Managing domestic trade for food security with environmental and economic equity in China

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Supplementary Methods

Estimation of embedded N emission in interprovincial grain trade

To evaluate the nitrogen-related environmental burdens embedded in interprovincial grain trade, we calculated both the total associated nitrogen losses from agricultural production. The virtual N embedded in traded grain refers to the N related pollutants emitted during the production of traded grains. To quantify nitrogen losses during production, we considered four key pathways: ammonia volatilization (NH3), nitrogen oxide (NO) emissions, nitrate leaching, and surface runoff. These losses were estimated using region-specific nitrogen application rates and standard emission factors based on IPCC guidelines and CHANS model. Ammonia and NO emissions were calculated as fixed fractions of applied nitrogen, while leaching and runoff were estimated using average loss coefficients calibrated to crop type. All calculations were based on annual provincial-level data, and the specific calculation is as follows:

$$N_{NH3} = \sum_{i=1}^{n} \left(VLTS_i \times N_{rate,i} \times EF_{NH3}\right)$$

$$N_{NO} = \sum_{i=1}^{n} \left(VLTS_i \times N_{rate,i} \times EF_{NO}\right)$$

$$N_{NO} = \sum_{i=1}^{n} \left(VLTS_i \times N_{rate,i} \times (EF_{leaching} + EF_{runoff}\right)$$

Where N_{NH3} is the total magnitude of NH_3 volatilization, $VLTS_i$ is the area of virtual cropland transferred from province i, $N_{rate.i}$ is the unit fertilization rate, specific provincial parameters are available in the Table S2, EF_{NH3}, EF_{NO} and $EF_{leaching}$ EF_{runoff} are the NH_3 and NO emission factors of nitrogen fertilizer, and the NO_3^- nitrogen loss to water coefficient includes the leaching and runoff, the relevant parameters can be found in the CHANS model. The parameters were determined from the built-in parameters of the CHANS model and took an empirical value of 9%, based on integrated parameters derived from extensive historical survey data within the CHANS model. Detailed parameters within the CHANS model can refer to Gu et al[1] and Xu et al[2].

Estimation of embedded GHG emission in interprovincial grain trade

The virtual GHG embedded in traded grain refers to the carbon related pollutants emitted during the grain production process, including CO_2, CH_4, and N_2O. To assess total associated GHG emissions from agricultural production, we accounted for methane (CH_4) emissions from rice paddies, nitrous oxide (N_2O) emissions from fertilizer use, and carbon dioxide (CO_2) emissions from agricultural machinery inputs and biomass burning. Emissions were calculated using crop-specific activity data and emission factors based on CHANS model. Methane emissions were estimated based on rice cultivation area and management regimes; N_2O emissions were derived from N input and direct and indirect emission factors; CO_2 emissions were calculated from diesel fuel use, biomass burning. All GHGs were expressed in CO_2-equivalents using global warming potential values (GWP100) of 27.9 for CH_4, 273 for N_2O, and 1 for CO_2[3,4]. The specific calculation is as follows:

$$CH_{4_{rice}} = \sum_{i=1}^{n} \left(VLTS_i \times A_{ratio,i} \times EF_{CH4} \times \frac{12}{16} \times 27.9\right)$$

Where $CH_{4_{rice}}$ refers to CH_4 emissions from flooding of rice paddies (kg CO_2-eq), and

$A_{ratio,i}$ is the proportion of rice cultivation area to grain crop area in province i. EF_{CH4} is the CH_4 emission factor of rice paddies, 12/16 is the molecular conversion factor, and 27.9 is conversion factor from CH_4 to CO_2[3] .

$$N2O_{fertilizer} = \sum_{i=1}^{n}(VLTS_i \times N_{rate,i} \times EF_{N2O} \times 273)$$

Where $N2O_{fertilizer}$ refers to the N_2O emissions from the application of nitrogen fertilizer (kg CO_2-eq), EF_{N2O} is the N_2O emission factor of nitrogen fertilizer, the relevant parameters can be found in the CHANS model. For the calculation of total GHG emissions, we converted N_2O and CH_4 emissions into their CO_2-equivalent (CO_2-e) values using the global warming potential (GWP) metrics provided by the Intergovernmental Panel on Climate Change (IPCC)[4]over a 100-year time horizon: GWP of 273 for N_2O and 27.9 for CH_4, respectively.

$$CO_{2_{biomass}} = \sum_{i=1}^{n}(T_i \times Straw_{ratio} \times EF_{CO2})$$

Where $CO2_{biomass}$ refers CO_2 emissions generated from straw burning, T_i denotes the amount of grain flowing from provinces i (kg). $Straw_{ratio}$ is ratio of straw to grain and EF_{CO2} is the CO_2 emission factor, which was determined from the built-in parameters of the CHANS model, 12/44 is the molecular conversion factor.

To estimate the carbon emissions from agricultural machinery embedded in interprovincial grain trade, we adopted a factor-based approach using CHANS model outputs. Specifically, we multiplied the estimated CO_2 emission intensity per unit of grain production (kg CO_2 per ton), derived from CHANS simulations, by the volume of traded grain between provinces. This provided a spatially explicit quantification of machinery-related CO_2 emissions embedded in grain flows.

$$CO_{2_{machinery}} = \sum_{i=1}^{n}(T_i \times EF_{CO2})$$

Where $CO2_{machinery}$ refers CO_2 emissions generated from agricultural machinery fossil fuel combustion, T_i denotes the amount of grain flowing from provinces i (kg). EF_{CO2} is the CO_2 emission factor, which was determined from the built-in parameters of the CHANS mode.

$$CO_{2_{soil}} = \sum_{i=1}^{n}\left(VLTS_i \times EF_{CO2} \times \frac{44}{12}\right)$$

Where $CO2_{soil}$ refers CO_2 emissions generated from soil respiration, $VLTS_i$ is the area of virtual cropland transferred from province i, EF_{CO2} is the CO_2 emission factor from soil, which was determined from the built-in parameters of the CHANS mode.

Estimation of embedded carbon sink in interprovincial grain trade

To quantify the carbon sink embedded in interprovincial grain trade, we evaluated two primary carbon sequestration pathways associated with grain production: carbon sequestration in crop biomass (CS_{crop}) and in cropland soil (CS_{soil}). The total embedded carbon sink, defined as the sum of these components, represents the sequestration ecosystem service provided by the grain-exporting region.

Carbon Sequestration in crop biomass: This component refers to the carbon fixed in the non-harvested parts of the plant (primarily straw and roots) through photosynthesis during the growing season. We estimated this based on the volume of grain traded between provinces. The calculation involved multiplying the traded volume of each crop type (rice, wheat, and maize) by its corresponding crop-specific straw-to-grain ratio and the average carbon content coefficient of the straw. These crop-specific parameters were sourced from published literature and the CHANS model parameter library. Carbon Sequestration in cropland soil: This component represents the net annual increase in soil organic carbon (SOC) associated with the “virtual cropland” transferred through trade. It was calculated by multiplying the area of virtual cropland transferred (*VLTSi*) by an average SOC sequestration rate for the given province and cropping system. This rate (in tons of C per hectare per year) is influenced by agricultural management practices such as tillage methods (e.g., conservation tillage), straw return levels, and irrigation. The values used were derived from long-term field experiment studies in relevant regions and simulation results from the CHANS model.

Supplementary Figure:

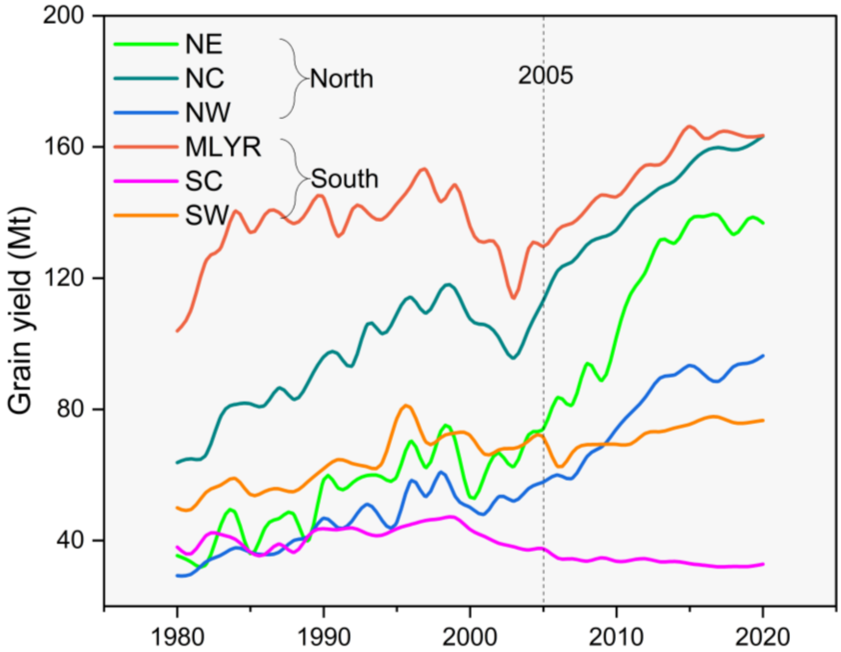

Fig. S1 Changes in grain production trends in different regions (Mt: million tons)

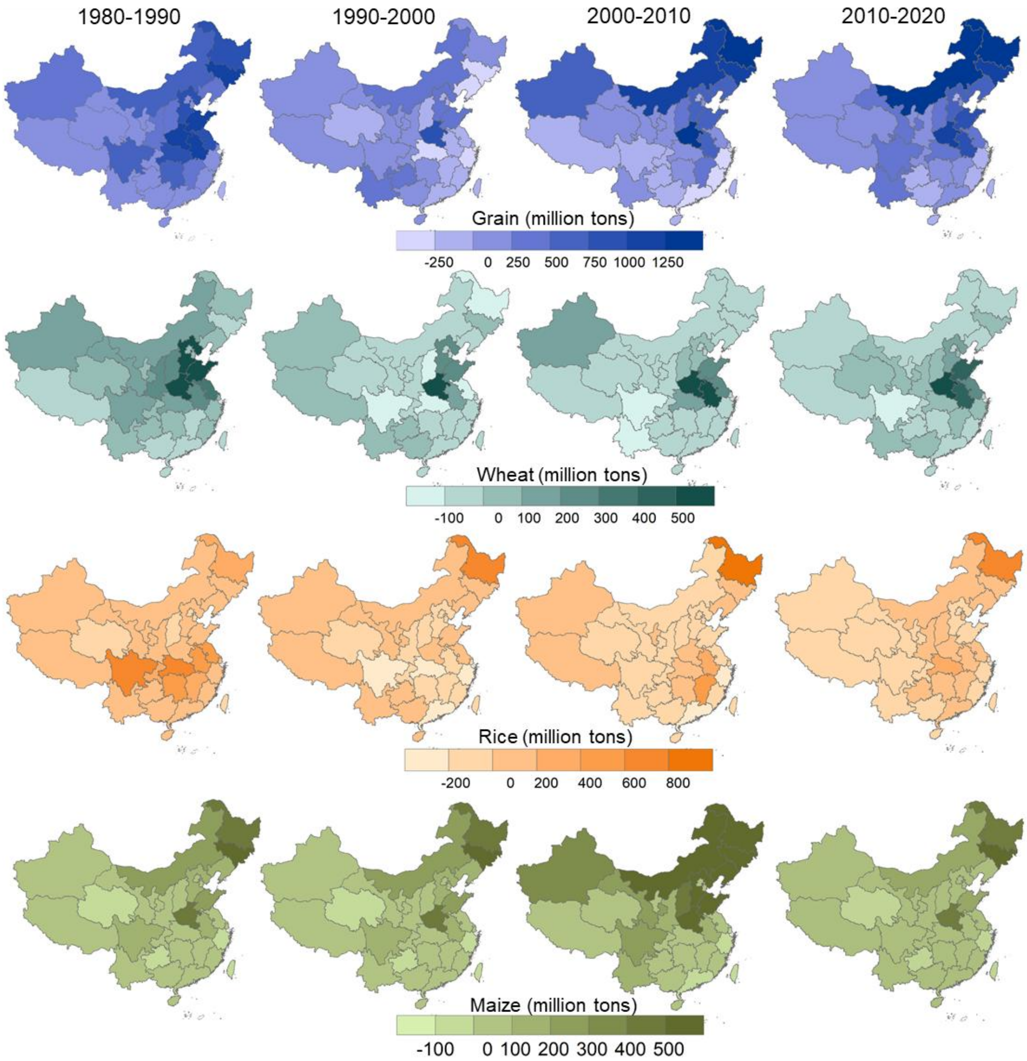

Fig. S2| Changes in spatial variation of grain production every decade in China
(From top to bottom: grain; wheat; rice; maize)

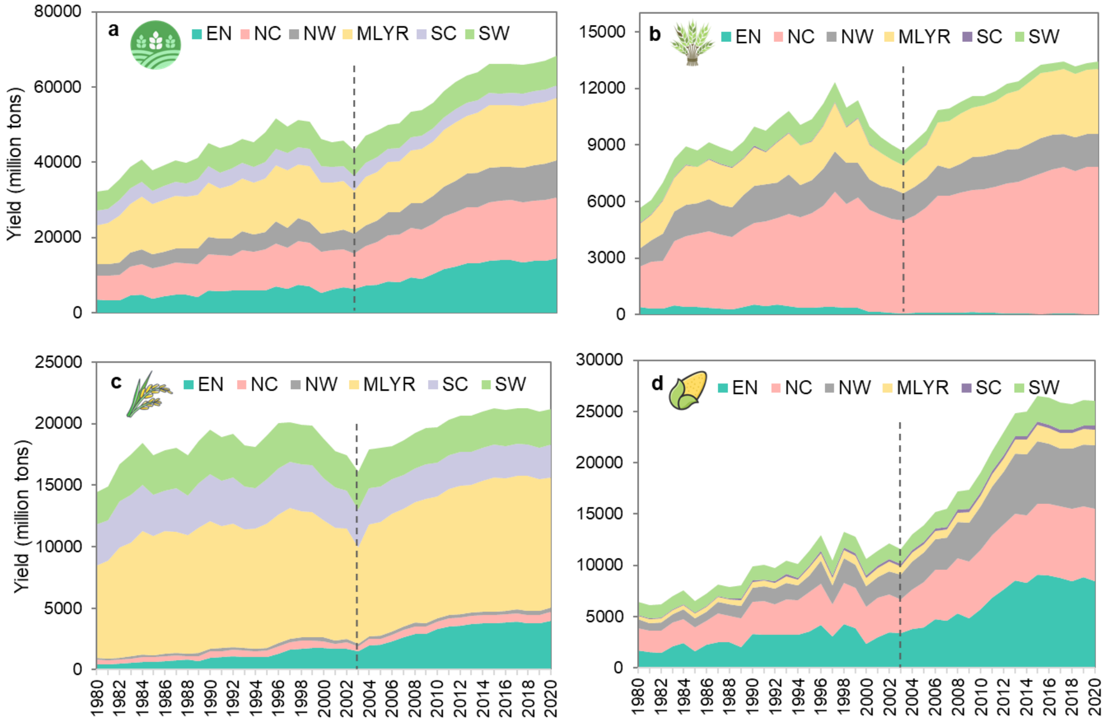

Fig. S3 | Changes in grain production from 1980 to 2020. (**a**) grain, (**b**) wheat, (**c**) rice, (**d**) maize; NE: Northeast Region, NC: North China Region, NW: northwest region, MLYR: Middle and Lower Yangtze River Region; SC: Southern China Region; SW: Southwest Region.

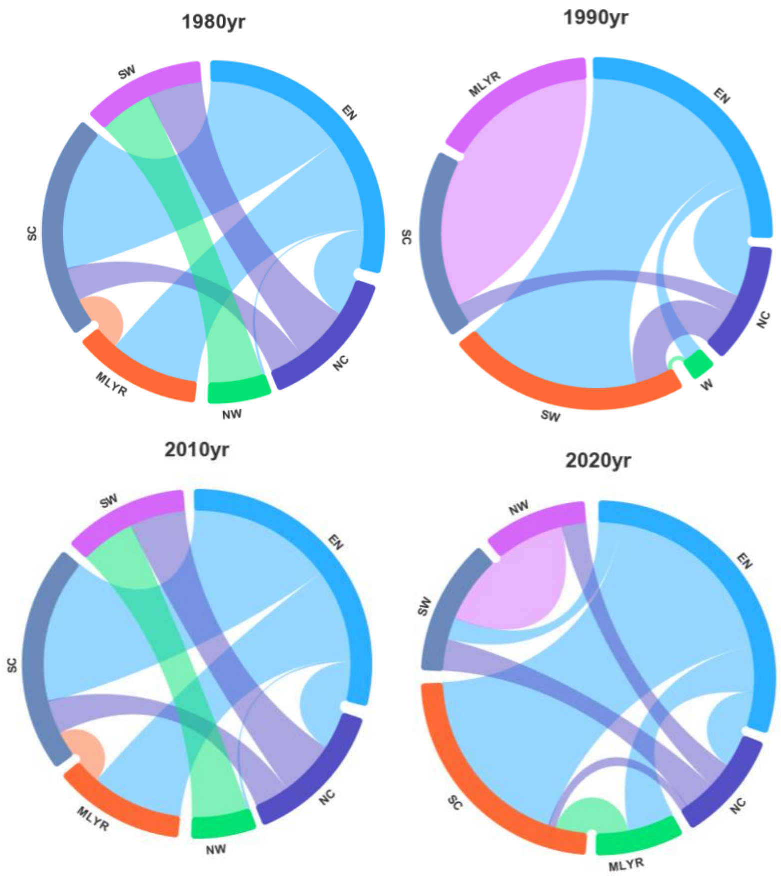

Fig. S4 | Simulation of trade flows of grains in China. NE: Northeast Region, NC: North China Region, NW: northwest region, MLYR: Middle and Lower Yangtze River Region; SC: Southern China Region; SW: Southwest Region.

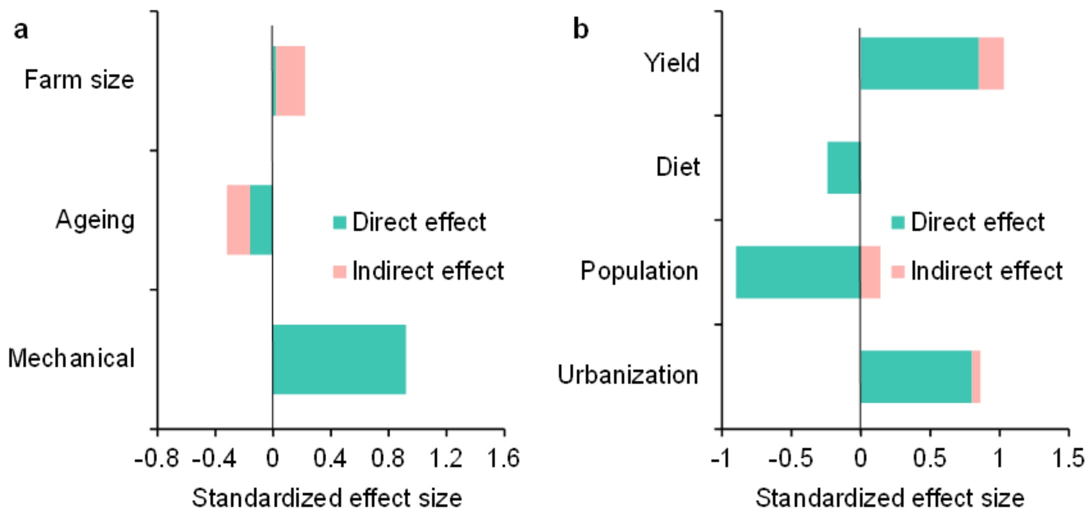

Fig. S5| Summed direct and indirect effects in Structural equation model. a: grain production. b: grain trade

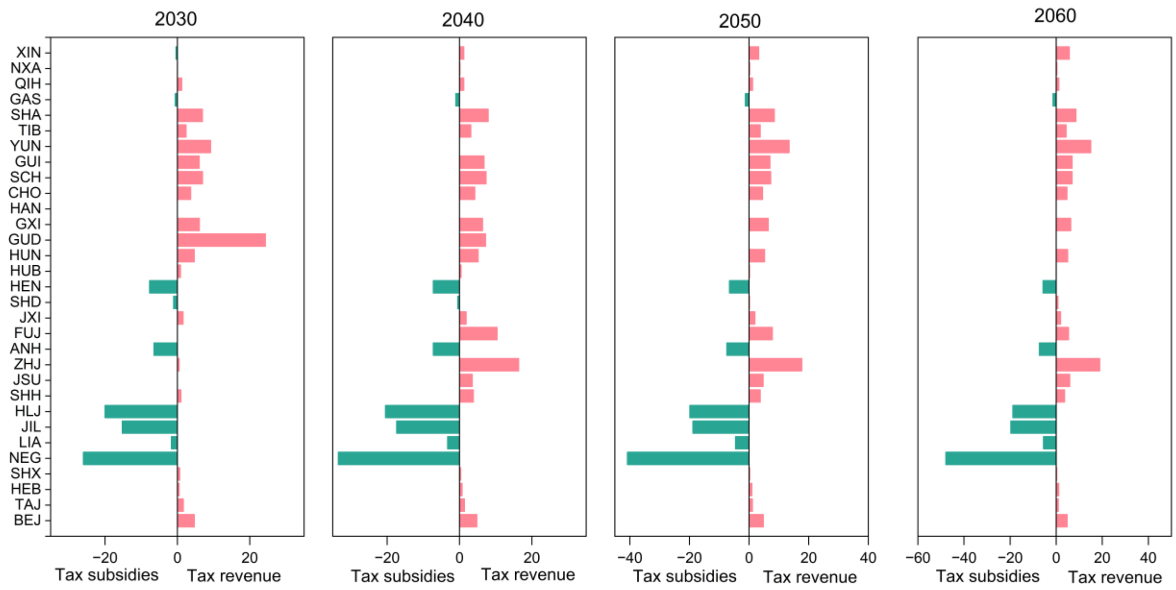

Fig. S6 | Tax amounts in different provinces under SSP scenario. The blue label on the left side of the horizontal axis represents the provinces that require subsidies, while the one on the right side represents the provinces that require taxes

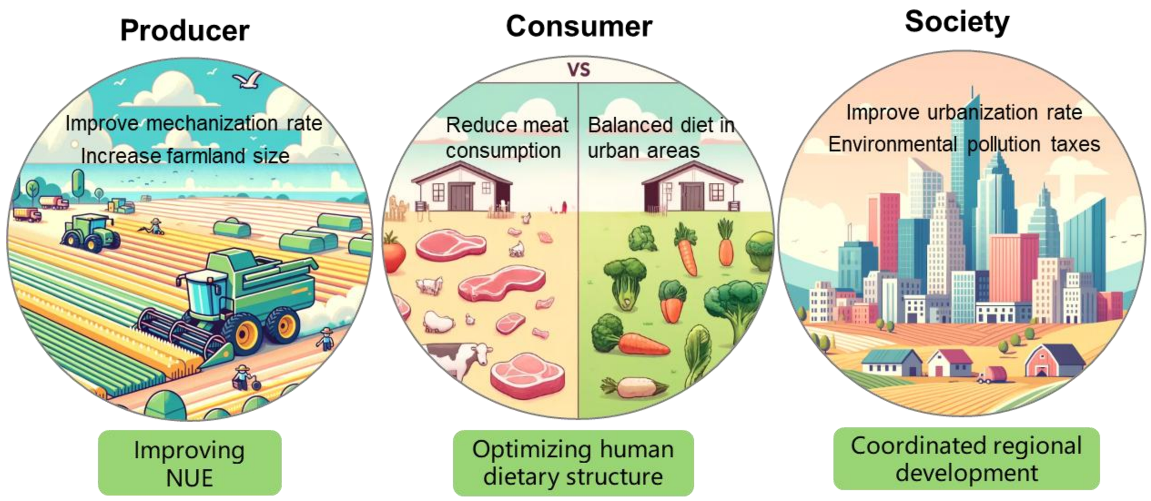

Fig. S7 | Opportunities for improvements for different stakeholders. A non-exhaustive range of promising options for farmers, manufacturers and consumers to reduce the environmental impacts of grain production.

Table S1 The abbreviation of agricultural region and 31 provinces, autonomous regions, and municipalities directly under the Central Government.

	Agricultural region	Abbreviation	Province	Abbreviation
The provinces of Northern China in this study 	North China	NC	Beijing	BEJ
			Tianjin	TAJ
			Hebei	HEB
			Henan	HEN
			Shandong	SHD
	Northeast Region	NE	Liaoning	LIA
			Jilin	JIL
			Heilongjiang	HLJ
	Northwest Region	NW	Shanxi	SHX
			Inner Mongolia	NEG
			Shanxi	SHA
			Gansu	GAS
			Qinghai	QIH
			Ningxia	NXA
			Xinjiang	XIN
The provinces of Southern China in this study 	Middle and Lower Yangtze River Region	MLYR	Shanghai	SHH
			Jiangsu	JSU
			Zhejiang	ZHJ
			Anhui	ANH
			Jiangxi	JXI
			Hubei	HUB
			Hunan	HUN
	Southwest Region	SW	Chongqing	CHO
			Sichuan	SCH
			Guizhou	GUI
			Yunnan	YUN
			Xizang	TIB
	Southern China Region	SC	Fujian	FUJ
			Guangdong	GUD
			Guangxi	GXI
			Hainan	HAN

Table S2 Fertilization rates for different crops in each province

Province	Rice	Wheat	Maize	Average
Beijing	171.7	267.2	161.7	200.2
Tianjin	178.1	269.2	159.9	202.4
Hebei	186.1	254.0	142.1	194.1
Shanxi	170.7	190.5	125.6	162.3
Inner Mongolia	171.6	368.5	201.6	247.3
Liaoning	138.5	233.1	140.8	170.8
Jilin	172.9	291.4	160.9	208.4
Heilongjiang	97.6	105.4	96.2	99.7
Shanghai	193.6	213.3	185.5	197.5
Jiangsu	228.2	209.6	240.1	226.0
Zhejiang	196.4	269.2	194.8	220.1
Anhui	201.4	228.4	179.0	202.9
Fujian	201.4	239.8	213.4	218.2
Jiangxi	119.4	123.4	116.9	119.9
Shandong	195.4	183.9	143.5	174.3
Henan	156.0	238.0	175.1	189.7
Hubei	148.0	133.0	182.7	154.5
Hunan	142.4	123.1	194.3	153.3
Guangdong	169.1	139.4	180.9	163.1
Guangxi	130.9	94.5	128.1	117.8
Hainan	161.4	123.1	187.6	157.3
Chongqing	155.1	135.1	171.1	153.8
Sichuan	166.7	130.7	179.6	159.0
Guizhou	110.2	65.1	148.1	107.8
Yunnan	172.0	170.3	224.4	188.9
Xizang	277.9	236.2	331.3	281.8
Shanxi	196.0	220.6	287.2	234.6
Gansu	188.4	177.1	253.5	206.4
Qinghai	197.4	158.4	193.4	183.1
Ningxia	196.0	231.8	250.8	226.2
Xinjiang	123.7	177.5	212.0	171.1

Data source: National Compilation of Cost-Benefit Data of Agricultural Products[5]

Table S3 The CH_4 emission factors of rice by provinces in China (kg ha^{-1})

Province	Rice	Province	Rice
Beijing	234.0	Henan	236.7
Tianjin	234.0	Hubei	236.7
Hebei	234.0	Hunan	236.7
Shanxi	234.0	Guangdong	236.7
Inner Mongolia	234.0	Guangxi	236.7
Liaoning	168.0	Hainan	236.7
Jilin	168.0	Chongqing	156.2
Heilongjiang	168.0	Sichuan	156.2
Shanghai	215.5	Guizhou	156.2
Jiangsu	215.5	Yunnan	156.2
Zhejiang	215.5	Xizang	156.2
Anhui	215.5	Shanxi	231.2
Fujian	215.5	Gansu	231.2
Jiangxi	215.5	Qinghai	231.2
Shandong	215.5	Ningxia	231.2
		Xinjiang	231.2

Note: Due to the differences in hydrothermal conditions in different regions, the CH_4 emission during the growth cycle of rice varies among regions. Studies have been conducted to consider the effects of each province.

Table S4 Data source description

Deposited data	Source	Identifier
Provincial grain yield (1980-2020)	China Statistical Yearbook or bulletin of each province, autonomous region, and municipality	https://data.cnki.net/yearBook?type=type&code=A
Provincial sown area (1980-2020)	China Statistical Yearbook or bulletin of each province, autonomous region, and municipality	https://data.cnki.net/yearBook?type=type&code=A
Provincial livestock production (1980-2020)	China Agricultural Statistical Yearbook	https://data.cnki.net/yearBook?type=type&code=A
Provincial socioeconomic data (1980-2020)	China Statistical Yearbook or bulletin of each province, autonomous region, and municipality	https://data.cnki.net/yearBook?type=type&code=A
Import and export volumes	China Agricultural Statistical Yearbook	https://cnki.nbsti.net/CSYDMirror/trade/yearbook/Single/N2022030154?z=Z009
The cost-benefit data of grain	National Compilation of Cost-Benefit Data of Agricultural Products	https://data.cnki.net/yearBook/single?id=N2021120016&pinyinCode=YNCSY
Provincial SSPs data (2020-2060)	Chen et al. (2020)	https://doi.org/10.6084/m9.figshare.c.4605713.v1
Meteorological data	National Meteorological Science Data Center	https://data.cma.cn/
The railroad network data	The National Geomatics Centre of China	https://www.ngcc.cn/
Other relevant parameters	CHANS model	https://person.zju.edu.cn/bjgu[1,6]

Table S5 | Water footprint of grain production in different provinces (m^3/kg)

Province	Water footprint	Green water footprint	Blue water footprint
Beijing	0.74	0.459	0.281
Tianjin	0.945	0.465	0.48
Hebei	0.725	0.437	0.288
Shanxi	0.639	0.363	0.276
Inner Mongolia	0.869	0.482	0.387
Liaoning	0.839	0.525	0.314
Jilin	0.737	0.526	0.211
Heilongjiang	1.197	0.71	0.487
Shanghai	1.915	0.546	1.369
Jiangsu	1.171	0.575	0.596
Zhejiang	1.735	0.609	1.126
Anhui	1.265	0.813	0.452
Fujian	1.886	0.596	1.29
Jiangxi	1.299	0.606	0.693
Shandong	0.623	0.451	0.172
Henan	0.76	0.59	0.17
Hubei	1.147	0.835	0.312
Hunan	1.145	0.616	0.529
Guangdong	1.898	0.88	1.018
Guangxi	1.948	0.924	1.024
Hainan	2.813	0.934	1.879
Chongqing	1.002	0.746	0.256
Sichuan	1.003	0.592	0.411
Guizhou	1.487	1.098	0.389
Yunnan	1.351	1.086	0.265
Xizang	2.206	0.569	1.637
Shanxi	1.273	0.925	0.348
Gansu	1.314	0.635	0.679
Qinghai	1.708	0.865	0.843
Ningxia	1.425	0.416	1.009
Xinjiang	1.335	0.197	1.138

Ref: Environmental impact of grain virtual water flows in China: From 1997 to 2014

Table S6 The turning points of temperature to yield

	U shape	TP
Grain	Inverted-U	11.27
Rice	Inverted-U	16.96
Wheat	Inverted-U	9.2
Maize	Inverted-U	10.6

The turning point (TP) of temperature (°C) is calculated based on regression results of models of equation (5). Regression results are listed in Supplementary Tables 10–12.

Table S7 | The Model Coefficients and P-values of structural equation model for grain yield shown in Figure 3d.

Predictor	Effect	Coefficients	P-values	Contribution
Mechanical	Direct effect	0.92	(0.000)	61%
Ageing	Direct effect	-0.16	(0.000)	25%
	Indirect → Mechanical	0.21		
Farm size	Direct effect	0.02	(0.142)	15%
	Indirect → Mechanical	0.2		

Table S8 | The Model Coefficients and P-values for structural equation model for grain trade shown in Figure 3f.

Predictor	Effect	Coefficients	P-values	Contribution
Urbanization	Direct effect	0.8	(0.000)	27%
	Indirect effect→Diet	0.06		
Population	Direct effect	-0.9	(0.000)	33%
	Indirect effect→Diet	-0.14		
Diet	Direct effect	-0.24	(0.001)	8%
Yield	Direct effect	0.85	(0.000)	32%
	Indirect effect→Diet	0.18		

Table S9 Monetized tax parameters for nitrogen pollution and GHG emissions

GHG (\$/t CO_{2e})	Low	10	The trading price in China's current carbon market is ~US\$10 (as the minimum cost)[7], while achieving the Paris Agreement's goal necessitates a cost-effective price of US\$100 (as the maximum cost)[8]. A carbon price of US\$50 is considered as medium value[9,10].
	Medium	50	
	High	100	
NH_3 (\$/kg)	Low	0.9	According to Law of China Environmental Protection Tax (LCEPT)[11], the tax value of air pollutants ranges from 1.2 to 12 CNY per kg. In this study, the average value of US\$0.9[c] is considered as the minimum price. Previous studies have concluded that China currently massively underestimates the social damage of NH_3[12]. Referring to Keeler et al[13], this study estimates the regional damage cost of NH_3 in China, and the value in 2020 is US\$23, regarded as the highest cost. The average value of tax law and damage cost US\$12 is taken as the medium value.
	Medium	12	
	High	23	
NOx (\$/kg)	Low	1.3	Based on the applicable tax laws for NOx in each province of China[14], the median value of US\$1.3 is taken as the minimum cost. Similarly, this study estimates the regional damage cost of NOx in China, which is far greater than the taxed price, taking the 2020 value of US\$24 as the maximum cost. The medium value was taken as the average of the two values US\$13.
	Medium	13	
	High	24	
NO3- (\$/kg)	Low	1	According to LCEPT, the average value of water pollution is considered as the minimum price (~US\$1.0). Similarly, this study estimates the regional damage cost of NO_3^- in China, taking the 2020 value of ~US\$18.9 as the maximum cost; and the medium value is taken as the average of the two values.
	Medium	10	
	High	18.9	

Note:

[a] The LCEPT specifies a pollution taxable equivalent of 9.09 for NH_3, but based on expert judgment, the social damages of NH_3 pollution are probably far underestimated here, and therefore the pollution taxable equivalent value for ammonia nitrogen is used here instead.

[b] The monetary treatment here aims to reflect the relative value of Nr and GHGs under climate objectives, policy intensity, and environmental damage.

[c] Based on China's National Bureau of Statistics, the exchange rate for the U.S. dollar to RMB in 2020 was 6.897.

REFERENCE:

1. Gu, B., Ju, X., Chang, J., Ge, Y. & Vitousek, P. M. Integrated reactive nitrogen budgets and future trends in China. *Proceedings of the National Academy of Sciences* **112**, 8792–8797 (2015).
2. Xu, X. *et al.* Integrated carbon and nitrogen management for cost-effective environmental policies in China. *Science* **388**, 1098–1103 (2025).
3. Intergovernmental Panel on Climate Change. *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. https://www.ipcc.ch/report/ar6/wg1/ (2021).
4. Intergovernmental Panel on Climate Change. *Climate Change: The IPCC Scientific Assessment*. (1990).
5. Wang, C. *et al.* An empirical model to estimate ammonia emission from cropland fertilization in China. *Environmental Pollution* **288**, 117982 (2021).
6. Zhang, X. *et al.* Ammonia Emissions May Be Substantially Underestimated in China. *Environmental Science & Technology* **51**, 12089–12096 (2017).
7. Shi, B., Li, N., Gao, Q. & Li, G. Market incentives, carbon quota allocation and carbon emission reduction: Evidence from China's carbon trading pilot policy. *Journal of Environmental Management* **319**, 115650 (2022).
8. Glanemann, N., Willner, S. N. & Levermann, A. Paris Climate Agreement passes the cost-benefit test. *Nat Commun* **11**, 110 (2020).
9. Tian, L., Ye, Q. & Zhen, Z. A new assessment model of social cost of carbon and its situation analysis in China. *Journal of Cleaner Production* **211**, 1434–1443 (2019).
10. Lu, N. *et al.* Biophysical and economic constraints on China's natural climate solutions. *Nat. Clim. Chang.* **12**, 847–853 (2022).
11. State Council of China, Environmental Protection Tax Law of the People's Republic of China (Draft for Comments). https://english.mofcom.gov.cn/Policies/LawsRegulations/art/2013/art_f1de59700ebd47c69367af1013f6daef.html (2015).
12. Gu, B. J. *et al.* Abating ammonia is more cost-effective than nitrogen oxides for mitigating PM2.5 air pollution. *SCIENCE* **374**, 758-+ (2021).
13. Keeler, B. L. *et al.* The social costs of nitrogen. *Science Advances* **2**, e1600219 (2016).
14. Liu, F. *et al.* Regionalized life-cycle monetization can support the transition to

sustainable rural food waste management in China. *Nat Food* **4**, 797–809 (2023).