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The Ecological and Environmental Effects of China's Food Imports: Retesting the Environmental Kuznets Curve

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This study explores the relationship between China's food imports and the ecological environment (mainly agricultural carbon emissions) of its trading partners. Using panel data from 15 major food trading partners from 2001 to 2021, we apply the Feasible Generalized Least Squares (FGLS) method to examine the relationship between China's food imports and agricultural carbon emissions of trading partners. The results indicate that the relationship supports the Environmental Kuznets Curve (EKC) hypothesis, exhibiting an inverted U–shape. This means that as food trade openness increases, trading partners' ecological environment first deteriorates and then improves after crossing a turning point. We also find that the EKC shape exhibits national and product heterogeneity. The EKC is inverted U–shaped for high–income countries and U–shaped for low–income countries. It is inverted U–shaped for soybean imports and U–shaped for corn imports. Based on 2021 data, expanding China's soybean imports from the United States, Brazil, and increasing corn imports from Brazil, Uruguay, Russia, the United States, and Myanmar are beneficial for improving the ecological environment of these countries. Furthermore, we discover that food trade impacts trading partners' ecological environment through production scale, industrial structure, and technological progress, with production scale being the main path for the inverted U–shaped curve. Increasing trade openness has a positive U–shaped impact on the environment through technological and structural effects, but not enough to offset the negative scale effects. Our study contributes by confirming the EKC relationship and turning point between food trade and ecological environment, clarifying its national and product heterogeneity, and identifying the main impact channels. The findings have policy implications for optimizing China's food import structure and promoting sustainable trade and development.

Key words: Agricultural carbon emissions, Environmental Kuznets curve, Feasible generalized least squares method, Food import

INTRODUCTION

Food security and environmental protection are important components of the United Nations Sustainable Development Goals. Trade is crucial for alleviating food insecurity in developing countries by transporting food from surplus producers to underproductive demanders (Sun *et al*. 2020). China, the country with the largest grain import scale in the world, imported nearly 10% of the world's total grain in 2022. At the same time, some scholars have linked the expanding food trade with increasingly severe environmental pollution. For example, Escobar *et al*. (2020) argue that over half of the greenhouse gas emissions caused by deforestation in Brazil from soybean cultivation from 2010 to 2015 are attributed to China's soybean imports. Leguizamón (2018) stated that the increase in demand for bulk products in countries such as China and India is an important reason for Argentina to expand its soybean exports. While the use of genetically modified technology, agricultural chemicals, and no–till machinery has improved production efficiency and economic benefits, it has also caused negative ecological consequences such as deforestation, farmer displacement, and health hazards.

Our research mainly examines the relationship between China's food imports and the ecological environment (mainly agricultural carbon emissions) of trading partners, aiming to answer whether China's expanding food imports have damaged their environment. On the one hand, China's food trade is expanding rapidly, and given rising per capita income and resource and environmental constraints, China's dependence on international food may continue to increase in the future. On the other hand, news of ecological damage in countries like Brazil and Argentina, the main sources of Chinese soybean imports, raises questions about the correlation between the two.

Existing literature has not reached a consistent conclusion on the relationship between agricultural trade and ecological environment (Balogh, 2022). There are studies finding agricultural trade exacerbates environmental pollution (Karimi *et al*., 2022), improves the ecological environment (Pata *et al*., 2023), or has ambiguous impacts (Iorember *et al*., 2022). Using the Feasible Generalized Least Squares (FGLS) model and 2001–2021 panel data on China's food trade with 15 major partners, we explore this issue from the unique perspective of China's food trade.

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We find the relationship between China's food imports and trading partners' environment follows the Environmental Kuznets Curve (EKC) hypothesis, exhibiting an inverted U–shape. As partners' food trade openness increases, their environment first deteriorates but gradually improves after crossing a turning point.

The contribution of this study is threefold: Firstly, we confirmed the EKC relationship between food trade and ecological environment and identified the turning point. Based on 2021 data, we clarified that with expanding food trade with China, there are countries with improved and deteriorated environments respectively. Secondly, we clarified that the relationship is not static, but exhibits national and product heterogeneity – the impact varies with partners' income level and food products. Thirdly, we discovered that food trade impacts the environment through production scale, industrial structure and technological progress, with scale effects dominating.

The remaining parts are structured as follows: Section 2 reviews theories and literature, Section 3 introduces data and models, Section 4 analyzes empirical results, and Section 5 summarizes with policy recommendations.

LITERATURE REVIEW AND RESEARCH HYPOTHESES

Environmental Kuznets Curve

The Environmental Kuznets Curve (EKC) hypothesis, inspired by Kuznets' 1955 findings on income levels and inequality, suggests an inverted U–shaped relationship between economic growth and environmental degradation. Confirmed by Grossman and Krueger (1991), the EKC posits that as per capita income rises, environmental degradation initially worsens but improves after reaching a certain income level. In early growth stages, priority is often given to development over environmental protection, leading to increased pollution. However, as income rises and environmental awareness grows, investments in cleaner technologies and stricter regulations typically lead to environmental improvements.

Many scholars have analyzed trade's impact on the environment using the EKC hypothesis by including trade openness terms in the model. Results support the EKC, but the shape varies from inverted U to U to linear negative (Selcuk *et al*., 2021; Chhabra *et al*., 2022; Rafiq *et al*., 2016; Iorember *et al*., 2022; Sun *et al*., 2020; Pata *et al*., 2023).

Literature Review

We reviewed literature on agricultural trade's impact on the environment and found mixed results:

(1) Agricultural trade exacerbates pollution. Trade transfers food from producing to consuming countries but leaves pollution in producing countries (Dalin and Rodríguez–Iturbe, 2016, O'Bannon *et al*., 2014). Exporting primary commodities increases greenhouse gas emissions (Drabo, 2017). The interaction between agriculture and energy has additional negative impacts (Balsalobre *et al*., 2019). Trade openness increases agricultural CO2 emissions in developing countries (Karimi *et al*., 2022) Food demand has led to agricultural expansion with negative impacts on resources and environment (Correa–Cano *et al*., 2022) International food transport generates substantial emissions (Cristea *et al*., 2011).

(2) Agricultural trade improves the environment. Trade openness and the environment are negatively correlated, so trade can reduce pollution (Pata *et al*., 2023; Sun *et al*., 2020) Food trade between the US and Mexico enables mutual benefit (Martinez–Melendez *et al*., 2016) Trade can alleviate nitrogen pollution impacts in China (Shi *et al*., 2016) Trade reforms improved Indonesia's environment despite slow growth (Strutt and Anderson, 2000).

(3) The impact is uncertain or insignificant, as many factors affect the agricultural environment (Xiong *et al*., 2016; Appiah *et al*., 2018; Balogh, 2022).

Mechanistic effect

Grossman and Krueger (1991) attribute EKC formation to scale, structural, and technological effects. Scale effects are negative; technology effects are positive; structural effects are uncertain. The intensity of the three varies at different development stages, forming the inverted U-shaped EKC. Similarly, agricultural emissions depend on scale and technology effects (Coderoni and Esposti, 2014). Balsalobre–Lorente *et al*.(2019) confirmed an inverted U–shaped EKC in BRICS, emphasizing scale effects dominate in agriculture's development stage. Pata *et al*.(2023) believe scale and composition effects may outweigh technology effects for developing countries.

Based on the theories and research, we propose the following hypotheses:

H1: Food imports and ecological environment follow the EKC with an inverted U–shape.

H2: Food imports impact the environment through production scale, industrial structure and technological progress.

METHODOLOGY

Economic model

To examine the relationship between food imports and ecological environment, we draw on previous models (Sun *et al*., 2019) and select the primary and quadratic terms of food imports as explanatory variables for ecological environment. The basic model of China's food imports and trading partners' ecological environment is:

$$\ln C_{it} = \alpha_0 + \beta_1 TO_{it} + \beta_2 TO^2_{it} + \beta_3 X_{it} + \mu_{it} \qquad (1)$$

Among them, $\ln C_{it}$ represents the logarithmic measurement of the ecological environment condition in country i during the t–th year; TO_{it} is food imports and its quadratic term; X_{it} are control variables including population, agricultural land proportion, etc; μ_{it} is the error term representing other factors affecting ecological environment.

Sample and data

We define food based on the standards of Elmorshdy *et al*. (2016) and Zhang *et al*. (2023), following the "Commodity Name and Protocol Coding System" (HS) formulated by the World Customs Organization. Food includes HS chapters 10 (grains), 0701 (potatoes), 0713 (dried beans), 0714 (edible tubers), and 1201 (soybeans).

China's food imports are growing rapidly. In volume, imports increased from 16.06 million tons in 2001 to over 100 million tons in 2017 and 2020–2022. In value, imports grew from $3.61 billion in 2001 to $84.47 billion in 2022, an average annual growth of 16.20% (see Figure 1). Soybeans and corn account for a relatively high proportion. From 2001–2022, soybean imports accounted for over 70% of total food imports, reaching a peak of 94.56% in 2008. Corn imports remained below 5% before 2020, but reached 11.60% in 2022 (see Figure 1).

Geographically, China's food import sources are relatively concentrated. From 2001–2022, 15 partners including Brazil, the US, Ukraine, Argentina, Canada, Thailand, France, Australia, Vietnam, Uruguay, India, Pakistan, Myanmar, Russia, and Cambodia accounted for 99% of total imports. The US and Brazil are the main sources, supplying over 50% of imports and reaching 81.12% in 2009 and 80.44% in 2018. Argentina is the third largest source (see Figure 2). Based on this analysis, we select 2001–2021 panel data for these 15 countries.

Variables description

We use per capita agricultural carbon emissions (ln*C*) as the dependent variable, food trade openness (*TO*) as the core explanatory variable, production scale (*SCA*), industrial structure (*STR*), technological progress (*TEC*) as mechanism variables, and population (*POP*), agricultural land proportion (*AL*), fiscal support for agriculture (*AOI*), Foreign Direct Investment (*FDI*) as control variables. Table 1 summarizes these key variables, including their abbreviations, full names, definitions, and references.

Data is from World Bank WDI, UN FAO, UN

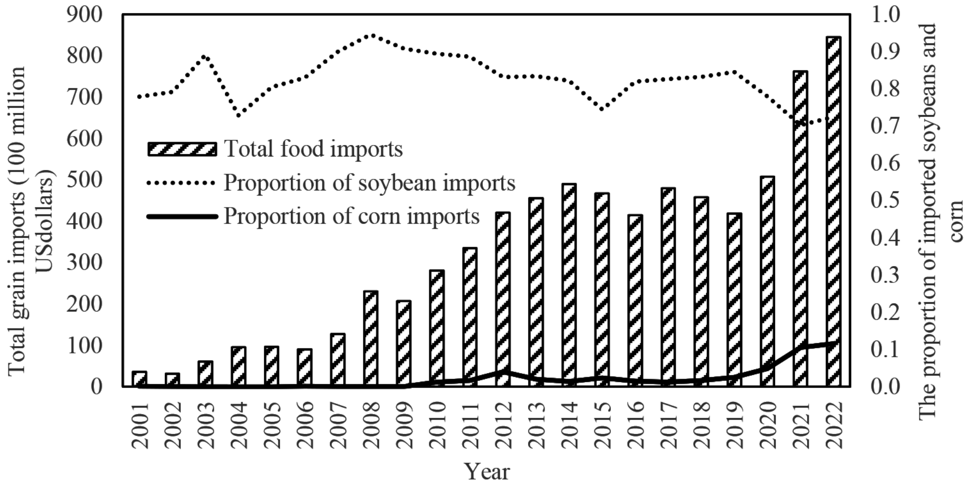

Fig. 1. Food imports and its product structure in China from 2001 to 2022.
Source: UN Comtrade Database

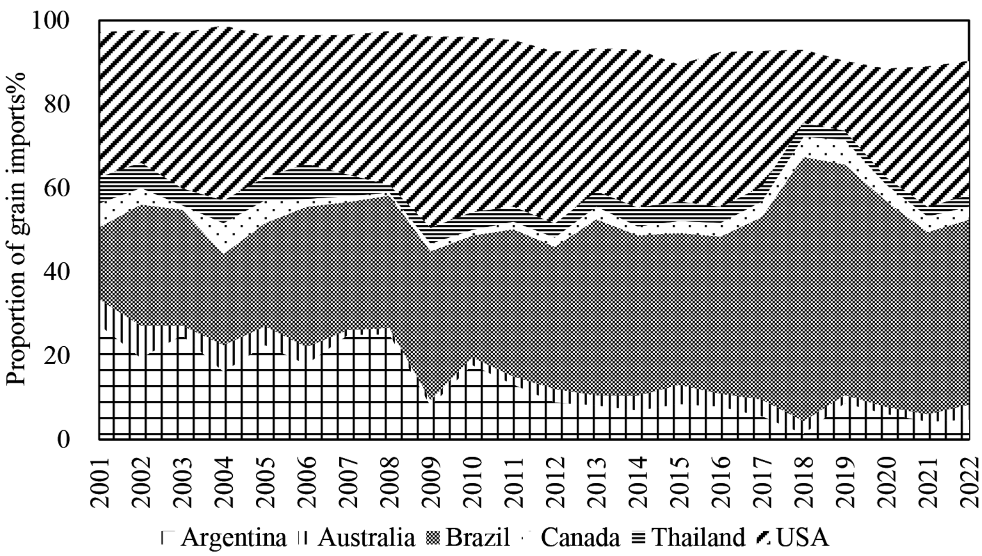

Fig. 2. Geographical Structure Characteristics of China's Food Imports from 2001 to 2022.
Source: UN Comtrade Database

Table 1. Summary of Key Variables, Definitions, and References

Variable Name	Abbr.	Definition/Calculation	Reference
Ecological Environment	*C*	The logarithm of per capita agricultural carbon emissions (metric tons)	FAO, 2022
Trade Openness	*TO*	The variable *TO* is calculated by dividing the food exports from trade partner countries to China by the value added of the primary industry in those trading partners, and then multiplying the result by 100%.	–
Production Scale	*SCA*	Crop production index; annual agricultural yield relative to the base period of 2014–2016, including all crops except feed crops.	Waheed *et al.*, 2018
Industrial Structure	*STR*	The ratio of the added value of the primary industry to GDP	Yu *et al.*, 2019
Technological Progress	*TEC*	Energy consumption per unit of output value; calculated by dividing agricultural energy consumption by the added value of the primary industry	Meijl and Tongeren, 1998
Population	*POP*	Population density of each country	Özokcu and Özdemir, 2017
Proportion of Agricultural Land	*AL*	The proportion of cultivated land, permanent crops, and permanent pasture land to total land area	FAO, 2022; Rehman *et al.*, 2022
Fiscal Support for Agriculture	*AOI*	Agricultural orientation index of government expenditure; calculated by dividing the proportion of agriculture to government expenditure by its share of GDP	Bostan *et al.*, 2016
Foreign Direct Investment	*FDI*	Net inflow of foreign direct investment	Ly–My *et al.*, 2023

Note: 1) Data sourced from FAO. Greenhouse gas emissions data are from agrifood systems. Food and Agriculture Statistics 2022 from https://www.fao.org/food–agriculture–statistics/data–release
2) The agricultural orientation index data for government expenditure is sourced from the FAO Sustainable Development Goals database https://www.fao.org/sustainable–development–goals–data–portal/data/.

Table 2. Descriptive Statistics

Variable	N	Mean	SD	Min	Max
ln*C*	315	1.246	0.796	-0.115	2.923
TO	315	3.249	4.685	0.000	32.153
TO^2	315	32.431	97.732	0.000	1033.786
SCA	315	88.807	17.693	34.600	131.170
STR	315	0.120	0.133	0.007	1.049
TEC	315	4.534	3.753	0.001	16.935
POP	315	103.829	120.362	2.509	473.419
AL	315	41.850	20.290	6.394	85.487
AOI	315	0.323	0.211	0.010	1.090
FDI	315	0.141	0.123	0.000	1.000

Comtrade, and EPS. 2021 agricultural emissions are calculated based on the past 5–year average growth rate. Missing values are filled using linear interpolation. Table 2 shows descriptive statistics.

RESULTS

Benchmark regression

We first conducted collinearity diagnostics, which showed Variance Inflation Factors (VIF) less than 7, indicating no multicollinearity. Wald and Breusch–Pagan LM tests revealed intra–group autocorrelation, homoscedasticity and heteroscedasticity, and contemporaneous correlation problems (see Table 3). The FGLS method was chosen to handle these issues simultaneously.

Table 4 shows the FGLS regression results. In column (1), only the primary and quadratic terms of food trade openness (*TO*) are included. The quadratic coefficient is negative and significant at the 1% level. After adding control variables in column (2), the *TO* quadratic term remains significant at 1%, indicating an inverted U-shaped relationship between China's food imports and trading partners' per capita agricultural carbon emissions (ln*C*), supporting the EKC hypothesis (H1). The turning point is at 4.29% trade openness. Based on 2021 data, seven countries (Argentina, Brazil, Canada, Myanmar, the US, Ukraine, and Uruguay) have crossed this point, and their emissions are decreasing with trade openness.

The control variables' coefficients are extremely significant. Population (*POP*) is positively correlated with emissions, consistent with Khan *et al.* (2022). Agricultural land ratio (*AL*) has a coefficient of 0.031, sig-

Table 3. LM and Wald tests

Breusch–Pagan LM test	Wald test	
Pr = 0.000	Prob > chi2=0.000	Prob > F = 0.000

Table 4. FGLS benchmark regression results of the impact of China's food imports on the ecological environment of trading partners

Variable	(1)	(2)
TO	0.001***	0.002***
	(0.001)	(0.001)
TO^2	–0.0002***	–0.0002***
	(0.000)	(0.000)
POP		0.002***
		(0.000)
AL		0.031***
		(0.001)
AOI		0.066***
		(0.008)
FDI		0.059***
		(0.012)
_cons	11.079***	14.800***
	(0.822)	(1.161)
N	315	315
curve	Inverted U–shaped	Inverted U–shaped
turning point	1.65	4.29

Note: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

nificant at 1%, indicating a 1% increase in *AL* leads to a 0.031 metric ton increase in emissions. Fiscal support for agriculture (*AOI*) is significantly positive at 1%, possibly because the growth rate of *AOI* was not significant from 2001–2021, and resources were not effectively invested in technology, environmental protection, and sustainable production. *FDI* has a coefficient of 0.059, significant at 1%, indicating more *FDI* increases environmental pressure in host countries, consistent with Pata *et al.* (2023).

Robustness test

We conducted robustness tests by adjusting the sample period and replacing the dependent variable. The results (Table 5, columns 1–2) remained consistent. We also addressed potential endogeneity by using the lagged *TO* as an instrumental variable (Fang *et al.* 2022). The results (Table 5, column 3) showed the instrumental variable is reasonable, and the *TO* quadratic coefficient direction is consistent with the baseline, validating our findings.

Heterogeneity analysis

We explored heterogeneity across countries and products.

Country–wise (Table 6), for high-income countries, the *TO* quadratic coefficient is negative and the curve is inverted U–shaped, supporting the EKC, with a turning point at 7.96% openness. The US, Brazil, and Argentina have crossed this point. For low-income countries, the curve is U–shaped, with a turning point at 7.85% openness. Except Ukraine, countries like Cambodia and India have not crossed it. Differences in development level lead to varying EKC results.

Product–wise (Table 6), for soybean imports, the curve is inverted U–shaped with a turning point at 6.74% openness. The US and Brazil have crossed it. For corn imports, the curve is U–shaped with a turning point at 5.05% openness. Except Ukraine, countries like Russia and Myanmar have not crossed it. Expanding corn imports from Brazil, Russia, Uruguay, the US, and Myanmar improves their environment (see Table 7).

Mechanism verification

Referring to Zhang (2022), we explored the mediating role of production scale (*SCA*), industrial structure (*STR*), and technological progress (*TEC*) using a two–step approach based on equation (3).

$$M_{it}=\alpha_0+\beta_1 TO_{it}+\beta_2 TO^2_{it}+\beta_3 X_{it}+\mu_{it} \qquad (3)$$

In equation (3), M_{it} represents the mechanism variables (production scale, industrial structure, and technological progress), while the core explanatory variable (TO_{it}) and control variable (X_{it}) remain consistent with the previous text. Empirical analysis was conducted on the data using FGLS, and the regression results are

Table 5. Results of robustness and endogeneity tests

	(1)	(2)	(3)
TO	0.001	0.002	–0.008
	(0.001)	(0.010)	(–0.98)
TO^2	–0.0003***	–0.020***	–0.0006*
	(0.000)	(0.007)	(–2.02)
POP	0.003***	0.002***	0.0448***
	(0.000)	(0.000)	(8.63)
AL	0.026***	0.033***	0.003
	(0.001)	(0.001)	(0.02)
AOI	0.065***	0.067***	0.024
	(0.011)	(0.006)	(0.26)
FDI	0.014	0.049***	0.001
	(0.010)	(0.010)	(1.39)
_cons	16.877***	12.362***	–0.698***
	(1.228)	(1.102)	(–3.33)
N	195	315	300
R^2	–	–	0.321
curve	Inverted U–shaped	Inverted U–shaped	Inverted U–shaped

Note: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Heterogeneity Analysis Results

	High–income countries	Low–income countries	Soybean	Corn
TO	0.006***	–0.033***	0.003**	–0.018**
	(0.002)	(0.007)	(0.002)	(0.008)
TO^2	–0.0004***	0.002***	–0.000***	0.002**
	(0.000)	(0.000)	(0.000)	(0.001)
POP	0.017***	–0.001**	–0.023***	0.050**
	(0.003)	(0.000)	(0.004)	(0.021)
AL	0.022***	0.016***	0.001	–0.015***
	(0.002)	(0.003)	(0.004)	(0.004)
AOI	0.059***	0.091***	0.031*	0.013**
	(0.016)	(0.034)	(0.017)	(0.006)
FDI	0.054**	–0.213	0.027	0.019
	(0.021)	(0.165)	(0.018)	(0.020)
_cons	30.805***	–26.402***	14.244***	3.096
	(2.920)	(4.275)	(2.493)	(2.735)
N	189	126	147	126
curve	Inverted U–shaped	U–shaped	Inverted U–shaped	U–shaped
turning point	7.96	7.85	6.74	5.05

Note: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

shown in Table 8.

Table 8 shows an inverted U–shaped relationship between *TO* and *SCA*, and U–shaped relationships between *TO* and *STR* and *TEC*, verifying H2. The absolute values of quadratic coefficients are smaller for *STR* and *TEC* than *SCA*, indicating the inverted U–shaped impact of food trade on the environment mainly occurs through the expansion of production scale. Increasing trade openness has a positive U–shaped impact on the environment through technological and structural effects, but not enough to offset the negative scale effects.

CONCLUSION

This study explores the relationship between China's

Table 7. Summary of EKC for soybeans and corn

	Soybean	Corn
curve	Inverted U–shaped	U–shaped
turning point	6.74	5.05
Crossing turning point countries	USA, Brazil	Ukraine
Not crossing turning point countries	Argentina,Canada, Russia, Ukraine, and Uruguay	Brazil, Russia, Uruguay, United States, and Myanmar

Table 8. Mechanism Verification

	SCA	*STR*	*TEC*
TO	2.077***	–0.001**	0.011**
	(0.116)	(0.000)	(0.004)
TO^2	–0.045***	0.0001***	0.001***
	(0.003)	(0.000)	(0.000)
control variables	YES	YES	YES
N	315	315	315
curve	Inverted U–shaped	U–shaped	U–shaped

Note: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

food imports and the ecological environment (mainly agricultural carbon emissions) of its trading partners using panel data from 15 major food trading partners from 2001 to 2021. Applying the Feasible Generalized Least Squares (FGLS) method, we find that the relationship supports the Environmental Kuznets Curve (EKC) hypothesis, exhibiting an inverted U–shape. This means that as the openness of food trade increases, the ecological environment of China's trading partners first deteriorates and then improves after crossing a turning point.

We also find that the shape of the EKC exhibits national and product heterogeneity. The EKC of relatively high–income countries is inverted U–shaped, while that of relatively low–income countries is U–shaped. The EKC of China's soybean imports is inverted U–shaped, but it is U–shaped for corn imports. Based on 2021 data, we clarify that expanding China's soybean imports from the United States, Brazil, and increasing corn imports from Brazil, Uruguay, Russia, the United States, and Myanmar are beneficial for improving the ecological environment of these countries.

Furthermore, we discover that food trade impacts the ecological environment of trading partners through production scale, industrial structure, and technological progress. Among these, production scale is the main path for the formation of the inverted U–shaped curve. When food trade openness increases, it has a positive U–shaped impact on the environment through technological and structural effects, but this is not enough to offset the negative impact brought by scale effects.

Our findings have important policy implications. Firstly, China should prioritize expanding food imports from countries that have crossed the EKC turning point to promote the improvement of their ecological environment. Secondly, when importing food from low–income countries, China should pay attention to their resource endowment and ecological carrying capacity, and avoid excessive expansion of food trade scale. Finally, China should actively guide its food import structure, appropriately expand the import market for important food types such as soybeans and build diversified food supply channels.

Despite its contributions, this study has some limitations that future research can address. For example, future studies can further explore the impact of China's food imports on the socio–economic aspects of trading partners, such as farmers' livelihoods and income distribution. Additionally, the impact of other types of food trade, such as meat and dairy products, on the ecological environment can be investigated.

AUTHOR CONTRIBUTIONS

H. Song, J. Yin, and Z. Wu designed this study. J. Wang was responsible for collecting and analyzing the data. H. Song wrote the manuscript. M. Yabe and Y. Takahashi supervised the research. Z. Wu assisted in editing the manuscript and approved the final version.

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