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Original Paper

Socio-economic and energy-environmental impacts of technological change on China's agricultural development under the carbon neutrality strategy

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ABSTRACT

Promoting agricultural modernisation through technological change is an important strategy for China. China's carbon neutrality strategy is leading to systemic socio-economic changes that could exacerbate the uncertainty of agricultural development. Therefore, applying a computable general equilibrium (CGE) model, this study characterises the agricultural sector in detail, introducing endogenous technological change proxied by research and development (R&D) to assess the impact of different technological change scenarios on agricultural development under the carbon neutrality target. The results show that allocating carbon revenue for R&D inputs can mitigate the significant negative impact of achieving carbon neutrality on knowledge capital and production in agricultural sectors. Overall, using carbon revenue only for R&D input in crop sectors has the optimal effect on increasing the agricultural sectors' knowledge capital, improving crop production and profit, reducing crop external dependence and promoting the synergistic reduction of carbon and pollutant emissions. However, this scenario has the largest negative impact on macro-economics and household welfare. In contrast, allocating carbon revenue to promote technological change in broader non-energy sectors or both crops and non-energy sectors can effectively mitigate negative socio-economic impacts, but the positive impact on agricultural development is minimal. These findings provide practical insights for the rational use of carbon revenue to expand agricultural R&D investment and ensure balanced agricultural and economic development under the carbon neutrality target.

1. Introduction

Agricultural development is critical to ensuring food security and contributing to United Nations' Sustainable Development Goal (SDG) 2 (Zero Hunger) (Zhang et al., 2020). As the global population and economy grow, food demand is increasing (Prosekov and Ivanova, 2018). In China, which uses only 7% of the world's arable land, feeding about 20% of the world's population (Cui and Shoemaker, 2018), it is particularly important to modernise agriculture to ensure sustainable food security. Meanwhile, China established ambitious carbon emissions goals of 'carbon peaking by 2030 and carbon neutrality by 2060', which will lead the systemic transformation of society and economy (Liu et al., 2022a). This has inevitably created considerable challenges and uncertainties for China's future agricultural development.

To meet the nation's growing demand for food, Chinese agriculture has rapidly developed in recent years. However, the development pattern is overly dependent on inputs such as water and fertiliser, leading to a series of resource and environmental problems (Cai et al., 2021; Zhao et al., 2021), which also make it difficult to ensure the long-term sustainable development of China's agriculture. To address these challenges, China is placing increasing emphasis on modernising its agriculture through technological innovation. Relevant government documents, such as the National Agricultural Modernisation Plan (2016–2020) and the

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14th Five-Year Plan to Promote Agricultural and Rural Modernisation, require strengthening the modernisation of China's agricultural industrial technology (SC, 2016, 2021a). The relevant documents related to China's deployment of carbon peaking and neutrality strategy also emphasise the need to coordinate carbon emissions reduction and agricultural development and promote agricultural technology progress to ensure food security (MARA, 2022; SC, 2021b).

A growing number of studies have investigated carbon reduction and technological change in the agricultural sector (Chavas and Nauges, 2020; Shan et al., 2022; Yang et al., 2022), most of which focus on accounting for carbon emissions in agriculture and analyses of the influencing factors (Escobar et al., 2020; Mrówczyńska-Kamińska et al., 2021). For example, Chen et al. (2021) analysed the carbon emissions inventories and carbon footprints of 16 major crop systems in China from 2001 to 2018. Some scholars have evaluated the impact of carbon emissions reduction strategies on agricultural development (Kong et al., 2022; Mardones and Lipski, 2020; Tang and Ma, 2022), mainly exploring the impact of carbon reduction policies or goals, including carbon tax (Hasegawa et al., 2018), temperature control targets (Frank et al., 2019) and carbon neutrality (Wei et al., 2022) on agricultural output, consumption, product prices and trade. For example, Dumortier and Elobeid (2021) assessed changes in production, prices and trade in agriculture resulting from US carbon taxes. In addition, a few studies have analysed the role of technological change in agricultural development (Aldieri et al., 2021; Wei et al., 2022). These studies consider technological change driven by research and development (R&D) investment to be an important driver of agricultural productivity and food supply (Rahman and Salim, 2013; Yang et al., 2021), which can increase agricultural output while saving production factor inputs (Smeets-Kristkova et al., 2016). For example, Adetutu and Ajayi (2020) assessed the impact of domestic and foreign R&D investment in the agricultural sector on agricultural productivity in sub-Saharan African countries, determining that knowledge stock is positively correlated with agricultural productivity growth.

Although some studies have analysed the impact of carbon emissions reduction or technological change on agricultural development, relatively minimal research has assessed the impact of technological change on agriculture in the process of carbon emissions reduction under the same framework, particularly relevant analyses related to the carbon neutrality target. Furthermore, the portrayal of agriculture's technological change in existing research is usually exogenous, lacking effective feedback regarding the impact of incentive policies on technological change. This study examines the impact of different ways of using carbon revenue to promote technological change in agriculture under China's carbon neutrality strategy. To this end, we subdivide the China's agricultural sector, introducing R&D-based endogenous technological change into a computable general equilibrium (CGE) model, aiming to assess the impact of endogenous technological change on agricultural development under the carbon neutrality target.

This study contributes to the existing literature in the following two aspects. First, the study characterises the agricultural sector in detail using the CGE model and introduces R&D-based endogenous technological change, overcoming the limitations of existing studies that typically set agricultural technological change exogenously. Second, this is the first study to explore the impact of different scenarios of endogenous technological change on China's agricultural development under the carbon neutral target, providing practical guidance for the coordinated management of deep decarbonisation and agricultural advancement.

The remainder of this study is organised as follows. Section 2 describes the methodology and data. Section 3 presents the policy scenario settings. Section 4 details the results and discussion. Finally, Section 5 summarises the main findings of this study, discussing some policy implications.

2. Methodology and data

2.1. Model framework

The analytical tool used in this study is the China Energy and Environmental Policy Analysis (CEEPA) model; a multi-sector dynamic recursive CGE model used in China. CEEPA adopts the basic concepts of the CGE model, with special attention regarding the detailed description of China's energy and environmental status. The CEEPA model has been used to study the socio-economic and environmental impacts of various energy and environmental policies in China, such as carbon tax (Liang et al., 2007; Liang and Wei, 2012), energy efficiency (Liang et al., 2009), export rebates (Fan et al., 2015), marginal abatement costs (Jiang et al., 2022c), the deployment of electric vehicle (Jiang et al., 2022d), and carbon trading (Jiang et al., 2022a). For a detailed description of CEEPA, please see Liang et al. (2014). In this study, we only describe the modules in CEEPA that are closely related to the purpose of the research.

2.1.1. Detailing agriculture sector in the CEEPA

China's 2017 input-output table covers five agricultural subsectors, including crops, livestock (ani), forestry (frs), fisheries (fsh) and agricultural services (agrser) (NBS, 2019a). The individual crop sector is refined into eight sectors in this study, referencing the input-output ratio of China's agricultural sector in version 10 of the Global Trade Analysis Project (GTAP 10) database (Aguiar et al., 2019), including rice (pdr), wheat (wht), cereals (gro), vegetables and fruits (v_f), oilseeds (osd), sugar (c_b), fibre crops (pfb) and other crops (ocr). This establishes a database to portray the differential impact of technological change on agricultural sectors under the carbon neutrality target.

2.1.2. Introducing endogenous technological change in the CEEPA

Knowledge capital stock has been introduced into CGE models in many studies to reflect endogenous technological change because of its significant role in endogenous economic growth theory. Referencing the modelling methods of Sue Wing (2006, 2003) and Wang et al. (2009), this study introduces the knowledge capital factor and the R&D investment accounts into the social accounting matrix (SAM).

Knowledge capital accounting measurement follows Terleckyj's method (Sue Wing, 2006; Wang et al., 2009), as shown in Eqs. (1)–(5). First, according to the China Science and Technology Statistical Yearbook (2018) (NBS, 2018a), the R&D input (INR_i) of each sector is estimated. Next, the R&D data is separated from the intermediate input matrix to obtain the R&D matrix. Then, the sum of the rows and columns of the R&D matrix is calculated, based on which we add one row in the factor input row to describe the knowledge capital input and one column in the final demand column to describe the R&D investment. The final account structure containing knowledge capital and R&D investment is shown in Fig. 1.

$$W_{i,j} = Z_{i,j} \Big/ \sum_j Z_{i,j} \cdot INR_i; \quad \text{If } Z_{i,j} \geq Z_{i,j} \Big/ \sum_j Z_{i,j} \cdot INR_i \tag{1}$$

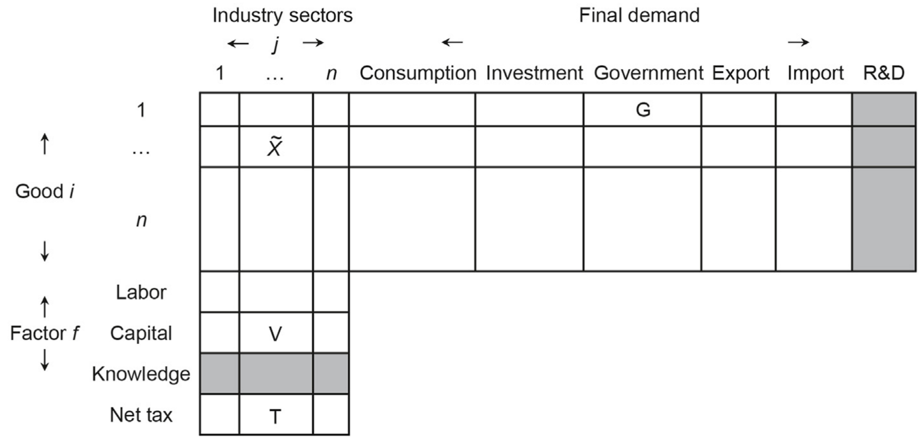

Fig. 1. Accounting structure incorporating knowledge capital (Wang et al., 2009).

$$W_{i,j} = Z_{i,j}; \quad \text{If } Z_{i,j} < Z_{i,j} \Big/ \sum_j Z_{i,j} \cdot INR_i \tag{2}$$

$$Z^A_{i,j} = Z_{i,j} - W_{i,j} \tag{3}$$

$$INR_i = \sum_j W_{i,j} \tag{4}$$

$$HR_j = \sum_i W_{i,j} \tag{5}$$

where $W_{i,j}$ indicates that the knowledge embedded in the product in sector i is put into sector j, $Z_{i,j}$ represents the intermediate product input by the i-th sector to the j-th sector, INR_i represents the R&D input of the i-th sector, $Z^A_{i,j}$ denotes the intermediate product input by the i-th sector into the j-th sector after adjustment, and HR_j denotes the knowledge factor input in sector j.

The production and the investment modules need to be modified accordingly. For the production module, another layer of nesting is needed at the top of the original production function nesting structure, i.e. knowledge factor inputs and non-knowledge inputs are combined in the form of a constant elasticity of substitution (CES) function to form sectoral output. The nesting CES production structure of the production sectors are shown in Figs. 2 and 3.

In the investment module, the introduction of technological change requires a re-description of the investment, as shown in Fig. 4. Total investment needs to distinguish between R&D and physical capital investment, and the CES function is used to describe the substitution between them. Both R&D and physical capital investment demand for investment goods are described based on the CES function, and various types of investment goods can be substituted for each other and substitution ability depends on the value of the elasticity of substitution.

2.2. Data source

The key database of a CGE model is the social accounting matrix (SAM), which describes the economy in a country or a region in a given period. In our model, the 2017 SAM table is built based on the China 2017 input–output table (NBS, 2019a), combined with

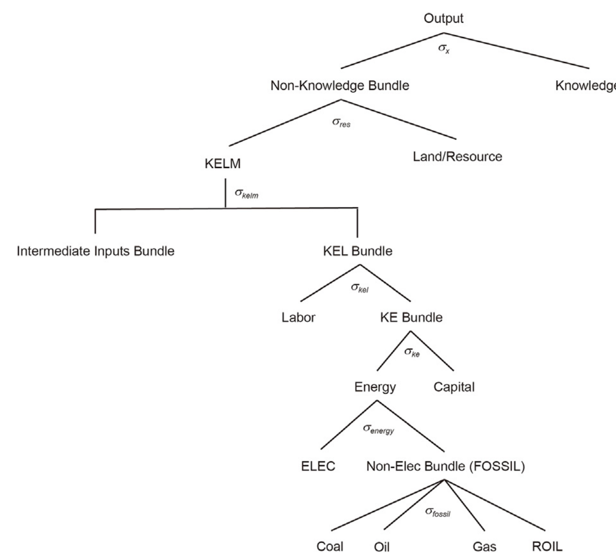

Fig. 2. Production structure of the agriculture and primary energy sectors in the model.

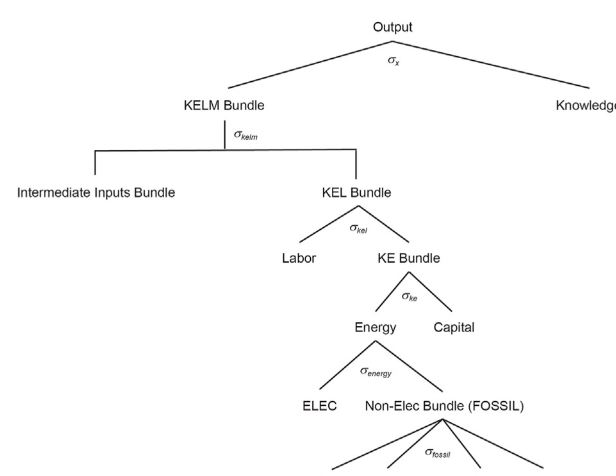

Fig. 3. Production structure of the general economic sector in the model.

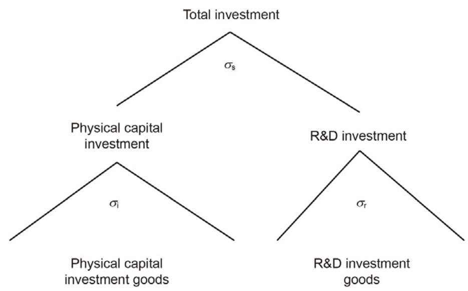

Fig. 4. Nesting CES structure of total investment.

Table 1
The elasticity parameters in the CEEPA Model.

Elasticities	Value	Elasticities	Value
σ_x	2.5	σ_{energy}	0.5
σ_{res}	0.6	σ_{fossil}	1
σ_{kelm}	0	σ_s	2.5
σ_{kel}	0.6	σ_i	1
σ_{ke}	0.9	σ_r	1

Data Source: (Liang et al., 2014; Wang et al., 2009)

miscellaneous yearbooks and literature (GAC, 2021, 2018; MOF, 2018; NBS, 2019b, 2018b, 2018c).

Notably, this study extends the general SAM table by introducing knowledge capital and R&D investment factors, for which the R&D investment data are obtained from the China Science and Technology Statistical Yearbook 2018 (NBS, 2018a). To categorize agriculture, this study references Wei et al. (2022), using the GTAP 10 database with the latest agricultural sub-sector data, splitting the individual crop sector into eight crop sub-sectors based on input-output ratios among agricultural sectors in China (Aguiar et al., 2019), resulting in 12 agricultural sectors.

2.3. Parameter calibration

For the parameters in the CEEPA model, the endogenous parameters are determined using the calibration method in which data in the SAM are substituted into each equation as base year equilibrium data and the equations are then solved to show the value of the parameters (Lofgren et al., 2002). Other parameters are obtained from related studies (Liang et al., 2014; Liu et al., 2015; Wang et al., 2009; Wu and Xuan, 2002), such as various elasticities of substitution, carbon emission factors and carbon oxidation rates. The relevant elasticity of substitution parameters are shown in Table 1.

3. Scenario setting

To explore the socio-economic and environmental impacts of technological change on the development of the agricultural sector under the carbon neutrality target, this study constructs a baseline scenario (BAU) which follows a moderate economic development path with no additional mitigation policies, establishing four additional policy scenarios which are presented in Table 2.

First, this study sets a common emissions reduction pathway to achieve the 2060 carbon neutrality target. The carbon pricing policy is implemented for fossil energy, and 50% of the carbon pricing revenue is used to subsidise renewable electricity and the remaining revenue is included in the government budget (RE scenario). According to related studies (Huang et al., 2020; Liu et al., 2022b), the national CO_2 reduction required from carbon sinks and negative emission technologies by 2060 is about 2.1 billion tonnes (about 20% of the carbon emissions in 2060 under this study's BAU). Therefore, the carbon neutrality target in this study refers to a more than 80% reduction in national carbon emissions of by 2060. In addition, the carbon price for this scenario is given endogenously by the model (an initial carbon price of about 65 Yuan/t CO_2 and an average annual growth rate of 10%), see Table 2.

This study further analyses the impact of different technological change scenarios on agricultural sectors, divided into three scenarios: (1) Only increase the R&D input of agricultural products (R&D_Only), (2) Increase R&D input in all non-energy sectors (R&D_Non) and (3) Increase R&D inputs in both crops and all non-energy sectors (R&D_Both). The detailed settings of technological change scenarios are presented in Table 2.

4. Results and discussion

4.1. Effects on agricultural sectors

4.1.1. Effects on knowledge capital factor of agricultural sectors

Table 3 shows the impact of each scenario on the knowledge capital factor in agricultural sectors in 2060. Under the RE scenario, achieving carbon neutrality will reduce agricultural sectors' knowledge capital. This is mainly because the high carbon price will increase agricultural sectors' production costs and compress the scale of agricultural production, reducing the input of knowledge capital factors in agricultural sectors accordingly. In comparison to BAU, the three technological change scenarios will generally increase agricultural sectors' investment in knowledge capital to different degrees. This is because allocating a portion of the carbon pricing revenue for R&D investment can change relative factor prices and the rate of return on R&D investment. This will increase the share of R&D investment in the final total demand, correspondingly raising the stock of social knowledge capital and

Table 2
Scenario description.

Scenario		Policy Description
Business as Usual	BAU	Follow the medium economic development path without additional mitigation policies
Achieving a carbon neutral emissions reduction pathway	RE	Carbon pricing is implemented from 2022, and the initial carbon price is endogenous (about 65 yuan/t CO_2), increasing by 10% annually. And 50% of carbon revenue is used to subsidise renewable electricity, and the remainder is included in government revenue
Only increase crops R&D input	R&D_Only	Based on the RE scenario, the remaining 50% of carbon revenue is allocated according to the proportion of crops' initial R&D input
Increase R&D input in all non-energy sectors[a]	R&D_Non	Based on the RE scenario, the remaining 50% of carbon revenue is allocated according to the proportion of non-energy sectors' initial R&D input
Increase R&D inputs in both crops and all non-energy sectors	R&D_Both	Based on the RE scenario, the remaining 10% of the carbon revenue is allocated according to the proportion of crops' initial R&D input, and the remaining 40% is based on the proportion of the initial R&D input of non-energy sectors

Note.
[a] To assess the technological change effect of increasing R&D inputs while avoiding causing more energy consumption, which is not conductive to the realization of carbon neutrality, this scenario only increases all non-energy R&D inputs.

Table 3
Impact of scenarios on knowledge capital factor in agricultural sectors in 2060.

	RE	R&D_Only	R&D_Non	R&D_Both		RE	R&D_Only	R&D_Non	R&D_Both
pdr	−6.60	267.45	58.96	101.65	Pfb	−7.15	5.70	58.01	47.38
wht	−6.93	156.41	58.38	78.53	Ocr	−2.93	2131.00	65.51	482.43
gro	−6.60	265.35	58.94	101.22	Ani	0.82	279.64	72.05	114.66
v_f	−6.91	128.38	58.43	72.87	Frs	−3.67	−8.20	64.38	49.61
osd	−7.46	5.61	57.45	46.90	Fsh	−0.20	16.34	70.24	59.33
c_b	−7.10	53.27	58.12	57.21	Agrser	−3.16	237.62	64.14	99.44

expanding the supply of knowledge capital in the factor market. The R&D_Only scenario has the best effect on promoting knowledge capital in agricultural sectors, followed by R&D_Both and the R&D_Non scenarios. The main reason for this is the difference in allocation schemes for the carbon pricing revenue to R&D investments in the three scenarios. The R&D_Only scenario uses carbon pricing revenue only for R&D investment in crop sectors, which significantly increases the accumulation of knowledge capital in crop sectors. In particular, the ocr sector would have the largest growth in knowledge capital in comparison to BAU. This is related to the share of knowledge capital factor in total output, indicating that the greater the share is, the greater the impact on the price of knowledge capital factor will be. The ocr sector has the largest share of knowledge capital factor in total output of all eight crop sectors and thus has the largest decrease in the price of its knowledge capital factor, resulting in the most significant increase in knowledge capital. In contrast, the other two technological change scenarios use carbon pricing revenue for R&D investment in wider sectors, which will reduce the allocated share of R&D investment in the agricultural sectors, exerting a relatively less positive impact on knowledge capital.

4.1.2. Effects on agricultural production

Figure 5 shows the impact of each policy scenario on agricultural production. Overall, the three technological change scenarios will reduce the negative impact of achieving carbon neutrality on crop production under the RE scenario to varying degrees, but uncertainty remains regarding the impact on frs, ani and fsh sectors. First, under the RE scenario, achieving carbon neutrality in 2060 will reduce production in all agricultural sectors (−0.32% to −2.15%) (Fig. 5(a)). The frs (−2.15%) sector will be the most negatively affected, followed by pdr (−1.36%), while osd (−0.12%) and ani (−0.32%) will be least affected. Overall, with the implementation of stricter carbon emissions reduction goals, the negative impact of agricultural production in the later stage of emissions reduction will gradually weaken. The carbon pricing will continue to increase the cost of using fossil fuel energy, compelling agricultural sectors to gradually replace fossil energy with clean energy to reduce the negative impact of carbon emissions reduction. Furthermore, under the assumption of full employment, deep emissions reduction will cause the labour force to shift from high-energy-consuming sectors to low-energy-consuming sectors such as agriculture, reducing a portion of the loss of agricultural production. The agricultural production trend presents the characteristics identified under the combined effect of these two influences. Among the three technological change scenarios, the R&D_Only scenario is the most favourable for most agricultural sector production. As illustrated in Fig. 5(b), the ocr sector's production will increase by 71.43% and v_f (18.86%), gro (17.82%) and pdr (14.62%) production will also be significantly increased. While production in frs (−6.07%), ani (−2.22%) and fsh (−2.19%) will be further reduced. The reason these results is primarily due to the differential impact of each technological change scenario on the knowledge capital of each agricultural sector. As previously noted, using carbon pricing revenue only for crops R&D investments (R&D_Only scenario) can significantly contribute to the knowledge capital of these sectors, increasing their technological change and production scale; however, this will crowd out the production factors of other sectors (such as frs, ani

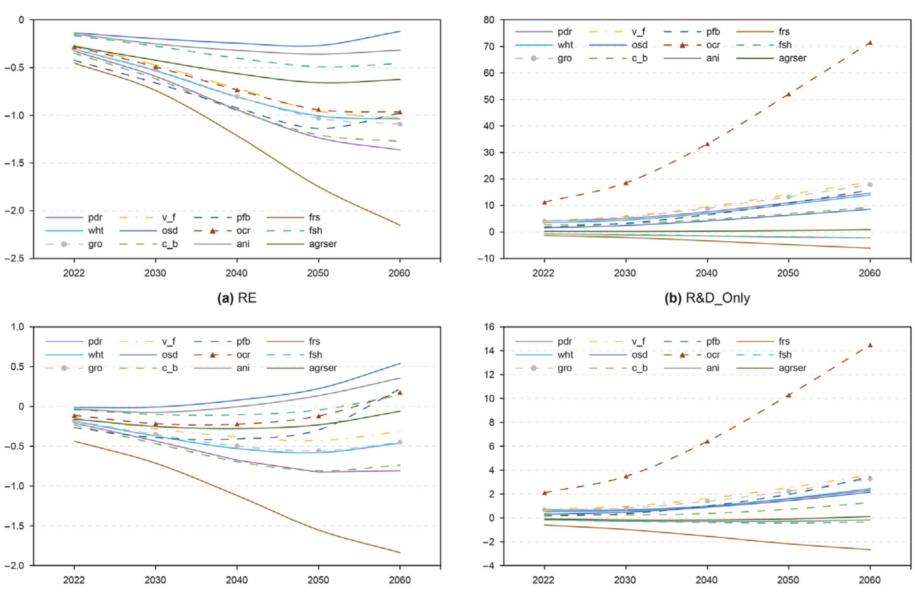

Fig. 5. Impact of policy scenarios on agricultural production (%).

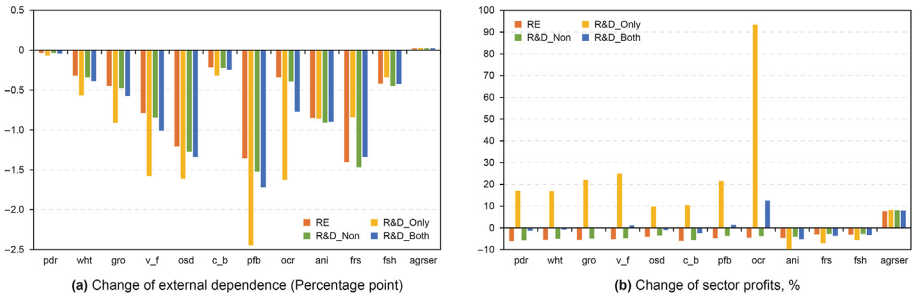

Fig. 6. Impact of the scenarios on agricultural sectors' external dependence and profits in 2060.

and fsh), which will be detrimental to their production. The positive effect of the R&D_Both scenario on different agricultural products is similar to that of R&D_Only scenario, but it is relatively lower. The R&D_Non scenario has the least effect on improving agricultural production, which is closely correlated to the least positive impact of this scenario on the knowledge capital factor in most agricultural sectors revealed above.

4.1.3. Effects on external dependence and profits of agricultural sectors

Overall, each technological change scenario under the carbon neutrality target will reduce each agricultural sector's external dependence to varying degrees (Fig. 6(a)). This is beneficial to China's strategy of maintaining the external dependence of various agricultural products within a reasonable range to achieve agricultural self-sufficiency. Agricultural sectors' external dependence refers to the ratio between the agriculture import volume and agriculture consumption volume, which directly reflects national food security. Agricultural products with high external dependence, such as osd and pfb, will be more affected. In contrast, the impact on agricultural products with high self-sufficiency, such as pdr, wht and gro (the three major food crops), is relatively small. This is because the negative impact of carbon pricing on the domestic sales price of agricultural products is smaller than the negative impact on their import price, resulting in a greater decline in agricultural imports and differing degrees of reduction in each agricultural product's external dependence. Furthermore, the change in the external dependence of agricultural productions with large import volume will be more obvious under a similar percentage reduction; thus, the external dependence of osd and pfb will decrease more. In addition, the R&D_Only scenario has the best effect on reducing the external dependence of crops, followed by R&D_Both, and R&D_Non, which is primarily related to the effect of each technological change scenario on promoting agricultural production. Better technological change can reduce the cost of agricultural production more effectively, lowering the price of agricultural products and making them more competitive in the international market.

Figure 6(b) shows the change in profits for all agricultural sectors under each scenario. In this study, sectoral profit refers to the sum of sectoral capital income and fixed factor income. The R&D_Only scenario will offset the negative impact of achieving carbon neutrality (RE) on each crop sector' profits and have a further positive impact. In contrast to the BAU scenario, the R&D_Only scenario will increase the profits of the three major food crop sectors (pdr, wht and gro) by 17.1%, 16.9% and 22.1% in 2060, respectively. In particular, the profit of the ocr sector will be boosted by 93.5%. Although the R&D_Non and R&D_Both scenarios can also mitigate the negative impact of carbon neutrality on crop sectors' profit to some extent, this effect is limited, particularly the R&D_Non scenario. The rationale behind for the above effects is mainly that the technological change scenarios have different results on agricultural sectors' capital incomes and fixed factor revenues through different R&D subsidy schemes.

4.1.4. Effects on agricultural carbon emissions

Figure 7 shows the impact of different technological change scenarios on agricultural carbon emissions reduction under the carbon neutrality target. Under the RE scenario, high carbon prices will force a reduction in carbon emissions of about 69.21%–74.14% from various agricultural sectors in 2060. In comparison, the three technological change scenarios would further weaken carbon emissions reduction effects in crop sectors but boost carbon emissions reduction effects in other agricultural sectors. Among them, the R&D_Only scenario has the most obvious weakening impact. By subsidising the R&D of crops, technological change scenarios will promote an increase in knowledge capital, which will replace part of the fossil energy input. At the same time, technological change will also increase fossil energy consumption by raising crop sectors' output, triggering an energy rebound effect. Under the combined effect of these two aspects, the carbon emissions reduction of crop sectors in each R&D_Only scenario will be further weakened. However, the R&D_Only scenario will reduce the production and carbon emissions of other agricultural sectors due to crowding out factor inputs. Similarly, R&D_Non and R&D_Both scenarios will also weaken crop sectors' carbon emissions reduction through the combined effect discussed above, and have a weak effect on other agricultural sectors.

4.2. Effects on the macro-economy

4.2.1. Effects on gross domestic product (GDP)

Figure 8(a) shows the impacts of various policy scenarios on GDP. Although in comparison to the RE scenario, the R&D_Only scenario is most beneficial to agricultural development, it will

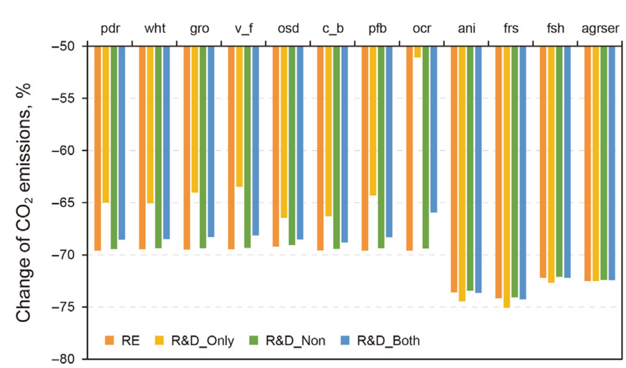

Fig. 7. Changes in carbon emissions from agricultural sectors under various scenarios in 2060.

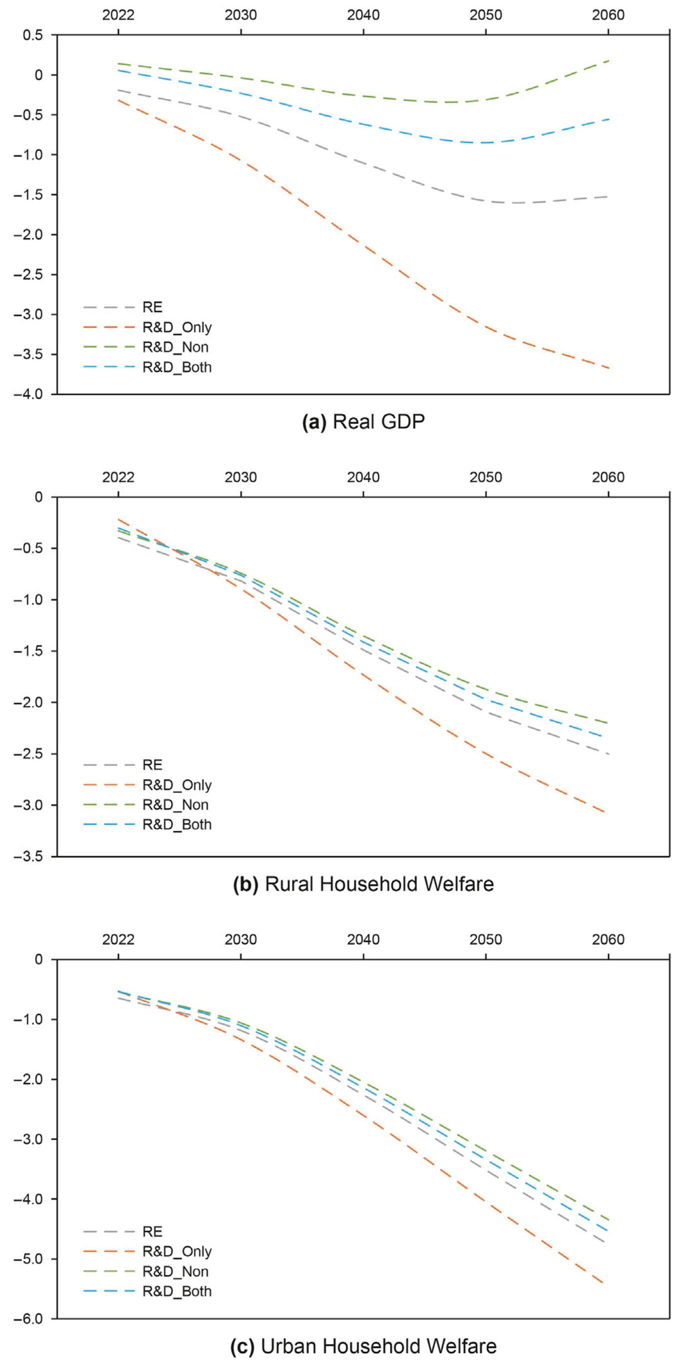

Fig. 8. Changes in GDP and household welfare in comparison to BAU (%).

further increase GDP loss, while R&D_Non and R&D_Both scenarios can effectively mitigate the GDP loss, particularly the R&D_Non scenario. The differential impact of each policy scenario on GDP can be explained by the GDP components (total consumption, total investment and net exports). Based on the balance of payments assumptions in the model, net exports remain unchanged in all scenarios. In the RE scenario, although the inclusion of carbon pricing revenue will increase government savings, high carbon prices will increase sectoral production costs, resulting in a decline of sectoral output, leading to a decline in total investment and total consumption. In comparison to the RE scenario, the R&D_Only scenario can effectively boost low-value-added agriculture output by using carbon pricing revenue for agricultural R&D inputs but reduce the output of other higher-value-added sectors, leading to further reductions in government savings and total investment. Although R&D_Non and R&D_Both scenarios have less positive impact on agricultural production than the R&D_Only scenario by promoting technological change in the wider sector, the scenarios can effectively offset some of the negative impacts on total investment and total consumption. In the long run, as R&D investment increases, each technological change scenario is increasingly effective in reducing GDP loss, and the R&D_Non scenario can offset the negative economic impact of achieving carbon neutrality by 2060. This is primarily because each technological change scenario leverages more knowledge capital in the production process and substitutes other factors such as capital and energy. This can reduce output losses in most sectors and even increase output in a few sectors, resulting in a gradual reduction in GDP loss and even reversing the negative impact on the economy over time.

4.2.2. Effects on household welfare

Figure 8(b) and (c) show changes in household welfare in urban and rural areas under different scenarios. In this study, household welfare is measured as a percent change based on Hicks-equivalent change (Fujimori et al., 2015; Jiang et al., 2022d). The results demonstrate that urban and rural household welfare continues to decline under all policy scenarios. The main reason is that the labour price in each policy scenario will decline to varying degrees, which will reduce the income of labor factors, resulting in a decline in urban and rural residents' disposable income, thereby reducing the level of consumption. Specifically, the R&D_Only scenario exhibits the highest welfare loss, the R&D_Non scenario is the lowest, and RE and R&D_Both scenarios are moderate. In addition, in all scenarios, rural households' welfare loss is smaller than that of urban households. The main reason is that, the proportion of transfer income is higher in the disposable income of rural households, so there is a smaller impact (Liang et al., 2013).

4.3. Effects on energy use and environment

4.3.1. Effects on energy use

Table 4 shows the change in energy intensity under each policy scenario. Under the carbon neutrality target, energy intensity decreases significantly in all scenarios. For example, under the RE scenario, energy intensity dramatically decreases from 16.25% in 2022 to 83.57% in 2060. In comparison to the RE scenario, the three technological change scenarios are more conducive to promoting energy intensity reduction, and in the long run, the larger the scope of R&D subsidies is, the better the effect of reducing energy intensity will be. This is because the R&D subsidy policy increases the supply of knowledge capital and enhances the substitution of physical inputs, particularly the substitution of energy. This reduces the share of energy input per unit of output value, resulting in a larger reduction in energy intensity in the three technological change scenarios than in the RE scenario.

Changes in energy consumption under each policy scenario are shown in Fig. 9, revealing that all policy scenarios will significantly reduce China's total energy consumption as the carbon neutrality

Table 4
Changes in energy intensity under each scenario (%).

	2022	2030	2040	2050	2060
RE	−16.25	−30.69	−50.37	−69.42	−83.57
R&D_Only	−16.64	−30.91	−50.52	−69.52	−83.65
R&D_Non	−16.47	−30.92	−50.61	−69.65	−83.75
R&D_Both	−16.50	−30.92	−50.60	−69.63	−83.74

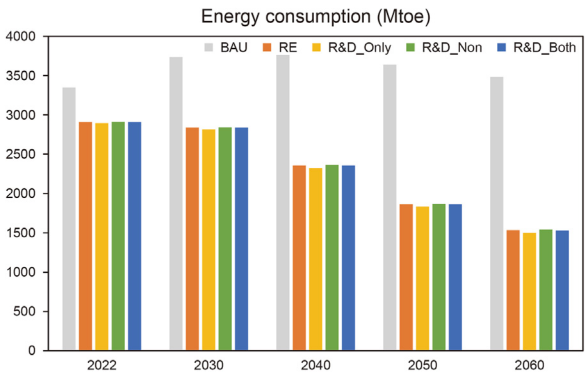

Fig. 9. Changes in energy consumption under various scenarios.

target is advanced, but there are some differences between the scenarios. Specifically, the R&D_Only scenario has the largest decline in total energy consumption, with a 57.0% decline by 2060, an increase of 1 percentage point over the RE scenario. This is because only raising the R&D subsidy for agricultural products increases the substitution of knowledge capital for energy while also reducing the output of other higher value-added sectors, further lowering energy input. Furthermore, the energy consumption for the R&D_Non scenario is slightly higher than the RE scenario. This is because although increased in knowledge capital improves energy substitution, economic development will drive increased in energy consumption, and the two effects will make the energy consumption higher in this scenario than in the RE scenario. Additionally, the energy consumption in the R&D_Both scenario is between the R&D_Only and R&D_Non scenarios because it increases R&D input in both crop sectors and all non-energy sectors.

4.3.2. Effects on CO2 and pollutant emissions

Figure 10(a) shows the national cumulative carbon emissions changes from 2022 to 2060 under different scenarios. Compared

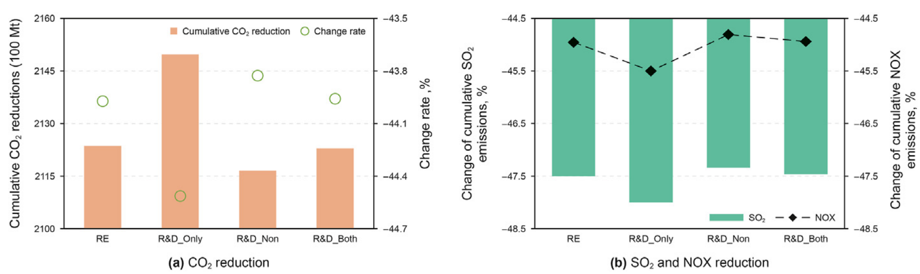

Fig. 10. Emissions reduction effect under each scenario.

Table 5
Sensitivity analysis under different elastic parameter scenarios.

Scenario	Indicator (%) (In, 2060)		Base	σ_E (0.5)		σ_{KE} (0.9)	
				Low	High	Low	High
RE	Agricultural production	pdr	−1.36	−1.53	−1.22	−1.66	−1.08
		wht	−1.04	−1.18	−0.92	−1.28	−0.81
		gro	−1.09	−1.23	−0.97	−1.35	−0.85
	Knowledge capital factor	pdr	−6.6	−7.13	−6.1	−8.28	−5.22
		wht	−6.93	−7.49	−6.4	−8.67	−5.49
		gro	−6.6	−7.14	−6.1	−8.28	−5.22
	GDP		−1.53	−1.57	−1.48	−2.0	−1.11
	Carbon emission		−79.98	−78.33	−81.46	−80.26	−79.67
R&D_Only	Agricultural production	pdr	14.63	16.19	13.24	16.49	13.15
		wht	13.93	15.4	12.62	15.7	12.52
		gro	17.82	19.71	16.15	20.12	15.99
	Knowledge capital factor	pdr	267.45	296.54	241.93	309.13	234.94
		wht	156.41	173.5	141.43	180.59	137.6
		gro	265.35	294.14	240.08	306.69	233.12
	GDP		−3.67	−3.93	−3.42	−4.41	−3.04
	Carbon emission		−80.44	−78.9	−81.84	−80.82	−80.05
R&D_Non	Agricultural production	pdr	−0.81	−0.91	−0.72	−1.03	−0.59
		wht	−0.46	−0.54	−0.4	−0.62	−0.3
		gro	−0.45	−0.52	−0.39	−0.62	−0.28
	Knowledge capital factor	pdr	58.96	64.65	53.89	66.19	53.33
		wht	58.38	64	53.37	65.47	52.86
		gro	58.94	64.64	53.87	66.18	53.31
	GDP		0.17	0.28	−0.08	−0.08	0.41
	Carbon emission		−79.83	−78.17	−81.33	−80.11	−79.53
R&D_Both	Agricultural production	pdr	2.32	2.56	2.1	2.53	2.18
		wht	2.44	2.69	2.23	2.69	2.28
		gro	3.25	3.59	2.95	3.61	3.01
	Knowledge capital factor	pdr	101.65	112.29	92.29	116.17	90.38
		wht	78.53	86.58	71.42	89.24	70.21
		gro	101.22	111.8	91.91	115.67	90.01
	GDP		−0.56	−0.52	−0.58	−0.91	−0.24
	Carbon emission		−79.95	−78.31	−81.43	−80.25	−79.63

with BAU, cumulative CO_2 emissions reduction under the RE scenario is 21.24 billion tonnes, representing a decrease of 44.0%. Among the three technological change scenarios, the scenario that only promotes technological change in crop sectors (R&D_Only) can further promote carbon emissions reduction by 44.5%. Because this scenario focuses on using carbon pricing revenue for R&D investment in crop sectors, this will increase the substitution of knowledge capital for energy and reduce carbon emissions and will also have a higher negative impact on the entire macro-economy, further contributing to carbon reduction. In contrast, the R&D_Non scenario has an energy rebound effect due to improved overall benefits, offsetting some of the carbon emissions reduction. Furthermore, the emissions reduction effect of the R&D_Both scenario is similar to that of RE.

Additionally, due to environmental synergies, achieving the carbon neutrality target also has a positive impact on the reduction of other major air pollutants such as sulfur dioxide (SO_2) and nitrogen oxides (NO_X) (Jiang et al., 2022b, 2023; Wang et al., 2020). Fig. 10(b) shows the cumulative SO_2 and NO_X emissions reductions from 2022 to 2060 under each scenario. Under the R&D_Only scenario, the synergistic emissions reduction effect of SO_2 and NO_X is the most obvious, with cumulative emissions reductions of 48.0% and 45.5%, respectively. In contrast, the R&D_Non scenario has the least synergistic reduction effect. In addition, the cumulative SO_2 emissions reduction rate is greater than the cumulative NO_X emissions reduction rate in all scenarios, because SO_2 and NO_X emissions include both energy and process-related emissions, of which the energy-related emissions for SO_2 account for a larger proportion.

4.4. Sensitivity analysis

Given the inherent limitations of the CGE model in setting different elasticity parameters, it is essential to conduct a sensitivity analysis for the key parameters in the model. Therefore, the elasticity of substitution between electricity and combined fossil energy (σ_E) and between energy and capital input (σ_{KE}) are chosen for the sensitivity analysis. These parameters are generally set to be 20% greater or smaller than the values in the baseline scenario, considering the feasibility of the model. The focus of this approach is on key indicators such as production and knowledge capital factors of the three major food crops (i.e. rice, wheat and cereals) in 2060, as shown in Table 5. The results show that changing these two elasticity of substitution parameters does not change the direction or ranking of the selected indicators under different scenarios, confirming the robustness of the model results.

5. Conclusions and policy implications

Recently, China has increasingly prioritised promoting the modernisation of agriculture through technological change to ensure food security supply. Under the broad impact of the national carbon neutrality strategy, assessing the impact of technological change on agriculture is critical to the coordinated management of agricultural development and carbon reduction targets. To this end, this study explores the impact of different technological change scenarios on China's agricultural development under the carbon neutrality target based on a CGE model that portrays the agricultural sector in detail and introduces R&D-based endogenous technological change.

The results show that achieving carbon neutrality would have a negative impact on agricultural sectors' knowledge capital factor and reduce the output of agricultural products by 0.32%–2.15%. However, by allocating carbon pricing revenue to R&D input in different distribution schemes, agricultural development can be promoted to different degrees. Overall, R&D input only for crop sectors (R&D_Only scenario) has the best positive impact on agricultural development and the environment in multiple aspects, including increasing the knowledge capital of agricultural sectors, increasing crop yields and profits, reducing crop external dependence, and promoting synergistic CO_2 and pollutant emissions reduction. Notably, this technological change scenario would increase agricultural carbon emissions and significantly increase GDP and household welfare loss. Conversely, the use of carbon pricing revenue for R&D inputs in the broader non-energy sectors (R&D_Non) or both crops and non-energy sectors (R&D_Both) could be effective in mitigating the negative macro-economic impact of achieving carbon neutrality, but the positive impact on agricultural development would be relatively limited.

Based on the findings of this study, we propose the following relevant policy recommendations to promote the use of technological change to advance agricultural development under the carbon neutrality target.

Carbon revenue can be used to expand agricultural R&D inputs, raising agricultural productivity and mitigating the negative impact of deep decarbonisation on agriculture. Our study shows that using carbon revenue to subsidise R&D inputs can effectively promote technological progress, offsetting the negative impact of the carbon neutrality target on agriculture in several ways. However, carbon revenue should be appropriately allocated to balance agricultural development, carbon reduction and overall economic benefits, as allocating carbon revenue only to R&D inputs in agricultural sectors can effectively promote agricultural development, but would lead to increased economic loss. In contrast, allocating carbon revenue to R&D inputs in crops and wider non-energy sectors can control energy consumption and also balance agricultural and economic development. In addition, green agricultural technology inputs should be strengthened to realise the dual benefits of greenhouse gas reduction and boosting agricultural production.

Although this study uses the CGE model to assess the impact of different technological progress scenarios on the development of Chinese agriculture under the carbon neutrality target, some limitations remain that could to be improved in our future work. For example, the CGE model used in this study is national level and does not consider the regional heterogeneity of agricultural production and achieving carbon neutrality targets in China. Therefore, we plan to explore this issue in future work using a multi-regional CGE model to assess the different impacts of technological progress on agriculture under regional carbon neutrality targets more specifically. In addition, only R&D-based technological progress is considered in this study, not the ‘learning-by-doing’ type of technological progress; therefore, we will further explore the economic and environmental impact of technological progress of these two forms.

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.

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