricultural GHG mitigation potential by agricultural product, greenhouse gas, emission source, region, and mitigation measure, highlights the spatial heterogeneity in the mitigation potential within Chinese agriculture, and explores the impact of carbon pricing on the implementation of agricultural GHG mitigation measures. Based on the model, we propose policy recommendations for GHG mitigation in Chinese agriculture.

This article is structured as follows: after this introduction section, Section 2 details the methodology; Section 3 presents research results; Section 4 discusses policy implications; and finally, Section 5 draws research conclusions and limitations.

2. Methods and data

First, we established inventories of agricultural GHG and mitigation measures. In the second step, the ATOM was developed based on these inventories and then employed to quantify China's agricultural GHG mitigation potential by 2060. Under a range of socioeconomic and carbon pricing scenarios, the model simulated GHG mitigation pathways from 2017 to 2060 in Chinese agriculture. In this research, only GHG emissions from food-related agricultural production were considered.

2.1. Agricultural GHG inventory

We used *Guidelines for the Preparation of Provincial Greenhouse Gas Inventories* to identify GHG emission factors of agricultural products in 31 provinces of mainland China (NDRC, 2011). In this study, major agricultural products in China were classified into 10 crops (rice, wheat, maize, other cereals, beans, tubers, oil, sugar, vegetables, and fruit) and six livestock products (beef, mutton, pork, chicken, milk, and eggs) according to the classification method adopted by the National Bureau of Statistics (NBS) of China.

The GHG emission factors of crop c ($\boldsymbol{EF_c}$) and livestock product l ($\boldsymbol{EF_l}$) are calculated according to Eqs. (1) and (2), respectively:

$$\boldsymbol{EF_c} = \boldsymbol{EF_{paddy,c}} + \boldsymbol{EF_{cropland,c}} \tag{1}$$

$$\boldsymbol{EF_l} = \boldsymbol{EF_{enteric,l}} + \boldsymbol{EF_{manure,l}} \tag{2}$$

where $\boldsymbol{EF_{paddy,c}}$ and $\boldsymbol{EF_{cropland,c}}$ are the GHG emission factors of rice cultivation and cropland for crop c, in units of $kgCO_2e$ kg^{-1}. $\boldsymbol{EF_{enteric,l}}$ and $\boldsymbol{EF_{manure,l}}$ are the GHG emission factors of enteric fermentation and manure management for livestock product l, in units of $kgCO_2e$ kg^{-1}. A detailed calculation methodology of the above GHG emission factors is provided in the supplementary material.

2.2. Agricultural GHG mitigation measures inventory

The agricultural GHG mitigation measures inventory was established with a focus on the reduction of non-CO_2 GHG emissions and the increase of soil organic carbon (SOC) stocks. Applicable GHG mitigation measures for Chinese agriculture were screened by investigating technical potentials, application prospects, and impacts on agricultural production. The screening criteria were as follows: (1) the measure can reduce non-CO_2 GHG emissions or increase SOC stocks of cropland, and the overall abatement effect is positive; (2) the measure will not have noticeable negative impacts on the agricultural output, consistent with

China's food security policy; (3) the measure has a stable abatement effect, along with high technical feasibility and promotion potential; and (4) there are few negative interactions among the selected measures. Based on the above criteria, eleven applicable GHG mitigation measures were ultimately selected, including seven measures for crop production and four measures for livestock production. Abatement rates and costs of mitigation measures were quantified based on data collected from relevant meta-analyses or field survey results. Tables 1a and 1b list the details of selected mitigation measures, as well as relevant references.

2.3. Structure of ATOM

Using the GAMS software (version 27.3), ATOM adopts a bottom-up approach to estimate future GHG emissions and mitigation potentials in agriculture of 31 provincial administrative regions in mainland China. The model chooses applicable measures from the agricultural GHG mitigation measures inventory and optimal application rates to minimise costs. The input to ATOM includes (1) future projections for the agricultural output; (2) GHG emission factors in agricultural production; (3) characteristics of agricultural GHG mitigation measures; and (4) assumptions of future carbon price pathways. The output of ATOM includes (1) future GHG emissions and mitigation potential in agriculture and (2) future development pathways of agricultural GHG mitigation measures. Scenario settings are based on shared socioeconomic pathways (SSPs) and different carbon price pathways. Fig. 1 shows the schematic structure of ATOM.

The GHG emissions from emission source s of crop c in region r ($\boldsymbol{G}_{c,s,r}$) are calculated as shown in Eq. (3):

$$\boldsymbol{G}_{c,s,r} = \boldsymbol{EF}_{c,s,r} \times \boldsymbol{O}_{c,r} \times \sum_{m1} \left(1 - \boldsymbol{\alpha}_{c,m1} \times \boldsymbol{R1}_{c,s,m1}\right) - \boldsymbol{A}_{c,r} \times \sum_{m1} \left(\boldsymbol{\alpha}_{c,m1} \times \boldsymbol{R2}_{c,s,m1}\right) \tag{3}$$

where $\boldsymbol{EF}_{c,s,r}$ is the emission factor for emission source s of crop c in region r, in units of $kgCO_2e\ kg^{-1}$; $\boldsymbol{O}_{c,r}$ is the output of crop c in region r, in units of kg; $\boldsymbol{\alpha}_{c,m1}$ is the application rate of measure $m1$ for crop c,

Table 1b
The agricultural GHG mitigation measures inventory part II: livestock production.

No.	Measure	Target	Abatement rate	Cost in 2017 (CNY tCO_2e^{-1})	References
L1	Anaerobic digestion of manure	Beef, pork, milk	MM CH_4: beef and milk −94.95% pork −93.41% MM N_2O: beef and milk −22.36% pork −60.48%	−39.4	(Duan et al., 2023, Liu and Yong, 2019, Wang et al., 2014, Yang et al., 2016)
L2	Dietary additives: tea saponins	Beef, mutton, milk	EF CH_4: beef −12% mutton −17% milk −15%	−68.9	(Wang et al., 2014)
	Dietary additives: probiotics	Mutton, milk	EF CH_4: mutton −1% milk −0.3%	−8706.3	(Wang et al., 2014)
	Dietary additives: lipids	Beef, mutton, milk	EF CH_4: beef −8% mutton −4% milk −6%	2398.3	(Wang et al., 2014)
L3	Silage promotion	Beef, mutton, milk	EF CH_4: beef −21% mutton −50% milk −20%	−1485.4	(Duan et al., 2023, Han et al., 2018, Zhang et al., 2020)
L4	Breed improvement	Mutton, pork, milk	EF CH_4: mutton −8% pork −4% milk −6%	−3162.0	(Wang et al., 2014)

Notes: MM means manure management, and EF means enteric fermentation. It is assumed that each livestock utilises only one feed additive.

Table 1a
The agricultural GHG mitigation measures inventory part I: crop production.

No.	Measure	Target	Abatement rate	Yield change	Cost in 2017 (CNY ha^{-1})	References
C1	Advanced irrigation and nitrogen fertiliser application	Rice	CH_4 reductions: −22.1% N_2O reductions: −4.2%	+5%	570.7	(Duan et al., 2023, Wang et al., 2016, Wang et al., 2014)
C2	Enhanced-efficiency fertilisers	All crops	N_2O reductions: rice −25.5% wheat −19.5% vegetables −21.6% fruit −18.6% other crops −19.7%		77.5	(Wang et al., 2014)
C3	Better nitrogen management	Wheat, maize, vegetables, fruit	N_2O reductions: wheat −13.6% maize −16.0% vegetables −47.3% fruit −55.1%	Wheat +5% maize +8% vegetables and fruit +10%	Wheat and maize −762.5 vegetables and fruit −2822.6	(Wang et al., 2014)
C4	Conservation tillage	Wheat, maize	SOC : +611 $kgCO_2e\ ha^{-1}$		−131.6	(Wang et al., 2014)
C5	Return of crop straw and residues	Wheat, maize	SOC: +263 $kgCO_2e\ ha^{-1}$		86.1	(Wang et al., 2014)
C6	Biochar addition	Rice, wheat, maize	SOC : +1563 $kgCO_2e\ ha^{-1}$	+10%	2700	(Bai et al., 2022, Campion et al., 2023, Li et al., 2024, Xia et al., 2023)
C7	Organic manure	All crops	SOC ($kgCO_2e\ ha^{-1}$): rice +460 wheat +689 maize +574 vegetables +185 fruit +462 other crops +631		648.1	(Wang et al., 2014)

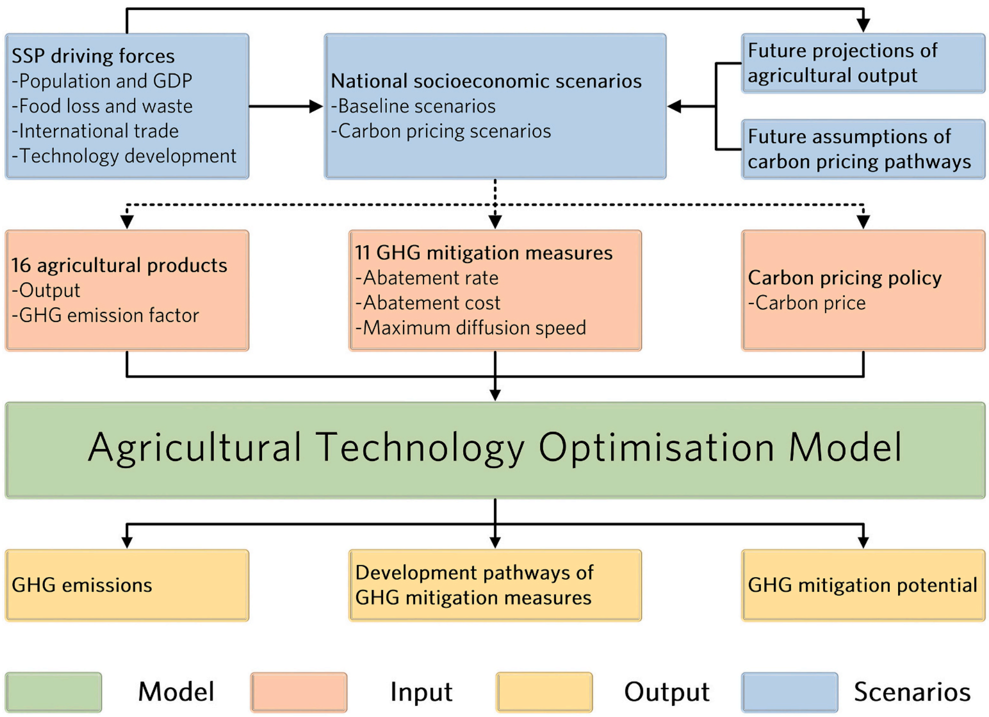

Fig. 1. Schematic structure of ATOM.

expressed as a percentage; $R1_{c,s,m1}$ and $R2_{c,s,m1}$ are the abatement rates of measure $m1$ for emission source s of crop c, expressed as a percentage and in units of $kgCO_2e\ ha^{-1}$, respectively; and $A_{c,r}$ is the area of crop c in region r, in units of ha. Considering the interations between different carbon sequestration measures, we set an interaction factor (0.8) to adjust the abatement rates of these measures.

The GHG emissions of livestock product l from source s in region r ($G_{l,s,r}$) are calculated as shown in Eq. (4):

$$G_{l,s,r} = EF_{l,s,r} \times O_{l,r} \times \sum_{m2} (1 - \alpha_{l,m2} \times R_{l,s,m2}) \tag{4}$$

where $EF_{l,s,r}$ is the emission factor for emission source s of livestock product l in region r, in units of $kgCO_2e\ kg^{-1}$; $\alpha_{l,m2}$ is the application rate of measure $m2$ for livestock product l, expressed as a percentage; $R_{l,s,m2}$ is the abatement rate of measure $m2$ for emission source s of livestock product l, expressed as a percentage; and $O_{l,r}$ is the output of livestock product l in region r, in units of kg.

For future projections, the model works in a recursive dynamic mode. The link between two consecutive years is established through the application of mitigation measures: the optimised application rates in one year are taken as the initial application rates in the next year. Panel data regression is used to forecast the future agricultural output. The regression analysis is performed according to Eq. (5), and the output of an agricultural product in region r in year t (O_r^t) is calculated as shown in Eq. (6). In both equations, geographical regions (r') are used because the historical output of some agricultural products was zero in some provincial administrative regions (r). The links between r' and r are demonstrated in the supplementary material (Table S2).

$$ln(O_{r'}/POP_{r'}) = A \times ln(GDP_{r'}/POP_{r'}) + B_{r'} \tag{5}$$

$$O_r^t = exp\left[A \times ln\left(GDP_{r'}^t/POP_{r'}^t\right) + B_{r'}\right] \times POP_{r'}^t \times O_r^{2017}/O_{r'}^{2017} \times \gamma^{t-2017} \tag{6}$$

where $O_{r'}$ is the output of an agricultural product in region r', in units of kg; $POP_{r'}$ is the population in region r'; $GDP_{r'}$ is the gross domestic product (GDP) in region r', in units of CNY; A and $B_{r'}$ are regression parameters; $GDP_{r'}^t$ is the projection of GDP in region r' in year t, in units of CNY; $POP_{r'}^t$ is the projection of population in region r'; O_r^{2017} is the output of an agricultural product in region r in 2017, in units of kg; $O_{r'}^{2017}$ is the output of an agricultural product in region r' in 2017, in units of kg; and γ is the adjustment parameter based on the SSP driving forces in the scenarios.

The main constraint in ATOM is the diffusion limitation of mitigation measures, as described by Eq. (7):

$$\alpha_m^t \le \alpha_m^{t+1} \le \alpha_m^t + \beta_m \le 1 \tag{7}$$

where α_m^t is the application rate of measure m in year t, expressed as a percentage, and β_m is the maximum diffusion speed of measure m, expressed as a percentage.

The area of crop c in region r in year t ($A_{c,r}^t$) was calculated as shown in Eq. (8):

$$A_{c,r}^t = \frac{O_{c,r}^t}{Y_{c,r}^{2017} \times \left[1 + \sum_{m1}\left(\alpha_{m1}^t \times YC_{c,m1}\right)\right]} \tag{8}$$

where $O_{c,r}^t$ is the output of crop c in region r in year t, kg; $Y_{c,r}^{2017}$ is the yield of crop c in region r in 2017, in units of $kg\ ha^{-1}$; and $YC_{c,m1}$ is the yield change rate of measure $m1$ for crop c, expressed as a percentage.

Carbon pricing in agriculture will create several costs for farmers, including abatement costs, emission costs, and administrative costs (NZME, 2019). We assume that the administrative costs are borne by the government. In ATOM, the cost is defined as the sum of the abatement cost and emission fee. Assuming an output-based free allocation of emissions units, the costs for crop production (CC) and livestock production (CL) are calculated as shown in Eqs. (9) and (10), respectively:

$$CC = \sum_c \sum_r \sum_{m1} \alpha_{c,m1} \times C_{c,m1} \times A_{c,r} + CP \times \sum_c \left(\sum_s \sum_r G_{c,s,r} - OA_c \right) \tag{9}$$

$$CL = \sum_{l}\sum_{s}\sum_{r}\sum_{m2}\alpha_{l,m2} \times R_{l,s,m2} \times EF_{l,s,r} \times C_{l,m2} \times O_{l,r} + CP \times \sum_{l}\left(\sum_{s}\sum_{r}G_{l,s,r} - OA_l\right) \tag{10}$$

where $C_{c,m1}$ is the abatement cost of measure $m1$ for crop c,in units of CNY ha^{-1}; CP is the carbon price, in units of CNY $kgCO_2e^{-1}$; OA_c and OA_l are the output-based free allocations of emissions units for crop c and livestock product l, respectively, in units of $kgCO_2e$; and $C_{l,m2}$ is the abatement cost of measure $m2$ for livestock product l in units of CNY $kgCO_2e^{-1}$.

The output-based free allocation of emissions units for an agricultural product (OA) is calculated according to Eq. (11):

$$OA = AR \times O \times \overline{GHG} \tag{11}$$

where AR is the allocation rate; O is the output of an agricultural product, kg; and $\overline{GHG}$ is the national average GHG emission factor of an agricultural product, $kgCO_2e\ kg^{-1}$.

By minimising the total cost (TC) (Eq. (12)), ATOM enables the following optimisation algorithm: when the carbon price is below the abatement cost of a measure, it will not be implemented; once the carbon price exceeds its abatement cost, it will be implemented and diffused. On the basis, the optimal measure portfolios are selected.

$$TC = CC + CL \rightarrow MIN \tag{12}$$

2.4. Scenario settings

SSPs are scenarios of projected socioeconomic global changes up to 2100, designed to facilitate comprehensive analysis of future climate change impacts, adaptation, and mitigation (O'Neill et al., 2017; van Vuuren et al., 2017). Table 2 lists the SSP driving forces considered in socioeconomic scenarios for China in this study. Based on SSP driving forces and assumptions of future carbon price pathways, 15 scenarios were established to examine agricultural GHG mitigation pathways in China from 2017 to 2060. In our scenario settings, the differences between various SSPs are demographic and economic status, agricultural output and technology diffusion speed. Under the SSP1 and SSP2 scenarios, the agricultural output will decrease due to the decrease in food loss and waste, while it will increase or decrease due to the increase in trade barriers under the SSP3 scenarios. On this basis, we set the adjustment parameter γ in Eq. (6) to adjust the future projections of agricultural output. The technology diffusion speed was set according to the historical level and decreased sequentially under the SSP1, SSP2, and SSP3 scenarios. Under the business-as-usual (BAU) scenarios, no mitigation measures will be diffused. Although the carbon price is zero under the zero-carbon price (ZCP) scenarios, negative cost mitigation measures will be adopted and diffused. Under the low carbon price (LCP), medium carbon price (MCP), and high carbon price (HCP) scenarios, different linear increases are used to achieve carbon prices of 500, 1000 and 2000 CNY tCO_2e^{-1}, respectively, in 2060.

Table 2
Considered SSP driving forces in socioeconomic scenarios for China.

Driving force	SSP1	SSP2	SSP3
Population growth	Low	Medium	High
Economic growth	Medium	Medium	Low
Food loss and waste	Low	Medium	High
International trade	No trade restrictions	No trade restrictions	Stronger reliance on domestic production
Technology development	Rapid	Medium	Slow

2.5. Data sources

Population, GDP, and agricultural activity-level data for previous years were obtained from official databases, including the open national data released by NBS, *China Agriculture Yearbook*, *China Animal Husbandry and Veterinary Yearbook*, and *China agricultural products cost–benefit compilation of information*. Historical application rates of agricultural GHG mitigation measures were from government publications, survey reports, and literature reviews (Table S3). Future projections of population and GDP were derived from previous research (Jiang et al., 2022). Since the base year of this dataset is different from our study, we use its growth rate of population and GDP to make the forecast.

2.6. Model validation and comparison with other studies

We verified the ATOM parameterisation by comparing historical estimates of GHG emissions in Chinese agriculture (without the application of mitigation measures) for the period 2007–2017 with China's national greenhouse gas inventories (MEE, 2016, 2018a, 2018b) and other existing datasets, including FAOSTAT by the Food and Agriculture Organisation of the United Nations (FAO) (Tubiello et al., 2013), the Emissions Database for Global Atmospheric Research (EDGAR) (Solazzo et al., 2021), and the United States Environmental Protection Agency (USEPA) (USEPA, 2019). We ensured consistency in the scope of emission sources when selecting comparative data and calculated them with the GWP100 values from IPCC AR6 (IPCC, 2022). Our results are generally consistent with the other datasets in terms of temporal trends (Fig. S1). Additionally, we compared this study with two previous studies (Table. S5).

3. Results

3.1. Agricultural GHG mitigation pathways in China

Model results showed that in 2017, GHG emissions in Chinese agriculture were 720.3 $MtCO_2e$, an increase of over 15% from a decade earlier; GHG emissions in crop production were 397.2 $MtCO_2e$, 72.1% of which were from three main staple crops in China (rice, wheat, and maize); GHG emissions in livestock production were 323.1 $MtCO_2e$, 54.1% of which were from the enteric fermentation of ruminants. Overall, cropland was the largest emission source, which constituted 31.0% of the total GHG emissions. Rice was the agricultural product that emitted the most GHGs (30.8%), followed by pork (15.8%), beef (12.4%), and mutton (10.2%). Hunan, Heilongjiang, and Guangxi provinces were the top three emitters, collectively contributing >20% of agricultural GHG emissions in China.

Fig. 2 shows the GHG emission pathways in Chinese agriculture from 2007 to 2060 under all 15 scenarios. Under the SSP1-BAU, SSP2-BAU, and SSP3-BAU scenarios, GHG emissions in Chinese agriculture are projected to reach 665.4 $MtCO_2e$, 734.9 $MtCO_2e$, and 782.3 $MtCO_2e$ in 2030; 576.5 $MtCO_2e$, 690.6 $MtCO_2e$, and 780.4 $MtCO_2e$ in 2060; and peak emissions in 2018, 2026, and 2048: 722.4 $MtCO_2e$, 736.0 $MtCO_2e$, 792.5 $MtCO_2e$, respectively. Because some GHG mitigation measures have net benefits, considerable GHG mitigation will be achieved in the future under the ZCP scenarios, but carbon pricing could help achieve greater GHG emission reductions. Under the SSP3-HCP scenario, because of the increase in agricultural production and the slow diffusion of technology, total emissions in 2060 will remain higher than the pre-2007 levels. However, even under the SSP1-BAU scenario, total agricultural GHG emissions in 2060 will be reduced to the pre-2007 levels, mainly due to the decline in agricultural production caused by the decrease in food loss and waste. Agricultural GHG emissions in 2060 under the SSP1-HCP scenario will be 267.1 $MtCO_2e$, <50% of the SSP1-BAU scenario. Because of the assumption of rapid technology diffusion underpinning SSP1 scenarios, the application of some measures will

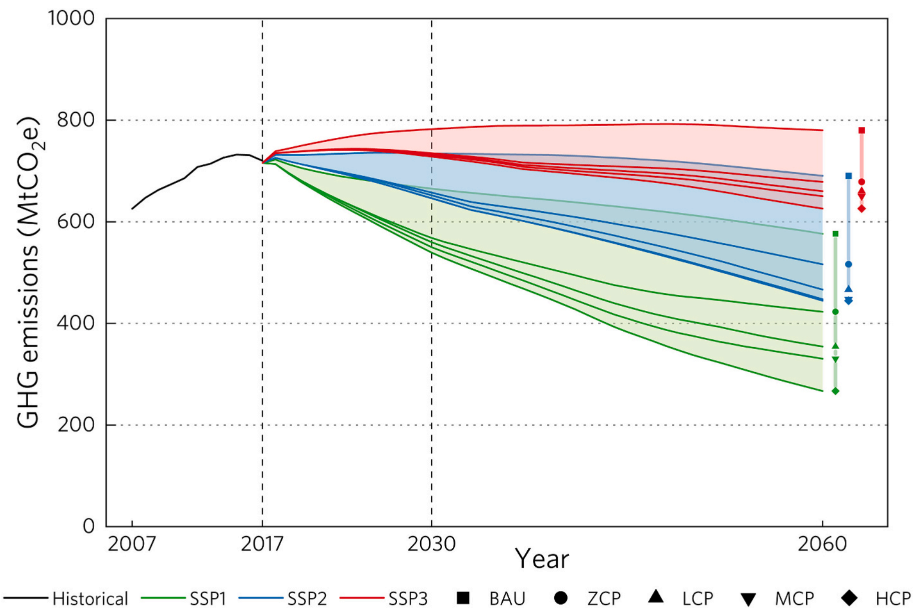

Fig. 2. GHG emission pathways in Chinese agriculture from 2007 to 2060.

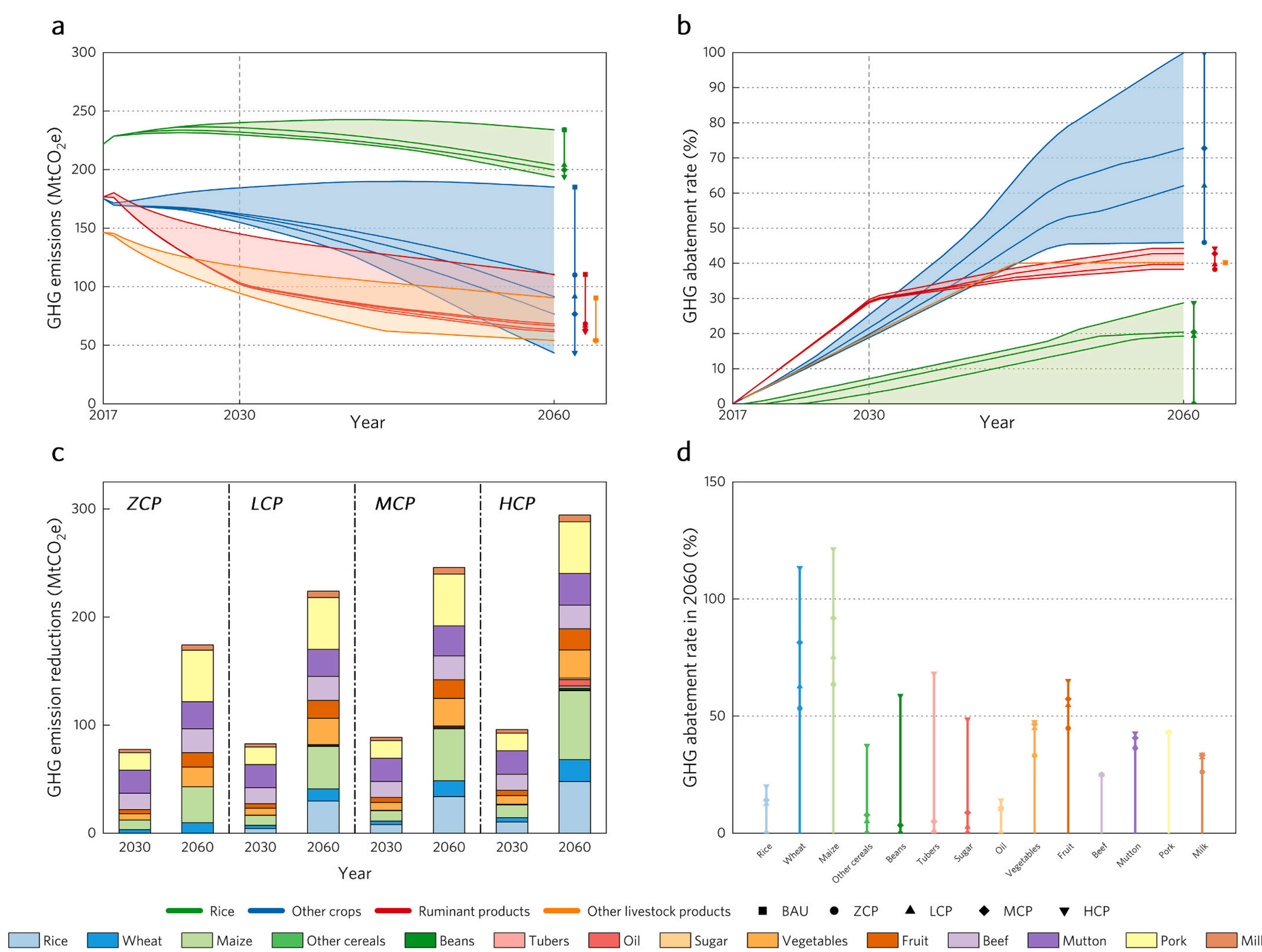

Fig. 3. GHG mitigation potentials of various agricultural products under the SSP2 scenarios. (a & b) GHG emissions and abatement rates of 4 groups of agricultural products (rice, other crops, ruminant products, and other livestock products) from 2017 to 2060; (c) GHG emission reductions of 16 agricultural products in 2030 and 2060; (d) GHG abatement rates of 16 agricultural products in 2060.

reach saturation before 2060, after which the overall speed of GHG mitigation will decline, especially at low carbon price levels .

3.2. Agricultural GHG mitigation potential: Agricultural products

Fig. 3 displays the GHG mitigation potentials of various agricultural products under the SSP2 scenarios. Under the SSP2-ZCP, SSP2-LCP, and SSP2-MCP scenarios, among the categories of agricultural products, ruminant products will consistently have the largest GHG emission reductions before 2030. There will be little variance in emission reductions or abatement rates from both groups of livestock products between different carbon pricing scenarios (Fig. 3a, and b). Under the SSP2-ZCP scenario, livestock products will contribute 66.5% and 51.2% of the total agricultural GHG emission reductions in 2030 and 2060, respectively. However, under the SSP2-HCP scenario, their contributions will decrease to 52.2% in 2030 and 27.6% in 2060. Because almost all the selected mitigation measures for livestock production have a negative cost (Table 1b), the increase in carbon price has minimal incremental impacts on mitigating GHG emissions from livestock products. Furthermore, under all carbon pricing scenarios, rice will consistently have the lowest GHG abatement rate from 2017 to 2060; ruminant products will have the highest GHG abatement rate for the pre-2030 period, while other crops will have the highest GHG abatement rate for most of the post-2030 period.

Under the SSP2-MCP scenario, the three agricultural products with the largest GHG emission reductions in 2060 will be pork, maize, and rice. The three main staple crops in China (rice, wheat, and maize) will contribute approximately 40% of the total agricultural GHG emission reductions in 2060. Interestingly, our results suggest that the carbon price has a potent impact on GHG mitigation in rice production. Under the SSP2-ZCP scenario, there will be no GHG emission reduction in rice paddies. However, an increase in the carbon price will promote reductions in CH_4 emissions from rice cultivation, linked with the diffusion of C1 (advanced irrigation and nitrogen fertiliser application), causing rice to become the crop with the second largest GHG emission reductions in 2060 under the SSP2-HCP scenario (Fig. 3c). In 2060, under the SSP2-MCP scenario, wheat and maize will be the two agricultural products with the highest GHG abatement rates: 81.5% and 91.7%, respectively; tubers will have the lowest GHG abatement rate of 5.0%. However, the GHG abatement rate of tubers will increase to 68.2% under the SSP2-HCP scenario, mainly due to the broad implementation of carbon sequestration measures. For the same reason, under the SSP2-HCP scenario, the GHG abatement rates of wheat and maize will exceed 1 in 2060 (Fig. 3d).

3.3. Agricultural GHG mitigation potential: GHGs and emission sources

Fig. 4 displays the emissions and proportion of emission reductions dissociated for different GHGs and SOC in 2060 under the SSP2 scenarios. Although reductions in the emission of each GHG differed among the various carbon pricing scenarios, they constituted similar proportions of the total agricultural GHG emission reductions under the same carbon price level. Non-CO_2 GHG mitigation will contribute 70.8–83.6% of the total agricultural GHG emission reductions in 2060 under the carbon pricing scenarios (Fig. 4a, and b). Additionally, as the carbon price increases, the proportion of SOC increases from 16.4% to 29.2% (Fig. 4c), indicating that carbon sequestration measures have the potential to strongly mitigate GHG emissions but that they necessitate strong policy support for their deployment.

In our analysis of the GHG mitigation potentials of different agricultural emission sources, we assumed that SOC contributed to GHG emission reductions in cropland. Fig. 5 shows the GHG emissions from various sources in 2017 and 2060 under the SSP2 scenarios. Cropland will contribute the largest GHG emission reductions under all carbon pricing scenarios. Under the SSP2-HCP scenario, GHG emissions from cropland will be 73.1 $MtCO_2e$ in 2060, accounting for 18.4% of total agricultural GHG emissions, while this proportion will be as high as 34.1% under the SSP2-BAU scenario; GHG emission reductions in cropland in 2060 will be 162.1 $MtCO_2e$, constituting 55.1% of the total emission reductions. Overall, carbon pricing is more important for reducing GHG emissions from cropland than from other sources.

3.4. Agricultural GHG mitigation potential: regional differences

We analyse regional differences in agricultural GHG mitigation potentials in 2060 based on the SSP2-MCP scenario. Fig. 6a illustrates China's provincial agricultural GHG emissions and abatement rates. In 2060, Hunan will have the largest agricultural GHG emissions: 49.6 $MtCO_2e$; Henan and Shandong will have the largest amount of agricultural GHG emission reductions: 22.9 $MtCO_2e$ and 19.6 $MtCO_2e$, respectively, primarily due to their large populations and substantial agricultural output. Shanxi and Jiangxi will have the highest and lowest

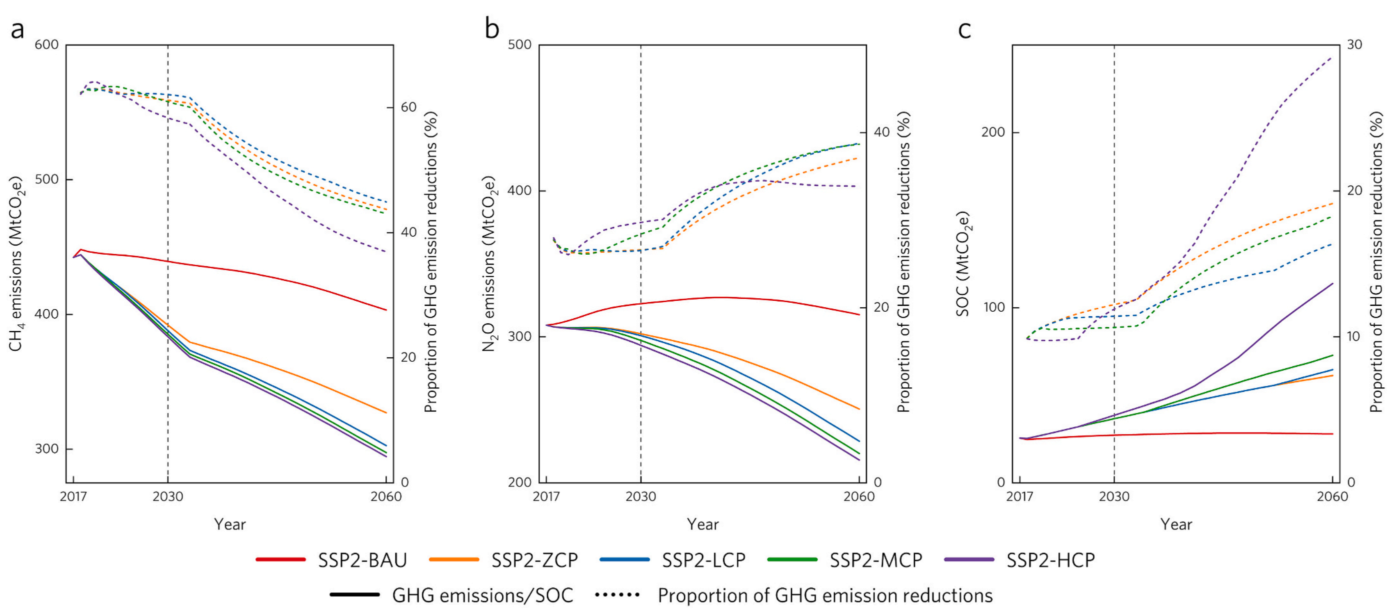

Fig. 4. Emissions and proportion of emission reductions from 2017 to 2060 under the SSP2 scenarios of (a) CH_4, (b) N_2O, and (c) SOC.

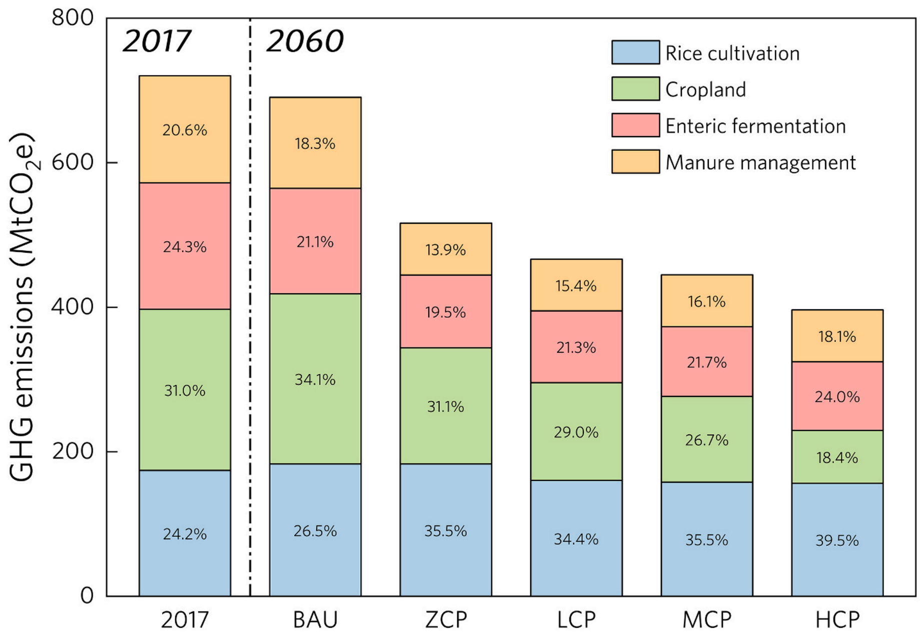

Fig. 5. GHG emissions from various sources in 2017 and 2060 under the SSP2 scenarios.

agricultural GHG abatement rates of 63.5% and 21.9%, respectively. Fig. 6b displays the proportion of China's provincial agricultural GHG emission reductions. In most northern provinces, the proportion for wheat will be higher than that for rice, while the opposite is true in most southern provinces, which is related to the spatial distribution pattern of crops in China. GHG emission reductions of livestock products will constitute a significant proportion in provinces centred on livestock production. In 2060, livestock products will contribute nearly 2/3 of total agricultural GHG emission reductions in Tibet.

We further analyse the differences in agricultural GHG mitigation potentials between six geographical regions (Table S4). In 2060, South Central China will have the largest amount of agricultural GHG emission reductions (75.9 $MtCO_2e$), followed by East China (56.5 $MtCO_2e$), which together account for >50% of the total amount. The GHG emission reductions of crop products will be higher than those of livestock products in all six regions. In Northeast China, livestock products will account for 28.6% of total agricultural GHG emission reductions, while in North China, the proportion will be approximately 50%. This result is corresponding to the spatial distribution of pastoral areas in China. Additionally, the overall GHG abatement rate varies across the six regions, with North China having a GHG abatement rate of 49.9%, which is nearly 19% more than that in South Central China.

3.5. *Agricultural GHG mitigation potential: mitigation measures*

Fig. 7 shows the GHG emission reductions contributed by various mitigation measures in 2060 under the SSP2 scenarios. The carbon price level has a great impact on C6 (biochar addition) and C7 (organic manure); a high carbon price is required to activate the GHG mitigation potential of this two measures. GHG emission reductions of C1 (advanced irrigation and nitrogen fertiliser application), C2 (enhanced-efficiency fertilisers), C5 (return of crop straw and residues) and L2 (dietary additives) will increase as the carbon price increases. In contrast, GHG emission reductions of other mitigation measures are less affected by the carbon price level because of their net benefits.

The maximum technical mitigation potential in 2060 was estimated assuming a 100% application rate for all selected measures. Fig. 8 displays the marginal abatement cost curve for Chinese agriculture in 2060 based on the SSP2 scenario assumptions. The maximum technical mitigation potential will be 554.1 $MtCO_2e$ in 2060, with 38.9% achieved by negative-cost measures and 56.6% achievable at a unit abatement cost below 250 CNY tCO_2e^{-1}. The maximum technical mitigation potential in 2060 will be 433.0 $MtCO_2e$ (78.2%) for crop production and 121.1 $MtCO_2e$ (21.8%) for livestock production. The agricultural GHG emission reductions resulting from these mitigation measures in 2060 under the SSP2-BAU, SSP2-ZCP, SSP2-LCP, SSP2-MCP, and SSP2-HCP scenarios will be 86.9, 261.1, 310.9, 332.8, and 381.2 $MtCO_2e$, respectively; these values correspond to 15.7%, 47.1%, 56.1%, 60.1%, and 68.8% of the maximum technical mitigation potential realised.

4. Discussion

4.1. *GHG mitigation potential in Chinese agriculture*

Rice has distinctive characteristics of GHG emission compared with other crops. It has high CH_4 emissions intensity (0.52–1.37 $kgCO_2e$ kg^{-1} in 2017). Significant mitigation potential is achievable through countermeasures such as improving both irrigation and fertilisation practices, but it is necessary to consider the impact of mitigation measures on the increase in N_2O emissions to achieve overall net GHG mitigation (Wang et al., 2022). Beef and mutton production also emit large amounts of CH_4 due to enteric fermentation in ruminants. China is the world's top pork producer and consumer (Wang, 2022). Although pork has lower GHG emissions per unit of output than beef and mutton, its total emissions are larger, and considerable mitigation potential is enabled by improving manure management. Additionally, there is significant heterogeneity across different regions in the mitigation potential. The GHG mitigation potential of crop production is much larger than that of livestock production in most provinces. However, livestock production accounts for a large proportion of the mitigation potential in China's major pastoral areas: Inner Mongolia, Tibet, Gansu, Qinghai, and Xinjiang.

The technical potential of cutting agricultural GHG emissions directly is limited because agricultural production inevitably produces large amounts of non-CO_2 GHGs. Therefore, full use of the carbon sequestration potential of cropland is needed to reduce net emissions while restoring the agricultural ecosystem. Carbon sequestration measures are generally more costly than reducing emissions directly, particularly with respect to biochar addition. Technological revolution is necessary to enhance the competitiveness of such measures. However,

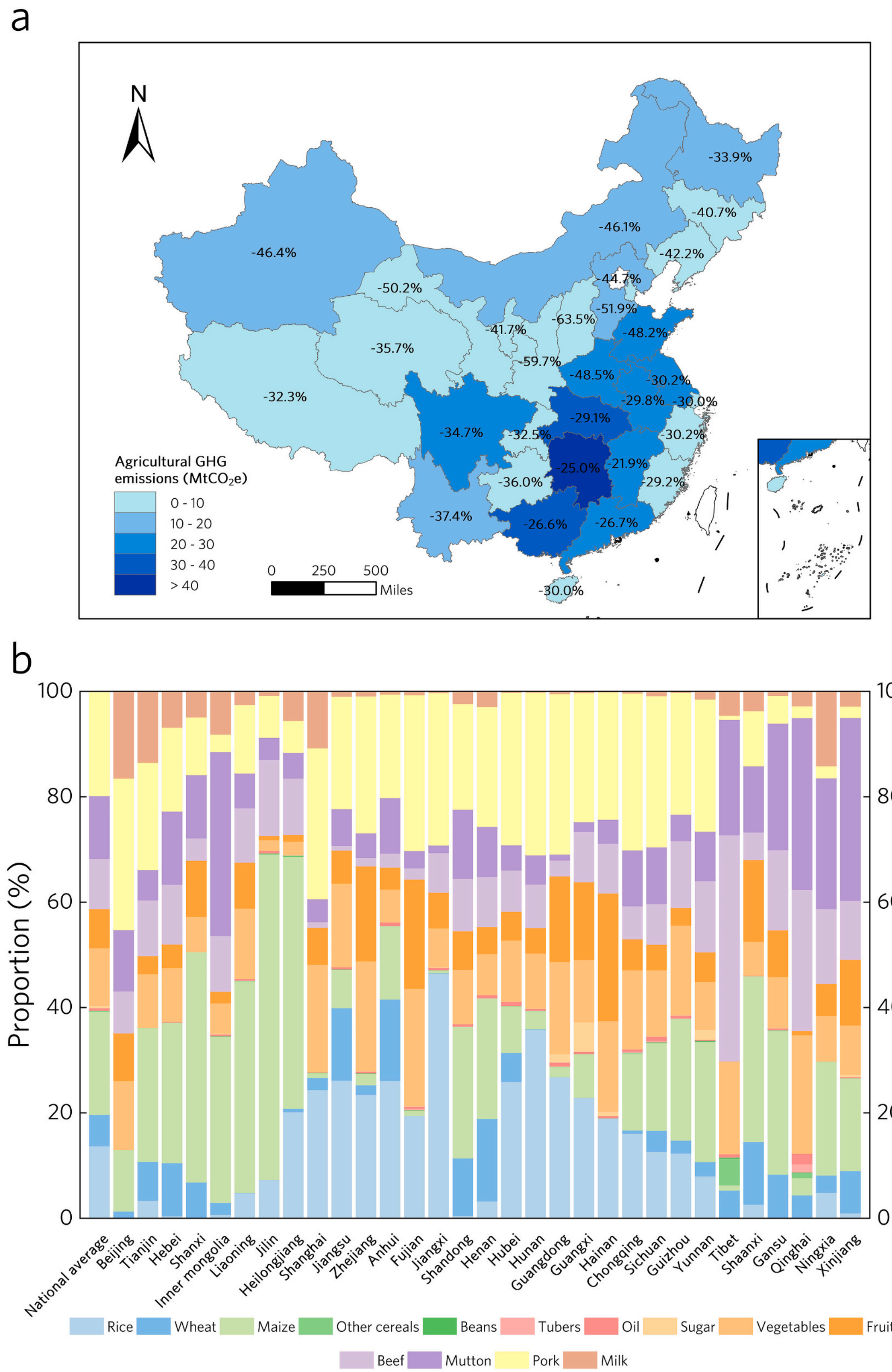

Fig. 6. Agricultural GHG mitigation potentials in different regions in 2060 under the SSP2-MCP scenario. (a) China's provincial agricultural GHG emissions and abatement rate; (b) Proportion of agricultural GHG emission reductions.

despite carbon sequestration measures, existing agricultural GHG mitigation measures are possibly insufficient to achieve carbon neutrality in Chinese agriculture by 2060. Therefore, we should try to achieve more GHG mitigation on the demand side or in other sectors. On the demand side, reducing the proportion of livestock products in the diet can help to reduce GHG emissions from agriculture (Duan et al., 2023; Mazac et al., 2022; Reay et al., 2012). Reductions in food loss and waste are also important for both GHG mitigation and food security (Amicarelli et al.,

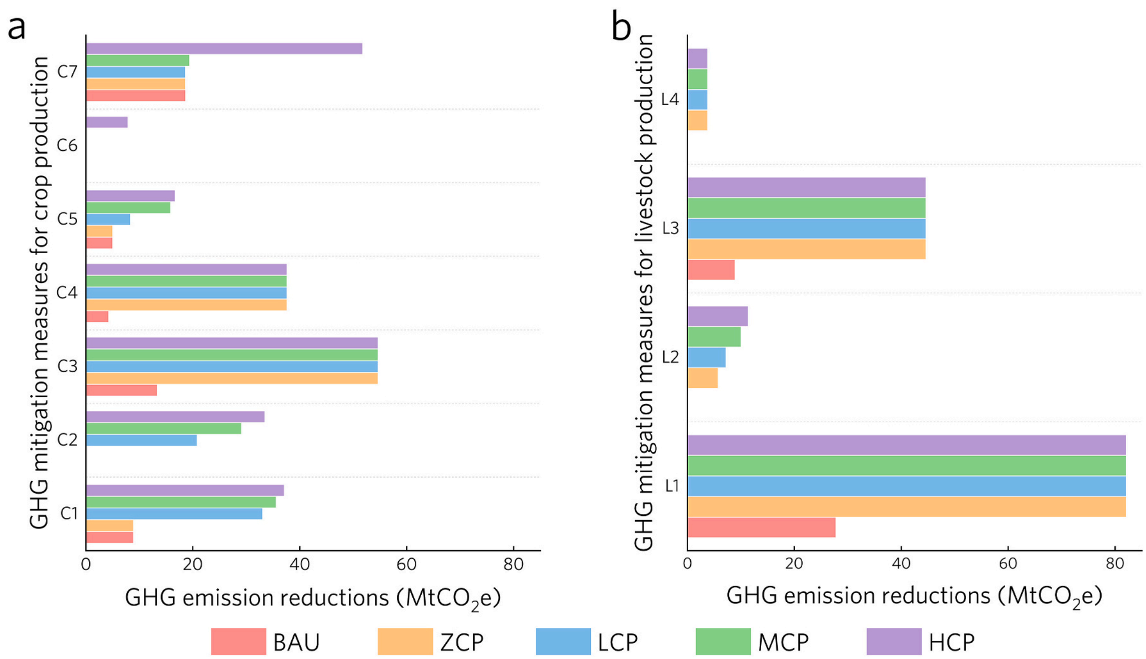

Fig. 7. GHG emission reductions contributed by mitigation measures for (a) crop production and (b) livestock production in 2060 under the SSP2 scenarios.

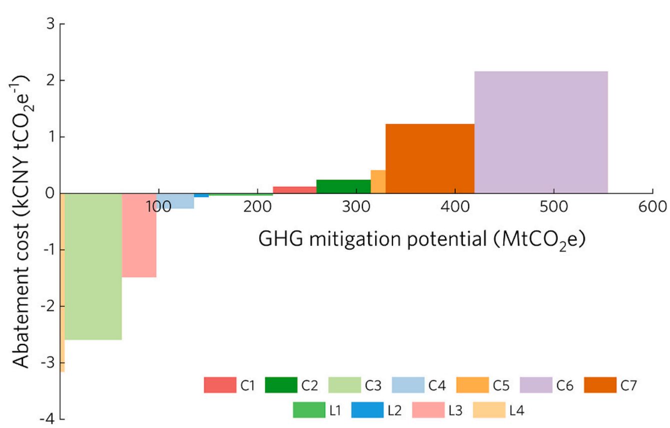

Fig. 8. Marginal abatement cost curve for Chinese agriculture in 2060 based on the SSP2 scenario assumptions.

2021; Bajželj et al., 2014; Reay et al., 2012). Sustainable development goal 12: responsible consumption and production has set the target of halving per capita food waste and losses by 2030 (UN, 2023). In the forestry sector, afforestation can provide long-term stable CO_2 abatement (Duffy et al., 2022; Lin et al., 2022). However, large forested areas require many years to establish, and the areas amenable to afforestation are limited (Forster et al., 2021). Bioenergy with carbon capture and storage (BECCS) is a negative emissions technology considered crucial to limit global warming to 1.5–2 °C, but large-scale bioenergy deployment remains limited because of biophysical, technical, and social challenges (Fridahl and Lehtveer, 2018; Fuss et al., 2014; Hanssen et al., 2020; Humpenöder et al., 2014). Additionally, both afforestation and BECCS will compete with crops for land, a conflict that must be managed properly (Bustamante et al., 2014).

Our results indicate that negative cost mitigation measures possess significant technical potential for agricultural GHG mitigation. Currently in China, nevertheless, these measures delivered only a small fraction of their maximum technical potential, as their implementation has been hindered by multiple obstacles. Some hidden costs or inefficiencies hampered the adoption of mitigation options that would have been profitable in the base situation (Vermont and De Cara, 2010). The applicability and cost of a mitigation measure vary according to the agricultural production scale (Grosjean et al., 2018; Moran et al., 2013). Some mitigation measures require economies of scale to ensure profitability (Chen et al., 2022). Furthermore, natural conditions, such as terrain and temperature, can also influence the abatement effect (Abalos et al., 2022). China's agricultural system is highly fragmented, such that farmers with large-scale farms are more likely to implement mitigation measures, whereas farmers with small-scale farms tend to adopt conservative approaches that avoid risk (Liu and Xu, 2023). The increase in large-scale farming, the establishment of intensive farms, and the raise in farmers' awareness of climate change are factors expected to favour GHG mitigation in Chinese agriculture.

4.2. Policy implications

The government should adopt counterstrategies to ensure that the agricultural sector remains on track to meet China's carbon neutrality goal. First, the realities of local agriculture should be addressed when specifying regional GHG mitigation strategies. For instance, the vast majority of GHG emissions and mitigation potentials in Tibet derive from beef and mutton. Therefore, implementing mitigation measures for ruminant livestock production, such as dietary additives, silage feed promotion, and breed improvement, is the key point for agricultural GHG mitigation. Second, the government should support and promote carbon sequestration measures by increasing investment in technology R&D, enhancing the promotion of technology, and lowering abatement costs to achieve good GHG abatement effects. Third, the government should raise public awareness and education on climate change mitigation and advocate low-carbon diets and reductions in food waste to achieve more GHG mitigation on the demand side. Finally, the government can look to put a price on agricultural GHG emissions to incentivise farmers to reduce emissions.

Carbon pricing is one of the most cost-effective tools for cutting GHG emissions (Olale et al., 2019; Tvinnereim and Mehling, 2018). In the agricultural sector, however, adopting a carbon pricing policy may face a number of challenges (Grosjean et al., 2018). On the one hand, the uncertainty affecting emissions and the resulting difficulties of monitoring emissions make carbon pricing challenging (Vermont and De

Cara, 2010). On the other hand, imposing a carbon tax will directly or indirectly increase farmers' financial burden and have negative impacts on economic growth and income inequality (Leahy et al., 2020; NZME, 2019; Zhao et al., 2022). Therefore, policies to mitigate these negative impacts are necessary, such as technical support and financial rebates (e.g., output-based subsidies or redistribution of tax revenues) (Olale et al., 2019). The government can also allocate a certain amount free allowances to farmers and adjust the allocation factors periodically according to the abatement effect (NZME, 2019). Additionally, due to regional disparities in the impacts of carbon tax, differentiated tax rates are necessary to protect the agricultural development in backwards areas and bridge regional development gaps (Xie et al., 2018).

With the modernisation of Chinese agriculture, the commercialisation rate of agricultural products has been gradually increasing, improving the feasibility of adopting a market-based carbon pricing policy in the agricultural sector (Chen, 2021). Existing research can provide references for pricing agricultural emissions in China. The government should establish clear mitigation targets for the agricultural sector, determine who will pay for the carbon price: farmers, processors, or consumers, and choose the core carbon pricing instrument: carbon taxes or carbon emissions trading (Azhgaliyeva and Rahut, 2022; Isermeyer et al., 2021; Ollikainen et al., 2020). It is essential to legislate and build an administration system for the carbon pricing policy, and establish harmonised measurement, reporting, and verification (MRV) standards for agricultural GHG mitigation (NZME, 2019; Perosa et al., 2023). Besides, border carbon adjustment policies should be formulated to minimise carbon leakage risks while ensuring carbon price incentives (Isermeyer et al., 2021; Stede et al., 2021). Particular attention should be paid to the characteristics of Chinese agriculture, such as massive CH_4 emissions from rice cultivation, millions of smallholder farmers, and significant spatial heterogeneity (Azhgaliyeva and Rahut, 2022; Cui et al., 2018). Moreover, it is necessary to provide instructions and technical support for policy audiences, and encourage investment in the R&D and innovation of cost-efficient agricultural GHG mitigation technologies to expand the range of mitigation options available (Azhgaliyeva and Rahut, 2022; NZME, 2019; Stepanyan et al., 2023).

5. Conclusions

Agricultural GHG mitigation is significant to achieve China's 'dual carbon' goal. By simulating GHG mitigation pathways in Chinese agriculture through a bottom-up agricultural technology optimisation model (ATOM), we find that Chinese agriculture theoretically possesses considerable technical potential for GHG mitigation. However, the implementation of agricultural GHG mitigation measures in China may be hindered by multiple obstacles, such as the highly fragmented agricultural system and hidden costs or inefficiencies of mitigation measures, which need to be overcome properly. Additionally, existing agricultural GHG mitigation measures are possibly insufficient to achieve carbon neutrality in Chinese agriculture by 2060, which means more GHG mitigation actions on the demand side or in other sectors are needed. We also find that there is spatial heterogeneity in the mitigation potential within Chinese agriculture. These findings are meaningful to policymakers so that they can adopt counterstrategies to ensure that the agricultural sector remains on track to meet China's 'dual carbon' goal.

This study has several limitations. First. there are uncertainties arising from data sources. For example, we substituted the national average data for missing provincial data in the emission factor calculation. Second, in scenario settings, the parameters based on SSP driving forces have uncertainties. ATOM utilised a panel data regression to forecast the future output of agricultural products. Tools like China Agricultural Monitoring and Early-warning System (CAMES) could help to make a better projection. Third, this study assumed no impacts of institutional barriers, financing issues, agricultural products market, farmers' psychology and behaviour on implementing agricultural GHG mitigation measures. All the above factors will have impacts on the actual abatement effect, and further research could focus on integrating these factors. Finally, most of the technical parameters in the current GHG mitigation measures inventory were derived from meta-analysis results. Some feasible agricultural GHG mitigation measures were not integrated into the inventory (Table 1a and b) due to a lack of technical parameters. Therefore, numerous field surveys are needed to develop a more detailed inventory.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on reasonable request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eiar.2023.107409.

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