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Comparative Study of Agricultural Value Added in China and India on CO_2 Emissions: Based on K-nearest Neighbor Algorithm

Abdelsamiea Tahsin Abdelsamiea[1], Mustafa Radwan[2], Mohamed F. Abd El-Aal[3]*

[1]Department of Economics, College of Business, Imam Mohammad Ibn Saud Islamic University (IMSIU), Riyadh, Saudi Arabia, [2]Department of Economics, Faculty of Commerce, Damietta University, Egypt, [3]Department of Economics, Faculty of Commerce, Arish University, North Sinai, Egypt. *Email: mohammed.fawzy@comm.aru.edu.eg

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ABSTRACT

This study contributes to the current discourse on the relationship between environmental sustainability and economic growth by examining the connections between poverty, carbon emissions, and the value generated in the agricultural sector. We assess the agricultural sectors of China and India, analyzing their roles in global carbon emissions through empirical data, econometric models, and machine learning techniques. We find a nonlinear relationship between economic growth and emissions; initially, development elevates carbon output, while subsequent progress encourages sustainability through technological innovations and policy initiatives. Among the machine learning methods employed, the K-Nearest Neighbors (KNN) algorithm demonstrated the highest predictive accuracy. The results indicate that China's agricultural sector is the dominant contributor to carbon emissions, accounting for 78.2%, while India's sector contributes 21.8%. These findings underscore the disparities in agricultural carbon footprints between the two nations and highlight the necessity of integrated strategies that balance economic growth with environmental protection. Policy implications involve implementing focused poverty reduction initiatives, renewable energy strategies, and sustainable farming methods to lessen the effects of climate change while promoting economic growth. The study highlights how artificial intelligence and machine learning can improve predictive accuracy and guide effective climate policies.

Keywords: K-Nearest Neighbor Algorithm; China's Agricultural Value Added; India's Agricultural Value Added; CO_2 Emissions
JEL Classifications: Q15, C63, C80, C81, C87

1. INTRODUCTION

Agriculture is critical in climate change and a significant source of global carbon emissions. Intensive farming techniques, rising population demands, and increased mechanization have positioned China and India as the leading agricultural economies, significantly contributing to carbon dioxide (CO_2) emissions. Agricultural emissions from China and India affect their ecosystems and play a significant role in global CO_2 levels and climate patterns. Therefore, understanding these agricultural carbon emissions' causes, challenges, and mitigation strategies is crucial for developing effective climate policies worldwide.

The primary causes of CO_2 emissions in agriculture are energy-intensive farming practices, animal management, fertilizer application, and soil degradation. According to the Intergovernmental Panel on Climate Change (IPCC, 2021), China and India are among the most significant agricultural contributors responsible for about 17–18% of global greenhouse gas (GHG) emissions. As the leading CO_2 emitter in the world, China's highly mechanized agricultural sector significantly raises its carbon footprint. Meanwhile, India also contributes heavily to farming emissions due to its extensive agricultural landscape and reliance on traditional farming methods. Examining these emissions concerning global CO_2 trends provides insights into the challenges and possible policy interventions for reducing emissions.

One major challenge China and India face in reducing agricultural value-added emissions is the tension between economic growth and environmental sustainability. In China, the swift development of industrialized agriculture, increased synthetic fertilizer usage, and energy consumption have resulted in considerable emissions. In contrast, although India's agriculture is less mechanized, it depends heavily on livestock and rice, which are significant methane and CO_2 emissions sources. Moreover, in both countries, policy initiatives usually focus on food security and economic growth, often overlooking environmental consequences.

Strategies aim to enhance farming efficiency by utilizing climate-smart methods and implementing carbon sequestration techniques to decrease CO_2 emissions in agriculture. China invests heavily in precision agriculture and sustainable land management to lower emissions. Meanwhile, India is advancing policies that promote organic farming, renewable energy in agriculture, and reforestation initiatives. Both countries should enhance their collaboration with international organizations and prioritize funding for research and development to create sustainable agricultural practices effectively.

China and India face a significant challenge in balancing economic growth with environmental sustainability while aiming to reduce agricultural emissions. In China, the swift development of industrial farming, coupled with synthetic fertilizers and energy use, has resulted in high emissions. Conversely, India's less mechanized agriculture relies heavily on livestock and rice, leading to considerable methane and CO_2 emissions. Additionally, policy initiatives in both nations frequently emphasize food security and economic growth, often overlooking their environmental repercussions.

Moreover, technological advancements and data-centric solutions are essential for lowering agricultural emissions. Breakthroughs in remote sensing, artificial intelligence, and blockchain offer fresh opportunities to monitor emissions and improve resource efficiency. The governments of the two nations should adopt tech-based policies that provide real-time data on agricultural emissions, empowering farmers to make informed decisions that reconcile productivity with sustainability.

This study will compare agricultural value added in China and India, examining their impact on global CO_2 levels. This research will contribute to a broader understanding of how these two significant economies can balance agricultural productivity with climate sustainability by evaluating sources, challenges, and mitigation strategies. This study's findings will offer crucial insights for researchers, governments, and environmentalists to formulate effective strategies to reduce agricultural carbon emissions in China and India while simultaneously tackling global climate challenges.

The K-Nearest Neighbors (KNN) algorithm examines carbon emissions in agriculture by identifying patterns and trends within extensive datasets. KNN empowers researchers to make well-informed decisions regarding sustainable farming practices by classifying and predicting emission levels rooted in historical data. This algorithm proficiently assesses similarities among diverse agricultural areas in China and India, aiding in formulating precise mitigation strategies. KNN's capability to handle non-linear data and adjust to intricate agricultural situations renders it a crucial resource for policymakers and environmental specialists.

2. LITERATURE REVIEW

Many papers and studies have explored various dimensions of agricultural carbon emissions, focusing on their drivers, reduction methods, and economic impacts. Huang et al. (2024) investigated carbon emissions from agriculture in China, highlighting significant influencing factors and regional disparities, especially noting a trend of increasing emissions in the central and western regions. Similarly, Cui (2024) evaluated the feasibility of Agricultural Carbon Trading (ACT) in China, emphasizing the role of policies in market development and comparing them with those in developed nations.

Wu et al. (2024) examined agricultural carbon emissions from 2000 to 2021, revealing a reverse U-shaped pattern with projected peak emissions around 2030. In a related study, Chen and Liu (2024) analyzed trends in agricultural carbon emissions, highlighting the increasing emphasis on strategies for emission reduction that align with China's dual carbon objectives. Moreover, Zhang et al. (2024) examined the inter-provincial movement of agricultural carbon emissions in China, uncovering a rise in net carbon transfer and changes in emission patterns.

Li et al. (2024) investigated uncertainties in assessing agricultural greenhouse gas (AGHG) emissions, emphasizing the importance of standardized methods. Duan et al. (2023) evaluated methane emissions in Chinese agriculture, pinpointing enteric fermentation as a significant factor. Wu et al. (2024) thoroughly reviewed strategies for reducing agricultural greenhouse gases, outlining opportunities and challenges at different scales.

Further studies examined the role of economic and technological factors in carbon emissions. A survey of China's digital economy (2024) demonstrated its effectiveness in reducing agricultural carbon emissions through technological advancements. Ji et al. (2024) identified regional disparities in emissions over the past 22 years, suggesting tailored low-carbon transition strategies. Zhao et al. (2024) examined agricultural carbon emission efficiency, demonstrating enhancements alongside economic growth.

Furthermore, Zhang et al. (2024) assessed the effects of carbon pricing on agriculture, finding that increased costs reduced emissions but had a more pronounced impact on lower-income households. Han et al. (2024) examined emission efficiency in China's state farms, identifying key carbon sources linked to rice farming, fertilizers, and land tilling. Concurrently, Song et al. (2023) investigated emissions from agricultural inputs over the past thirty years, revealing a slowdown in the growth rate and inconsistent patterns in carbon emissions compared to agricultural production.

Numerous studies worldwide have examined agricultural carbon emissions in India. Jiao et al. (2022) investigated CO_2 emissions in both China and India, finding a weak decoupling from economic growth in China and inconsistent trends in India. Bai et al. (2023) analyzed the influence of agricultural productive services (APS) on carbon emissions and determined that APS can reduce emissions, accompanied by a negative spatial spillover effect. Li and Meng (2024) looked into agricultural trade liberalization, highlighting its contribution to lowering carbon emissions through technology spillovers and industrial optimization.

Wangyel, Lee, and Son (2017) investigated low carbon development pathways in Indian agriculture, identifying feasible interventions for promoting low carbon technologies while highlighting challenges such as lack of financial incentives and enabling policies. Ghosh (2018) explored the causality between CO2 emissions and energy consumption in Indian agriculture, identifying a bidirectional relationship and long-run equilibrium. Jain et al. (2016) quantified greenhouse gas emissions from soils under major crops in Northwest India, finding highest N2O emissions in pulses and significant variation in global warming potential. Maheswarappa, Srinivasan, and Lal (2011) assessed the carbon footprint and sustainability of Indian agricultural production systems, reporting agronomic growth but unquantified environmental costs. Sahai et al. (2011) examined emissions from field burning of agricultural residues in India, showing that residue burning contributed substantially to biomass-related GHG emissions. Ilampooranan (2023) revised nitrous oxide emission rates in Indian agricultural landscapes, providing new insights into emission dynamics. Nelson et al. (2009) evaluated greenhouse gas mitigation issues in Indian agriculture, identifying cost-effective mitigation options though based on data of varying quality.

Other studies focused on mitigating agricultural emissions. Sun et al. (2022) investigated rural financing constraints, finding that alleviating constraints increased emissions intensity but could be offset by mechanization. A study by Guru et al. (2022) in India assessed carbon emissions from agricultural equipment and identified sustainable methods to mitigate these effects. At the same time, Sun and Jin (2022) examined the geographical distribution of carbon emissions in China's agricultural sector and recommended regional collaboration on methods for reducing emissions.

Numerous studies have explored the impact of carbon credit systems and mitigation policies. Monga and Kaushal (2024) analyzed carbon credit mechanisms in Indian agriculture, highlighting the significance of soil health management for carbon sequestration. Patange et al. (2024) evaluated non- CO_2 greenhouse gas reduction in India, pointing out that Uttar Pradesh holds the most significant potential for improvement. Khurana et al. (2024) examined the possibility of carbon credits, indicating that carbon trading could promote sustainable farming practices.

Other relevant studies examined emissions from agricultural practices. Deshpande et al. (2023) quantified emissions from agrarian residue burning, showing a 75% increase since 2011. In their 2022 study, Hemingway et al. analyzed emissions from crops and livestock in an Indian village, revealing differences attributed to agricultural practices. Meanwhile, Gupta et al. (2023) examined how renewable energy and foreign direct investment (FDI) reduce long-term CO_2 emissions in Indian agriculture.

Numerous studies have investigated the impact of cattle on emissions. Patra (2017) examined variations in carbon footprint by analyzing methane and nitrous oxide emissions from animal products in different Indian states. Kumari et al. (2019) used climate data to study methane emissions associated with Indian livestock and how these emissions relate to climate change. Pathak (2013) looked into mitigation strategies in Indian agriculture, emphasizing soil management practices aligned with climate objectives.

Despite extensive research on agricultural carbon emissions, there is a significant gap in the application of advanced machine-learning techniques for accurate emission prediction and mitigation strategies. Many recent studies depend on traditional statistical models and econometric methods, frequently overlooking the complexities of emission trends. This research aims to fill that gap using the K-Nearest Neighbors (KNN) algorithm, improving predictive accuracy and revealing intricate relationships within agricultural emission data. By utilizing KNN, this study seeks to offer a more substantial, data-driven approach to understanding and mitigating agricultural carbon emissions, thereby contributing new insights to the existing literature.

These studies highlight the multifaceted nature of agricultural carbon emissions, underscoring the importance of policy measures, technological advancements, economic incentives, and sustainable farming practices in mitigating emissions and fostering a low-carbon agrarian sector.

3. EMPIRICAL FRAMEWORK

The baseline empirical model is formulated to quantify the elasticity of global CO_2 emissions for agricultural emissions from China and India. Given the data's wide-ranging values and potential heteroscedasticity, all variables are transformed using the natural logarithm. The regression model is specified as follows:

$$Ln(World\ CO_2) = ln(China\ Agricultural\ value\ added) + ln(India\ Agricultural\ value\ added)$$

Where,

- Ln ($World\ CO_2$) represents the natural logarithm of global CO_2 emissions (dependent variable).
- Ln (*China Agricultural value added*): denotes the natural logarithms of agricultural value-added emissions from China>
- Ln (*India Agricultural value added*): denotes the natural logarithms of agricultural value-added emissions from India.

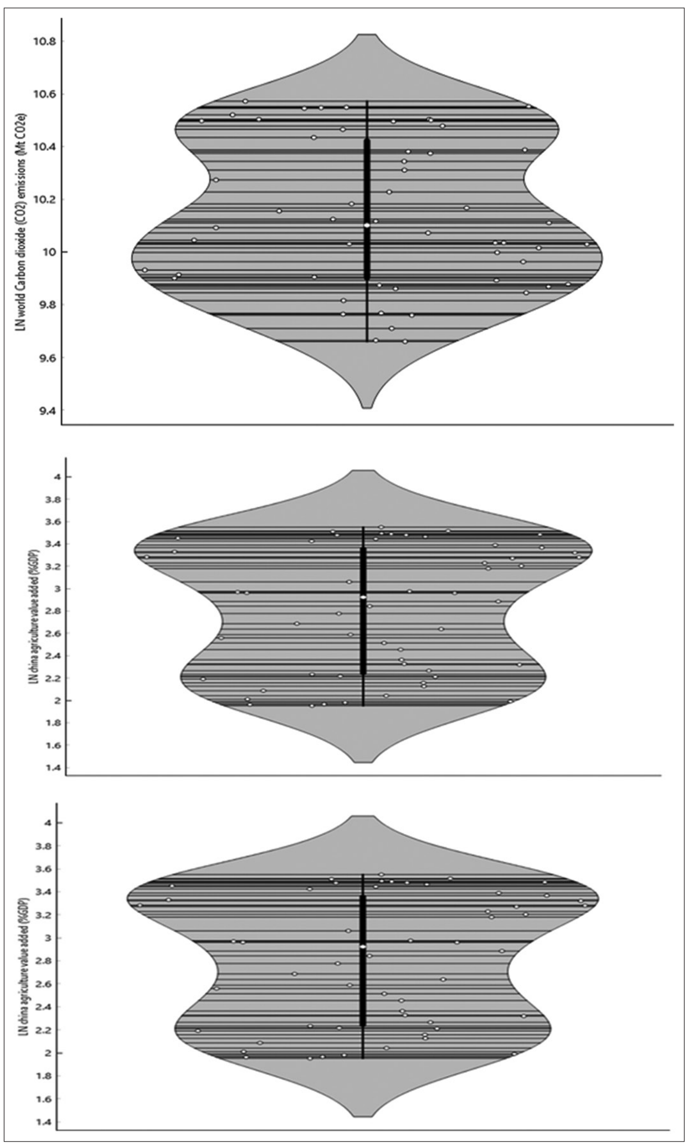
4. DATA

The dataset for this study is obtained from the World Bank's open data portal, offering comprehensive, dependable, and globally comparable information on environmental and economic indicators. Our analysis mainly centers on global CO_2 emissions (the dependent variable) and agricultural value added from China and India (the independent variables). These variables were chosen to reflect the role of agricultural practices in shaping the global carbon footprint over the significant period from 1970 to 2023.

World CO_2 emissions data represent the total carbon dioxide emissions from all sectors worldwide, providing a solid baseline for assessing the impact of industrial, economic, and environmental changes on climate change. In contrast, China and India's agricultural value-added data specifically focus on emissions from farming activities such as fertilizer application, soil management, and energy use in agricultural production. The long-term dataset from 1970 to 2023 enables a detailed analysis of trends, policy impacts, and technological advancements influencing farming practices over time.

Data from the World Bank is rigorously compiled and verified using inputs from multiple governmental and international sources, ensuring high accuracy and consistency. This uniformity is especially critical when analyzing trends across several decades, as it enables a reliable comparison of how agricultural emissions in China and India have evolved about global CO_2 emissions. A wide temporal range provides essential insights into emission trend dynamics and the effectiveness of different mitigation strategies.

Figure 1: Data violin plot



Before analysis, several preprocessing steps were conducted on the dataset. These steps included addressing missing values, standardizing data scales, and synchronizing time records. We applied a natural logarithm transformation to stabilize variance, lessen the impact of outliers, and normalize the data distribution. This method significantly enhances the effectiveness of analytical algorithms, especially the K-Nearest Neighbors (KNN) algorithm, which is crucial for our research, as shown in Figure 1.

This comprehensive dataset is the foundation for understanding how agricultural practices in China and India influence global CO_2 emissions. By analyzing over fifty years of data, this study seeks to unveil long-term trends and relationships, offering vital insights that could shape national and international strategies for reducing agricultural carbon emissions.

5. METHODOLOGY

KNN is a well-known instance-based, nonparametric machine learning method for applications such as regression and classification. Using the average values of the K nearest data points in the feature space, KNN predicts a continuous target variable in regression situations. The idea that related data points have similar behaviors makes this method helpful in handling complicated and nonlinear datasets (Hastie et al., 2009).

5.1. Distance Metrics

KNN regression evaluates similar data points using a selected distance measure. The distance functions that are most commonly utilized are as follows:

- Euclidean distance:

$$d\left(x_i, x_j\right) = \sqrt{\sum_{k=1}^{n}\left(x_{ik} - x_{jk}\right)^2}$$

- Manhattan distance:

$$d\left(x_i, x_j\right) = \sum_{k=1}^{n}\left|x_{ik} - x_{jk}\right|$$

- Minkowski distance (generalized form):

$$d\left(x_i, x_j\right) = \left(\sum_{k=1}^{n}\left|x_{ik} - x_{jk}\right|^p\right)^{\frac{1}{p}}$$

The choice of distance measure significantly affects model performance, depending on the data type.

5.2. Prediction Function in KNN Regression

Following the identification of the K-nearest neighbors, the following formula is used to determine the predicted value $\hat{y}$ for a new data point:

$$\hat{y} = \frac{1}{K}\sum_{i=1}^{K} y_i$$

Where y_i refers to the K-nearest neighbors' target values.

Alternatively, distance-weighted KNN regression assigns greater weights to closer neighbors:

$$\hat{y} = \frac{\sum_{i=1}^{K} w_i y_i}{\sum_{i=1}^{K} w_i}$$

Where the weight w_i is commonly understood to be the inverse of distance:

5.3. Model Evaluation Metrics

Several error measures are used to evaluate KNN regression's performance:

- Mean squared error (MSE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2$$

- Root mean squared error (RMSE):

$$RMSE = \sqrt{MSE}$$

- Mean absolute error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|$$

- R-squared (R^2):

Table 1: The ML algorithms prediction

Model	MSE	RMSE	MAE	MAPE	R2
KNN	0.001	0.034	0.027	0.003	0.985
GB	0.001	0.036	0.030	0.003	0.983
RF	0.002	0.041	0.030	0.003	0.978
DT	0.002	0.047	0.036	0.004	0.971
SVM	0.003	0.058	0.050	0.005	0.956

Source: Made by author

Table 2: KNN feature importance

KNN feature selection	Score
China Agriculture value added (%GDP)	0.782147
India Agriculture value added (%GDP)	0.217853

Source: Made by author

$$R^2 = 1 - \frac{\sum\left(y_i - \hat{y}_i\right)^2}{\sum\left(y_i - \bar{y}\right)^2}$$

A lower MSE or RMSE and R^2 a higher number implies improved model performance, as shown in Table 1.

Table 1 shows that the KNN algorithm is more accurate than others, with a higher R_2 and lowest MSE. Therefore, the paper depends on KNN to determine local regression coefficients, as shown in Table 2.

Table 2 highlights the fact that The Chinese agricultural sector is the largest generator of carbon emissions compared to its Indian counterpart, with a contribution rate of 78.2, compared to 21.8% for the Indian agricultural sector.

6. CONCLUSION

This research demonstrates a notable inverse relationship between global CO_2 emissions and agricultural value added in China and India. It employs the K-Nearest Neighbors (KNN) algorithm to assess data from 1970 to 2023. Significantly, The Chinese agricultural sector is the largest generator of carbon emissions compared to its Indian counterpart, with a contribution rate of 78.2, compared to 21.8% for the Indian agricultural sector.

Moreover, these findings underscore the critical need for policymakers to invest in sustainable agricultural practices and cutting-edge technologies. China and India can further reduce their carbon footprints while promoting economic growth by focusing on precision agriculture, integrating renewable energy, and managing resources innovatively. Future research should investigate additional machine learning techniques to enhance predictive models and evaluate the effects of emerging agricultural innovations on greenhouse gas emissions, ultimately aiding in developing more targeted and effective global environmental policy strategies.

In this context, utilizing the KNN algorithm effectively showcases machine learning's ability to unravel complex environmental and economic connections. As datasets expand, including more variables—such as climate policies, technological developments, and socioeconomic factors—can enhance our comprehension of the relationship between agricultural practices and emissions. This interdisciplinary method enriches our understanding of sustainable development strategies. It establishes a foundation for more robust and adaptable policy frameworks capable of addressing the intricate challenges posed by climate change.

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REFERENCES

Bai, Z., Wang, T., Xu, J., Li, C. (2023), Can agricultural productive services inhibit carbon emissions? Evidence from China. Land, 12(7), 1313.

Chen, Z., Liu, N. (2024), Evolution of agricultural carbon emission research in China: A historical analysis and emerging trends. Frontiers in Environmental Science, 2024, 1359477.

Cui, Z.L. (2024), Enhancing the advancement of agricultural carbon emission reduction via China's agricultural carbon trading. Science, Technology and Social Development Proceedings Series, 1, 320-327.

Deshpande, M., Kumar, N., Pillai, D., Krishna, V., Jain, M. (2023), Greenhouse gas emissions from agricultural residue burning have increased by 75 % since 2011 across India. Science of The Total Environment, 2023, 166944.

Duan, Y., Gao, Y., Zhao, J., Xue, Y., Zhang, W., Wu, W., Jiang, H., Cao, D. (2023), Agricultural methane emissions in China: Inventories, driving forces and mitigation strategies. Environmental Science and Technology, 57, 13292-13303.

Ghosh, S. (2018), Carbon dioxide emissions, energy consumption in agriculture: A causality analysis for India. Arthaniti: Journal of Economic Theory and Practice, 17(2), 183-207.

Gupta, M., Singh, R., Choudhary, T.F., Yadav, N. (2023), Sustainable transformation: Assessing the impact of renewable energy, foreign direct investment, and carbon emissions on agricultural production in India.

Guru, P.K., Shrivastava, A.K., Tiwari, P., Khandai, S., Chandel, N.S. (2022), Estimation of carbon emissions of agricultural machinery use in India. ORYZA-An International Journal on Rice, 59(3), 260-268.

Han, G., Xu, J., Zhang, X., Pan, X. (2024), Efficiency and driving factors of agricultural carbon emissions: A Study in Chinese state farms. Agriculture, 14(9), 1454.

Hastie, T., Tibshirani, R., Friedman, J.H., Friedman, J.H. (2009), The Elements of Statistical Learning: Data Mining, Inference, and Prediction. Vol. 2. New York: Springer. p. 1-758.

Hemingway, C., Vigne, M., Aubron, C. (2022), Agricultural greenhouse gas emissions of an Indian village - Who is to blame: Crops or livestock? Science of The Total Environment, 856, 159145.

Huang, X., Wu, X., Guo, X., Shen, Y. (2024), Agricultural carbon emissions in China: Measurement, spatiotemporal evolution, and influencing factors analysis. Frontiers in Environmental Science, 12, 1488047.

Ilampooranan, I. (2023), Nitrous oxide emissions dynamics in Indian agricultural landscapes: Revised emission rates and new insights. Agriculture, Ecosystems and Environment, 356, 108639.

IPCC. (2021), Climate Change 2021: The Physical Science Basis. Intergovernmental Panel on Climate Change. Switzerland: IPCC.

Jain, N., Arora, P., Tomer, R., Mishra, S.V., Bhatia, A., Pathak, H., Chakraborty, D., Kumar, V., Dubey, D.S., Harit, R.C., Singh, J.P. (2016), Greenhouse gases emission from soils under major crops in Northwest India. Science of The Total Environment, 542(542), 551-561.

Ji, M., Li, J., Zhang, M. (2024), What drives the agricultural carbon emissions for low-carbon transition? Evidence from China. Environmental Impact Assessment Review, 105, 107440.

Jiao, Z., Xing, Z., Zhang, G., Ma, X., Wang, H. (2022), Comparing decoupling and driving forces of CO_2 emissions in China and India. Frontiers in Environmental Science, 10, 847062.

Khurana, A., Kajale, D., Cariappa, A.A., Krishna, V.V. (2024), Shaping India's climate future: A perspective on harnessing carbon credits from agriculture. Outlook on Agriculture, 53(2), 113-130.

Kumari, S., Hiloidhari, M., Naik, S.N., Dahiya, R.P. (2019), Methane Emission Assessment from Indian Livestock and Its Role in Climate Change Using Climate Metrics. London: IntechOpen.

Li, G., Meng, A. (2024), Agricultural carbon reduction in China: The synergy effect of trade and technology on sustainable development. Environmental Research, 252, 119025.

Li, H., Jin, X., Zhao, R., Han, B., Zhou, Y., Tittonell, P. (2024), Assessing uncertainties and discrepancies in agricultural greenhouse gas emissions estimation in China: A comprehensive review. Environmental Impact Assessment Review, 106, 107498.

Maheswarappa, H.P., Srinivasan, V., Lal, R. (2011), Carbon footprint and sustainability of agricultural production systems in India. Journal of Crop Improvement, 25(4), 303-322.

Monga, M., Kaushal, S. (2024), Rational outlook on carbon credit and carbon footprints in Indian agricultural system: A comprehensive review. Asian Journal of Current Research, 9, 107-119.

Nelson, G.C., Robertson, R., Msangi, S., Zhu, T., Liao, X.L., Jawajar, P. (2009), Greenhouse gas mitigation: Issues for Indian agriculture. Research Papers in Economics. p. 900. Available from: https://ideas.repec.org/p/fpr/ifprid/900.html

Patange, O., Purohit, P., Avashia, V., Klimont, Z., Garg, A. (2024), Mitigation of non-CO_2 greenhouse gases from the Indian agriculture sector. Environmental Research Letters, 19, 074020.

Pathak, H. (2013), Greenhouse gas mitigation in Indian agriculture. Annals of Agricultural Research, 34(2), 37514.

Patra, A.K. (2017), Accounting for methane and nitrous oxide emissions and carbon footprints of livestock food products in different states of India. Journal of Cleaner Production, 162, 678-686.

Sahai, S., Sharma, C., Singh, S., Gupta, P.K. (2011), Assessment of trace gases, carbon and nitrogen emissions from field burning of agricultural residues in India. Nutrient Cycling in Agroecosystems, 89(2), 143-157.

Song, S., Zhao, S., Ma, Y. (2023), Carbon emissions from agricultural inputs in China over the past three decades. Agriculture, 13(5), 919.

Sun, B., Sun, R., Gao, K., Zhang, Y., Wang, S., Bai, P. (2024), Analyzing the mechanism among rural financing constraint mitigation, agricultural development, and carbon emissions in China: A sustainable development paradigm. Energy and Environment, 35(4), 1850-1870.

Sun, Y., Jin, Y. (2022), Structural decomposition of the spatial and temporal patterns and sources of spatial variation in agricultural carbon emissions in China. BCP Business and Management, 28, 42-51.

Wangyel, S., Lee, W.K., Son, Y. (2017), Low carbon development pathways in Indian agriculture. Change and Adaptation in Socio-Ecological Systems, 3(1), 18-26.

World Bank. World Development Indicators. Available from: https://databank.worldbank.org/source/world-development-indicators

Wu, H., Yang, Y., Shen, Y. (2024), Agricultural carbon emissions in China: Estimation, influencing factors, and projection of peak emissions. Polish Journal of Environmental Studies, 33, 4791-4806.

Wu, J., Xu, Y., Liu, Z. (2024), A comprehensive review on agricultural greenhouse gas emission reductions in China: opportunities and challenges. Carbon Footprints, 3(4), 17.

Zhang, Q., Li, B., Liu, J., Deng, Y., Zhang, R., Wu, W., Geng, Y. (2024), Assessing the distributional impacts of ambitious carbon pricing in China's agricultural sector. Ecological Economics, 217, 108082.

Zhang, X., Zhang, J., Fu, W., Pei, Z., Zhang, B., Zhuang, M. (2024), Analysis of agricultural carbon emissions transfer of inter-provincial trade in China. PLoS One, 19(11), e0311744.

Zhao, X., Yang, D., Duan, X. (2024), Temporal and spatial evolution characteristics and decoupling trend of Chinese agricultural carbon emission efficiency. PLoS One, 19(10), e0311562.