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Impact of Grain Production on Agricultural Carbon Emission in Jharkhand, India: An Empirical Analysis

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Abstract

This study intends to determine the inter-relationship among carbon emissions and economic development from agriculture in Jharkhand, during 2005-2022, utilizing decoupling and decomposition analysis. The decoupling analysis revealed a weakly decoupled state for 7 years, followed by strongly decoupled and strongly coupled states for 3 years, an expansively coupled state for 2 years, a weakly coupled state for one year, and a recessively decoupled state for one year. This suggests that there was no consistent evolutionary path from the coupled state to the decoupled state. However, the empirical findings of the Log Mean Divisia Index method suggest that the rise in agricultural carbon emissions from 2005 to 2022 is primarily due to the effects of agricultural economics followed by the agricultural labor force. Additionally, factors such as the intensity of agricultural carbon emissions and agricultural structure tend to decrease agricultural carbon emissions, with the intensity of emissions having the largest impact on reducing emissions. Furthermore, the combination of decoupling and decomposition analysis suggests that the environmental pressure declined with a rise in the agricultural economy in 2008, 2009, and 2018. The intensity of agricultural carbon emissions significantly contributed to reducing overall emissions during these years. Overall, efforts to reduce carbon emissions from the agricultural sector in Jharkhand are still ineffective.

Keywords: Low-carbon agriculture; Grain production; Decouple; Decomposition method.

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1. Introduction

Global climate change is causing serious environmental problems worldwide due to greenhouse gas emissions driving global warming [1]. Modern agricultural activities significantly impact greenhouse gas emissions because of their substantial material inputs, high energy consumption, and levels of pollutant discharge. Food safety and climate emergency driven by greenhouse gas (GHG) emissions are critical global issues today. Based on the International Panel on Climate Change (IPCC) report, they accounted for

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around 13 % of carbon dioxide (CO_2), 44 % of methane (CH_4), and 81 % of nitrous oxide (N_2O) emissions from human activities globally during 2007-2016, representing 23% of total greenhouse gas emissions from the agriculture, forestry, and other land uses sector. Suppose, they consider emissions from both pre-and post-production in the global food system, in that case, emissions are estimated to be 21-37 % of total greenhouse emissions from the agriculture, forestry, and other land uses (AFOLU) sector globally [2].

India's net greenhouse gas emissions rose from 1585.51 million tonnes in 2005 to 2952.87 million tonnes in 2018. Net greenhouse emissions from the agriculture, forestry, and other land uses (AFOLU) sector were 16 % in 2005 and 6 % in 2018, respectively. It indicates that net agriculture, forestry, and other land uses (AFOLU) emissions declined at a rate of 3.09 %, from 256.70 million tonnes of CO_2 equivalent in 2005, to 170.58 million tonnes of CO_2 equivalent in 2018 [3]. On the other hand, Jharkhand's net greenhouse emissions rose from 60.47 million tonnes CO_2 equivalent in 2005 to 115.20 million tonnes CO_2 equivalent in 2018, in which the share net agriculture, forestry, and other land uses (AFOLU) sector emissions increased at a rate of 3.41 % from 6.29 million tonnes CO_2 equivalent in 2005 to 9.72 million tonnes CO_2 equivalent in 2018 [4].

In Jharkhand, the primary farming method is rainfed agriculture, with only about 10–12 % of the net cultivation area being served by a limited irrigation system. The rainfall pattern of Ranchi, Jharkhand has an increasing trend with a negative correlation with temperature [5]. These agricultural challenges are contributing to a considerable food grain shortage in Jharkhand. Over the 21st century, the production of crops rose from 2.02 million tonnes to 7.83 million tonnes, indicating a compound annual growth rate of 106 %. Additionally, fertilizer consumption in gross cropped areas has increased from 44.1 kg per hectare in 2001 to 109 kg per hectare in 2022, which translates to a compound annual growth rate of 104 %. In the past two decades, there has been a significant increase in the use of chemical products in agriculture. This rise has contributed to higher net emissions from agricultural activities, posing a major challenge to achieving sustainable agricultural development [6].

For the empirical findings on agricultural carbon emissions versus the produce value from agriculture, the concept of decoupling elasticity, and the decomposition method were used to examine the inter-relationships between carbon emissions and value-added from agricultural activities. In general, low-carbon agriculture is a modern farming method that increases output rapidly while using minimal chemical products and producing nominal carbon emissions, achieved through technological, policy, and management enhancements [7,8]. For example, He *et al.* [9] propose in their study that enhancing low carbon efficiency requires adapting the improvement and dissemination of appropriate agricultural green production technologies to local production conditions. They also advocate for improving the farm mechanization and Innovation system. However, many empirical studies indicate the interrelation between environmental deterioration and economic development [10-17]. Moreover, various researchers have investigated the connection between carbon emissions and economic development from agriculture [18-20]. For instance, an analysis conducted by Gessesse *et al.* [18] in China revealed an inverted U-shape curve between CO_2 emissions, and Gross Domestic Product. Also, this study suggests there is no evidence of long-term causality from CO_2 emissions, and the income to energy utilization, which implies that the structure of economic development should be restructured towards a more energy-efficient and decarbonized economy. Sui *et al.* [19] noted that the growth of the agrarian economy has significantly contributed to the increase in carbon emissions from agriculture in Jilin province. Furthermore, the variations in agrarian carbon emissions have been influenced by economic policies, followed by environmental policies. On the other hand, Wang *et al*. [20] discovered an inverted U-shape curve correlation between agricultural economic growth and carbon emissions from agriculture in Henan Province, China over the period 2000-2019. Furthermore, the characteristics of CO_2-Environmental Kuznet Curve and decoupling state suggest that environmental policies have promoted decoupling. However, these policies faced time lags and lacked continuity, which could hinder efforts to reduce carbon emissions. Nonetheless, several quantitative studies show a connection between agricultural economic expansion and carbon emissions [21,22]. This study investigates the inter-relationships between production level and carbon emissions from the agricultural sector in Jharkhand over the period 2005-2022. This type of research has been conducted on a larger scale, but agricultural production is significantly affected by climate change. Consequently, studying climate variables on a broader scale may not be particularly useful [23,24]. In contrast, this study was performed on a regional scale, making it more effective in understanding agricultural carbon emissions associated with grain production. Research on the impact of grain production on agricultural carbon emissions in Jharkhand is essential for climate sustainability. Agriculture, especially rice cultivation and fertilizer use, significantly contributes to greenhouse gas emissions. Understanding these emissions is crucial for developing climate-smart policies and low-carbon farming techniques. This study can also improve soil health, enhance farmer resilience, and guide carbon credit programs. A comparative analysis with other states can help optimize sustainable agricultural practices. Overall, this research is essential for food security, rural development, and environmental sustainability in Jharkhand. It will assist the state in transitioning toward a low-carbon and climate-resilient agricultural future.

The rest of this paper is structured in the following manner: the study region is described in Section 2, the technique and data collection are covered in Section 3, the empirical analysis results are shown in Section 4, and the study is concluded in the last section.

2. Description of the Study Area

Jharkhand is a state in the eastern India, established on 15th November 2000. The state spans an area of 79,714 square kilometers, with 29.61 % covered by forests. Jharkhand possesses about 40 % of India's total mineral resources and is often referred to as the "Land of Forests". Ranchi serves as its capital. The state's average elevation above mean sea level is 909 feet. For the financial year 2023-24, the Gross Domestic Product is approximately Rs. 4.23 lakh crore, with a per capita income of Rs. 1,07,336. Jharkhand is the fastest-growing state economy in terms of Gross Domestic Product. According to the 2011 census, Jharkhand has a population of 32,988,134, with 24.05 % living in urban areas and 75.95 % in rural areas. Fig. 1 displays the study area's location map.

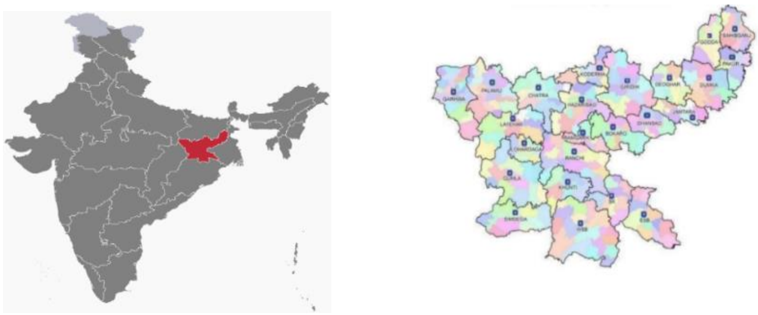

Fig. 1. Location map of Jharkhand, India.

3. Material and Methods

In this study, the interrelation between production level and carbon emissions from agricultural activities is examined using the decouple and decomposition methods. The data for the output value and gross output value from grain production has been collected from the Directorate of Economics and Statistics, Government of Jharkhand at the constant price 2011-12. The agricultural sector's carbon emissions dataset for the period 2005-2022 is taken from GHG Platform-India. The data on the agricultural labor force is collected from the "Handbook of Statistics on Indian States, 2023".

3.1. *Linear regression model*

The analysis of variance is a statistical tool that helps to study the impact of one or more independent variables on the dependent variable. The dependent variable may be either quantitative or qualitative. Linear regression [25] is a statistical model that examines the linear relationship between a dependent variable (say) 'E' and one or more independent variables (say) 'G'. This simple linear regression model can be expressed as

$$\mathrm{E} = \alpha + \beta \mathrm{G} \tag{1}$$

In logarithmic form, equation (1) can be written as

$$\ln \mathrm{E} = \alpha + \beta \ln \mathrm{G} \tag{2}$$

where 'α', and 'β' represents the intercept and slope of the line, respectively, and 'ln' refers to the natural logarithmic function.

3.1.1. *Coefficient of determinaton (R^2)*

The coefficient of determination or R-square (R^2) is a measure that indicates the goodness of fit of a model. It always lies between the values 0 and 1. The general equation of R-squared is defined as

$$R^2 = 1 - \frac{RSS}{TSS} \tag{3}$$

where, 'RSS' is the residual or error sum of squares, and 'TSS' is the total sum of squares. An R-squared close to 1 indicates a strong correlation between the model and the data, while an R-squared close to 0 indicates that the model is no better than fitting the mean.

3.2. *Decoupling degrees*

The decoupling index [26] is defined as follows

$$DI_t = \frac{\Delta C}{\Delta P} = \left(\frac{C_t - C_{t-1}}{C_{t-1}}\right) \Big/ \left(\frac{P_t - P_{t-1}}{P_{t-1}}\right) \tag{4}$$

where DI_t represents the change in one unit of CO_2 emissions (C) with respect to produce value (P) from agriculture during the initial phase $(t-1)$, and the final phase (t). C_{t-1} and C_t represent the agricultural carbon emissions at the initial, and the final phases, respectively, and P_{t-1} and P_t indicates the agricultural produce value at the initial, and the final phases, respectively. ΔC and ΔP represent the change rates of agricultural carbon emissions, and production value between the final and initial phases, respectively.

Table 1. Decoupling degrees.

Decoupling State	ΔC (%)	ΔP (%)	DI	Relationship
Expansively Coupled	$\Delta C > 0$	$\Delta P > 0$	$DI > 1$	The economy is growing, but the environment is deteriorating rapidly.
Strongly Coupled	$\Delta C > 0$	$\Delta P < 0$	$DI > 1$	The economy is declining, and the environment is worsening.
Weakly Coupled	$\Delta C > 0$	$\Delta P < 0$	$0 < DI < 1$	The economic recession is occurring more quickly than the rate at which environmental conditions are improving.
Weakly Decoupled	$\Delta C > 0$	$\Delta P > 0$	$0 < DI < 1$	Economic growth is occurring at a faster rate than the degradation of the environment.
Strongly Decoupled	$\Delta C < 0$	$\Delta P > 0$	$DI < 1$	As the economy improves, the pressure on the environment decreases.
Recessively Decoupled	$\Delta C < 0$	$\Delta P < 0$	$DI > 1$	The economy is shrinking, while the environment is improving.

The connection between the produce value and carbon emissions from agricultural activities is divided into six decoupling degrees based on the change rate of agricultural carbon emissions, agricultural produce value, and the decoupling index (Table 1). The decoupling degree model of agricultural carbon emissions and grain production is given in Fig. 2.

The recessive state indicates that agricultural carbon emissions decrease more rapidly than the agricultural produce value over the same phase, and the expansive coupling indicates that the value of agricultural production increases concurrently with higher carbon emissions in agriculture. Weak decoupling occurs when both agrarian carbon emissions and produce value from agriculture increase simultaneously, while weak coupling means that agrarian carbon emissions decrease more slowly than agricultural produce value increases. However, strong decoupling suggests that improvements in agrarian carbon emissions become negligible or even negative as agricultural production value increases, and strong coupling indicates increased carbon emissions from agriculture, resulting in a decline in farm production value simultaneously (Table 1).

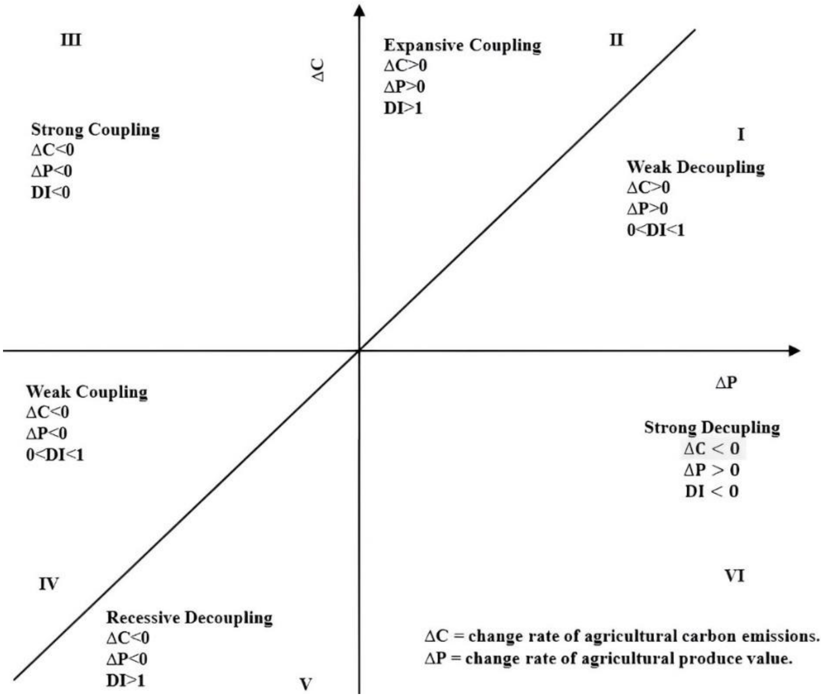

Fig. 2. Decoupling degree model of agrarian carbon emissions and produce value from agriculture.

3.3. *Decomposition method: Log Mean Divisia Index (LMDI)*

This method [27] incorporates both multiplicative and additive factor decomposition, which might be interchanged. The variation in agrarian carbon emissions from the initial phase to the final phase can be attributed to four factors: the intensity of agrarian carbon emissions, agrarian structure, agrarian economy, and agrarian labor force effects.

$$C = \frac{C}{P} \times \frac{P}{GP} \times \frac{GP}{L} \times L$$

$$C = CIE \times SE \times EE \times LE \tag{5}$$

where CIE refers to the agrarian carbon emissions intensity effect (in tons/Rs.), and is defined as the ratio of carbon emissions (C) from agriculture to the value of agricultural production level (P); SE represents agrarian structure effect (%), which indicates the proportion of production level (P) within the total production level (GP) from agriculture; EE denotes agrarian economic effect and is defined as the ratio of total produce value (GP) from agriculture to the agricultural labor force (L) (Rs. per person), and LE represents the agrarian labor force effect (here, LE = L) (in person).

According to the principle of additive decomposition, the overall impact of carbon emissions from agriculture can be expressed as follows:

$$\Delta C_{tot.} = C_t - C_{t-1}$$

$$\Delta C_{tot.} = \Delta CIE + \Delta SE + \Delta EE + \Delta LE \tag{6}$$

Where ΔCIE denotes the variation in agrarian carbon emissions intensity effect, which represents the ratio of the annual variation in agricultural carbon emissions to the change in agricultural production value; ΔSE denotes the annual variation in the proportion of agricultural produce value relative to the total gross agricultural produce value; ΔEE measures the annual variation in total agrarian produce value per agrarian labor force unit; and ΔLE implies that annual variation in the total agrarian labor force. Also, each effect defined in the above relation is given by

$$\Delta CIE = \sum \frac{(C_t - C_{t-1})}{(\ln C_t - \ln C_{t-1})} \ln\left(\frac{(CIE)_t}{(CIE)_{t-1}}\right) \tag{7}$$

$$\Delta SE = \sum \frac{(C_t - C_{t-1})}{(\ln C_t - \ln C_{t-1})} \ln\left(\frac{(SE)_t}{(SE)_{t-1}}\right) \tag{8}$$

$$\Delta EE = \sum \frac{(C_t - C_{t-1})}{(\ln C_t - \ln C_{t-1})} \ln\left(\frac{(EE)_t}{(EE)_{t-1}}\right) \tag{9}$$

$$\Delta LE = \sum \frac{(C_t - C_{t-1})}{(\ln C_t - \ln C_{t-1})} \ln\left(\frac{(LE)_t}{(LE)_{t-1}}\right) \tag{10}$$

4. Empirical Findings

Table 2. Descriptive statistical analysis of variables.

Variable	Unit	Mean	Maximum	Minimum	Std. Dev.
C	Tonnes	7667092	10303058	5952609	1586698
P	Lacs (Rs.)	1692054	2448064	835736	459009
GP	Lacs (Rs.)	2175292	3058653	1047948	614253
CIE	Tonnes/Lacs	4.78711	7.522894	3.293549	1.32335
SE	%	0.78111	0.84	0.65	0.04862
EE	Rs. Per Capita	8222.89	11362	4638	1821.79
LE	10,000 persons	2608.17	2957	2259	219.277

The descriptive statistical analysis of the raw dataset of selected variables, in which 'C' refers to agricultural carbon emissions; 'P' and 'GP' represent the production value and the gross production value from agriculture, respectively; 'CIE' refers to the agrarian carbon emission intensity effect; 'SE'refers to the agrarian structure effect; 'EE' represents agrarian economic effect; 'LE' refers to the agrarian labor force (Table 2).

4.1. *Result of regression analysis*

The agricultural carbon emissions rose from 6.29 Mt (in Million Tonnes) in 2005 to 9.71 Mt (in Million Tonnes) in 2022, with an average annual growth rate of 3.013 % [Fig. 3]. The agriculture output value increased from 8.36 Lacs rupees in 2005 to 23.6 Lacs rupees in 2022, with an average annual growth rate of 7.05 % (Fig. 4). Based on regression analysis, there is a positive impact of grain production on agrarian carbon emissions for the period 2005-2022. This suggests that for every 1% increase in grain production, there is a corresponding 35 % increase in agrarian carbon emissions (Table 3).

According to the estimated result, the change features in both production level and carbon emissions from agriculture are represented in the scatter plot (Fig. 5). However, this does not illustrate any underlying relationships between agricultural carbon emissions and economic growth in agriculture. It is essential to determine the range to which carbon emissions can be separated from produce value from agriculture; thus, a decoupling analysis will be conducted.

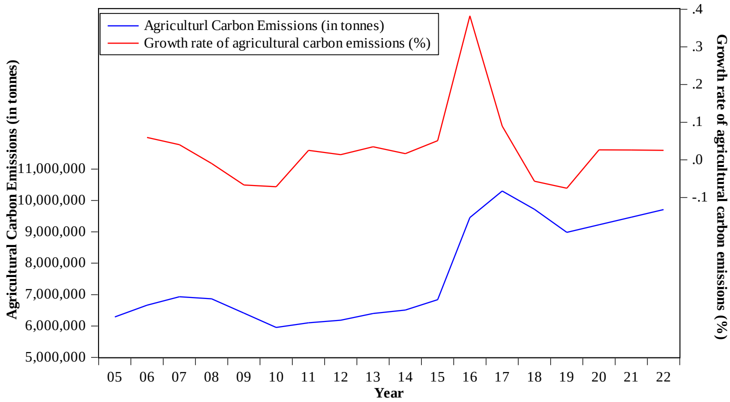

Fig. 3. Jharkhand's agricultural CO_2 emissions and growth rates during 2005-2022.

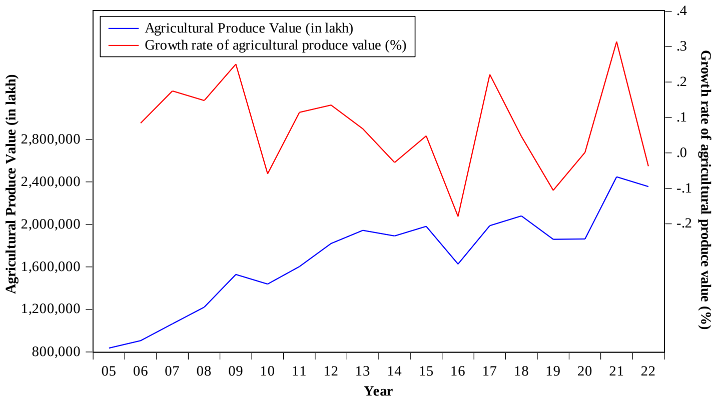

Fig. 4. Jharkhand's agricultural output value and growth rates during 2005-2022.

Table 3. An estimated result of the regression model.

Equation: $\ln(C) = \text{Const.} + \alpha\ln(p)$			
Variable	Coefficient	t-Statistic	Prob.
ln (p)	0.351678	2.55734	0.0211
Const.	10.80376	5.49252	0.01
F-statistic	6.54001		
Prob(F-statistic)	0.021088		

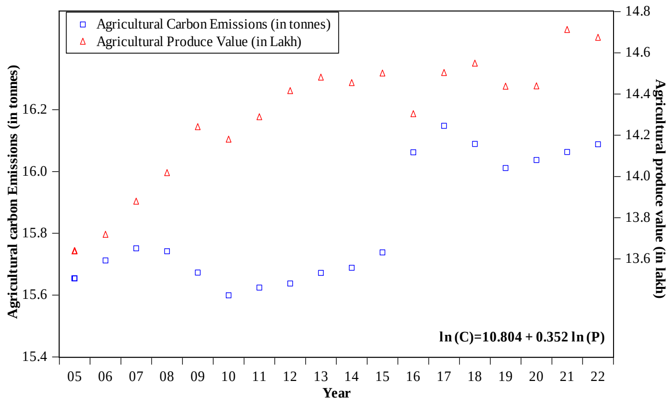

Fig. 5. Carbon emissions and produce value from agriculture in Jharkhand, India.

4.2. *Results of the decoupling analysis*

Considering the criteria of decoupling degrees (Table 2 and Fig. 2), the outcomes of the decoupling analysis of agrarian carbon emissions related to production value from agriculture are shown in Table 4 and Fig. 6. There are six types of decoupling degrees observed in Jharkhand over the period 2005-2022. These are as follows: Recessive decoupling, which occurred in one year (2010); Strong decoupling, which took place over three years (2008, 2009, and 2018); Weak decoupling, experienced for seven years (2006, 2007, 2011, 2012, 2013, 2017, and 2021); Expensive coupling, which was noted for two years (2015 and 2020); Strong coupling, observed over three years (2014, 2016, and 2022); Weak coupling, which occurred in one year (2019).

The combined duration of the recessive, strong, and weak decoupling stages over the chosen period is ten years, which is a prominent sign of the connection between production level and carbon emissions from agriculture (Table 4).

Table 4. Decoupling states in agrarian carbon emissions in Jharkhand, India.

Year	Change rate in agricultural carbon emissions (ΔC %)	Change rate in agricultural output value (ΔP %)	Decoupling Index (DI)	Decoupling States
2005-06	0.060	0.084	0.710	Weakly decoupled
2006-07	0.040	0.175	0.231	Weakly decoupled
2007-08	-0.010	0.148	-0.065	Strongly decoupled

2008-09	-0.067	0.251	-0.266	Strongly decoupled
2009-10	-0.071	-0.059	1.207	Recessively decoupled
2010-11	0.025	0.115	0.221	Weakly decoupled
2011-12	0.014	0.135	0.101	Weakly decoupled
2012-13	0.035	0.068	0.510	Weakly decoupled
2013-14	0.017	-0.027	-0.621	Strongly coupled
2014-15	0.051	0.048	1.058	Expansively coupled
2015-16	0.383	-0.179	-2.134	Strongly coupled
2016-17	0.090	0.221	0.405	Weakly decoupled
2017-18	-0.057	0.046	-1.220	Strongly decoupled
2018-19	-0.075	-0.106	0.714	Weakly coupled
2019-20	0.027	0.001	19.684	Expansively coupled
2020-21	0.026	0.314	0.083	Weakly decoupled
2021-22	0.025	-0.037	-0.678	Strongly coupled

4.2.1. ***Decoupling states***

Strong decoupling occurs when agricultural produce value changes at a positive rate, agricultural carbon emissions change at a negative pace, and a negative decoupling elasticity. It implies that the model of agricultural development, which formerly relied on high emissions and inputs to achieve rapid economic expansion, is now shifting to one that emphasizes reduced emissions and inputs. As a result, there is less pressure on the ecological environment in rural areas. The strong decoupling state is observed for the years 2008, 2009, and 2018 wherein the agricultural carbon emission decreased by 1 %, 7 %, and 6 %, respectively and the agricultural production increased by 15 %, 25 %, and 5 %, respectively. At these three time points, special events played a role in the significant strong decoupling.

Weak decoupling describes a situation where both carbon emissions and produce value in agriculture increase at a positive rate, with the decoupling index falling between 0 and 1. This state persisted for 7 years but was not consistent throughout the selected period, occurring in the years 2006, 2007, 2011, 2012, 2013, 2017, and 2021. This suggests that the implementation of numerous laws and initiatives is somewhat limiting the increase in carbon emissions from agriculture. However, the absolute reduction in carbon emissions during this period is smaller than the growth in agricultural economic output, leading to a continued increase in agricultural carbon emissions. Therefore, additional measures to reduce carbon emissions should be implemented.

The recessive decoupling occurred in 2010, with a change rate of carbon emissions and produce value at '-0.07' and '-0.06' from agriculture, respectively and the decoupling index is '1.21'. It concludes that the agricultural carbon emissions reduction rate is faster than the rate of declining agricultural output value.

4.2.2. *Coupling states*

The coupling states occurred for 6 years in the selected period, which is not a better indication of the relationship among the selected variables. Strong coupling refers to the worst scenario in decoupling analysis where the agricultural production value declines while agrarian carbon emissions increase. For 3 years, strong coupling occurred intermittently in 2014, 2016, and 2022. This suggests that agricultural output value decreased due to specific factors like drought, while agricultural carbon emissions rose rapidly.

There is a significant weak coupling due to low willingness among farmers to grow crops, resulting in a negative change in the produce value and carbon emissions from agriculture, respectively. The weak coupling is evident in 2019, indicating that the decline in agricultural carbon emissions was slower than the decline in agricultural output value.

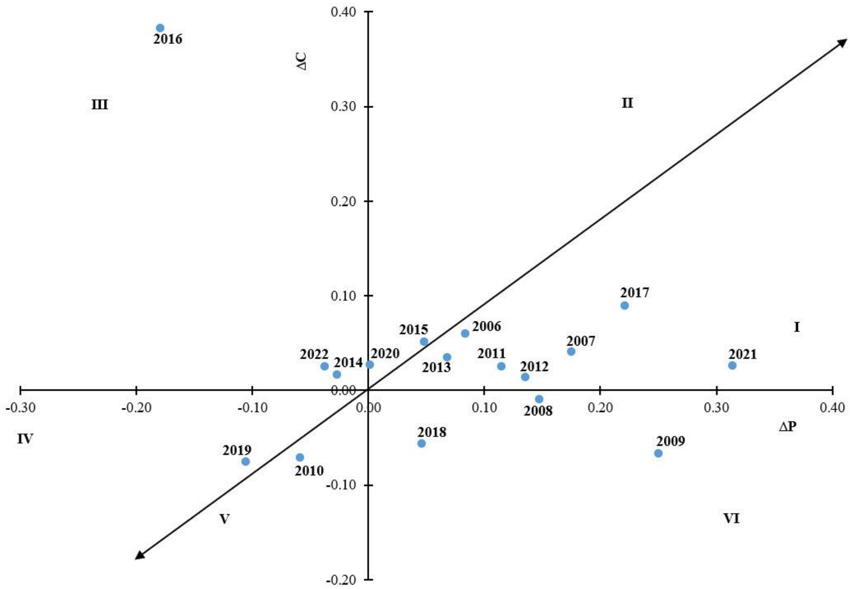

Fig. 6. Agriculture's decoupling distribution.

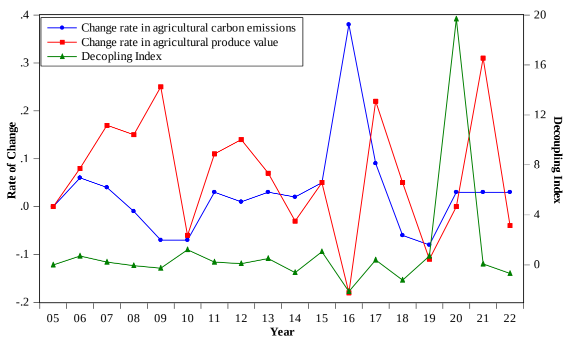

Fig. 7. Decoupling index in Jharkhand, India during 2005-2022.

The expansive coupling occurred in 2015 and 2020, respectively. As a result, the change in agrarian carbon emissions is 0.05 in 2015 and 0.03 in 2020, while the change rate in produce value from agriculture is 0.05 in 2015 and 0.001 in 2020. The decoupling elasticity is 1.06 in 2015 and 19.68 in 2020. This suggests that grain production led to increased agrarian carbon emissions in these specific years.

The variance in decoupling elasticity values is displayed in Figs. 6 and 7. The decoupling elasticity varies according to the several features of agricultural produce value and carbon emissions. Furthermore, decoupling occurred only at specific nodes, in the years 2008, 2009, and 2018, followed by coupling in 2019 and 2020, decoupling in 2021, and coupling in 2022. As a result, there is no stable decoupling between produce value and carbon emissions from agriculture during the selected period, and typically, carbon emissions rise alongside the growth in agricultural economic value.

4.3. *Results of the Log Mean Divisia Index decomposition method*

According to equations (5)-(10), the decomposition results of the agricultural carbon emissions in Jharkhand, India from 2005 to 2022 are given in Table 5 and Figs. 8 and 9.

The overall variation in agrarian carbon emissions ($\Delta C_{tot.}$) is 3.42 million tonnes between 2005 and 2022. The main factors contributing to agrarian carbon emissions are the agrarian economic effect (ΔEE), and labor force effect (ΔLE), with contributions of 6.31 million tonnes and 2.12 million tonnes, respectively, while the intensity effect of agricultural carbon emission(ΔCIE) and the agricultural structure effect (ΔSE) are the negative contributors to agrarian carbon emissions, with cumulative contributions of -4.74 million tonnes and -0.27 million tonnes, respectively. This suggests that agricultural development significantly contributes to agrarian carbon emissions in Jharkhand, India. Furthermore, it has been observed that the strength of carbon emissions has the greatest hindering influence on the change in agrarian carbon emissions, and the agricultural structure effect is also a noteworthy negative factor. The intensity effect of agrarian carbon emissions has consistently been an inhibiting factor of agrarian carbon emissions for the first seven years after that it is not stable. Additionally, the changing trend of the farming structure effect suggests that its inhibiting factor of agrarian carbon emissions is not consistent. The combined impact of agricultural carbon emissions intensity and structural factors is insufficient to balance the agricultural economic impact between 2005 and 2022. Four decomposition factors exhibited varying quantities and directional influences of agrarian carbon emissions in Jharkhand, India between 2005 and 2022.

Table 5. Decomposition results of agricultural carbon emission changes in Jharkhand, India (in Million Tonnes (10^5 tons)).

Year	Carbon Emission Intensity Effect (ΔCIE)	Structure Effect (ΔSE)	Economic Effect (ΔEE)	Labor Force Effect (ΔLF)	Total Effect ($\Delta C_{tot.}$)
2005-06	-0.15	-0.06	0.46	0.12	0.38
2006-07	-0.83	-0.61	1.59	0.12	0.27
2007-08	-1.02	0.68	0.15	0.12	-0.07
2008-09	-1.94	0.32	1.05	0.11	-0.46
2009-10	-0.08	-0.20	-0.28	0.10	-0.46

2010-11	-0.50	0.02	0.54	0.10	0.15
2011-12	-0.70	0.02	0.66	0.10	0.08
2012-13	-0.20	0.06	0.26	0.10	0.22
2013-14	0.28	-0.06	-0.22	0.10	0.11
2014-15	0.02	-1.47	1.68	0.10	0.33
2015-16	4.21	1.10	-2.82	0.12	2.62
2016-17	-1.13	-0.10	1.93	0.15	0.85
2017-18	-1.04	0.24	0.07	0.15	-0.58
2018-19	0.31	-0.39	-0.79	0.14	-0.73
2019-20	0.23	0.92	-1.04	0.13	0.24
2020-21	-2.31	0.39	2.03	0.13	0.24
2021-22	0.60	-0.83	0.33	0.13	0.24
2005-22	-4.74	-0.27	6.31	2.12	3.42

4.4. *Results of integrating decoupling with decomposition analysis*

The strong decoupling states appeared for three years: 2008, 2009, and 2018. The agricultural economic growth rate of the strong decoupling is a positive value ($\Delta P > 0$), while the change rate of agricultural carbon emissions is a negative value ($\Delta C < 0$). Based on the LMDI method, positive agricultural economic effect ($\Delta EE > 0$) drove a rise in agrarian carbon emissions, while the intensity of negative agrarian carbon emissions ($\Delta CIE < 0$) inhibited them. Further, it has been observed that ΔCIE inhibiting power exceeded ΔEE driving power in agrarian carbon emissions in the same phase, neutralizing agrarian carbon emissions driven by the agrarian economic effect (ΔEE). Therefore, the intensity of agrarian carbon emissions significantly contributed to emission reductions during these years, resulting in a strong decoupling. This suggests that the environmental pressure declined with a rise in the economic structure for the same period.

Weak decoupling states occurred for 7 years during the study period: 2006, 2007, 2011, 2012, 2013, 2017, and 2021. In each weak decoupling state, both the rate of change of produce value and carbon emissions from agriculture are positive ($\Delta P, \Delta C > 0$). On the other hand, the decomposition analysis indicates that the agricultural sector has a positive economic effect ($\Delta EE > 0$), increasing agrarian carbon emissions. However, the intensity effect of carbon emissions from agriculture ($\Delta CIE < 0$) has a negative value, which limits the rise in agrarian carbon emissions, similar to what occurs in the strong decoupling state to some extent.

On further analysis, unlike the strong decoupling state, the driving power of agricultural economic effect (ΔEE) is stronger than the inhibiting power of intensity effect of agrarian carbon emission (ΔCIE) in agrarian carbon emissions for the years: 2006, 2007, 2011, 2013, and 2017, the inhabiting power of agrarian carbon emission intensity effect is insufficient to contend with agrarian economic impact. However, in the years 2012 and 2021, the inhibiting influence of ΔCIE surpassed the driving power of ΔEE in agrarian carbon emissions, similar to a strong decoupling stage. Notably, the impact of the agrarian labor force is positive, whereas the agricultural structure effect does not seem to show a consistent variation trend.

Regarding the recessive decoupling state, which occurred in 2010, both the rate of change of agrarian carbon emissions and output value from grain production have a negative value ($\Delta C, \Delta P < 0$). As the result of decomposition analysis, both the intensity effect of agrarian carbon emission ($\Delta CIE < 0$) and agrarian economic effect ($\Delta EE < 0$) have a negative value, which inhibits agricultural carbon emissions. Additionally, the agrarian structure effect ($\Delta SE < 0$) and agrarian labor force effect ($\Delta LE > 0$) have negative and positive values, respectively. The combined effect of inhibiting powers of ΔCIE, ΔSE, and ΔEE, reduces the driving power of ΔLE in agrarian carbon emissions for the same time node. It suggests that the agricultural carbon emissions decline in the recessive decoupling state.

Strong coupling states occurred in 2014, 2016, and 2022, due to the absence of long-term incentive policies for grain production. In these time nodes, the change rate of agrarian carbon emissions is positive ($\Delta C > 0$), and the change rate of produce value from agriculture is negative ($\Delta P < 0$). The decomposition analysis suggests that in 2014 and 2016, a positive agricultural carbon emission intensity effect ($\Delta CIE > 0$), with the contribution of 0.28 million tons and 4.21 million tonnes of agrarian carbon emissions, while the negative agrarian economic impact ($\Delta EE < 0$), with the contribution of -0.22 million tonnes and -2.82 million tonnes of agrarian carbon emissions, respectively. The agricultural structure effect has a negative (2014) and positive (2016) value, while the agrarian labor force positively influences carbon emissions in agriculture for the same period. On the other hand, both the intensity effect of agrarian carbon emission ($\Delta CIE > 0$) and agrarian economic effect ($\Delta EE > 0$) are positive driving factors of the rise in agricultural carbon emissions, with the contribution of 0.6 million tonnes and 0.33 million tonnes of agrarian carbon emissions in 2022. Additionally, the negative agricultural structure and positive agricultural labor force effects contributed to -0.83 million tonnes and 0.13 million tonnes of agrarian carbon emissions. This concludes that the inhibiting power of the agricultural structure effect is not sufficient to pretend the rise of agricultural carbon emissions in 2022. Consequently, agricultural economic growth declined while agrarian carbon emissions increased during the same period.

The weak coupling state, which appeared in 2019, indicates that both rates of change of carbon emissions and produce value from agriculture are negative ($\Delta C,\ \Delta P < 0$). On the other hand, decomposition analysis suggests that the strength of agrarian carbon emissions is positive ($\Delta CIE > 0$), which drives the rise in agrarian carbon emissions, while the agricultural economic effect is a negative value ($\Delta EE < 0$), which implies a reduction of carbon emissions from agriculture. Additionally, the agrarian structural effect ($\Delta SE < 0$) and the agrarian labor force effect ($\Delta LE > 0$) have negative and positive values. However, the total inhabiting power of the agricultural economic effect and agricultural structure effect is stronger than the total driving power of the intensity effect of agrarian carbon emission and agrarian labor force effect in 2019. This concludes that the inhibiting factor is sufficient to neutralize agrarian carbon emissions. It suggests that the agrarian carbon emissions decline in the weak coupling state.

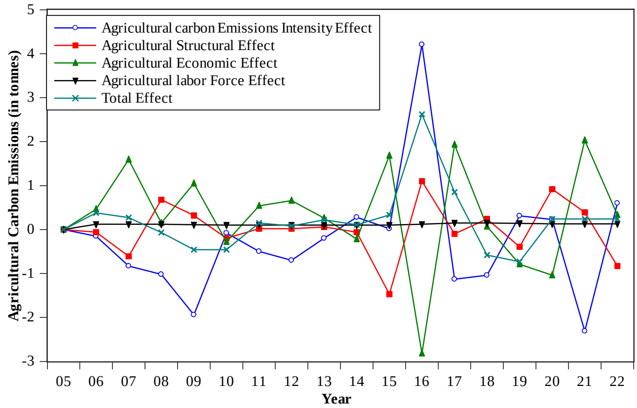

Fig. 8. Analysis of the factors contributing to variations in agrarian carbon emissions in Jharkhand over the period 2005-2022.

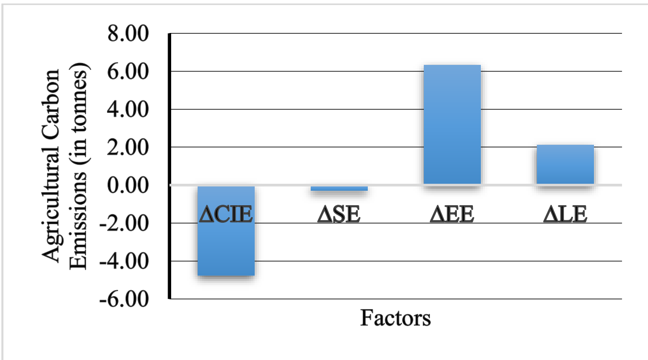

Fig. 9. The total impact of four factors on carbon emissions from agriculture in Jharkhand.

The expansive coupling state occurred for two-time nodes during the study period, in which the rate of change of agricultural carbon emissions ($\Delta C > 0$) and produce value ($\Delta P > 0$) are positive. On the other hand, decomposition analysis suggests that the positive driving factors are mainly the intensity of agricultural carbon emissions ($\Delta CIE > 0$), agrarian economic effect ($\Delta EE > 0$), and agrarian labor force effect ($\Delta LE > 0$) in the agrarian carbon emissions. In contrast, the agrarian structural impact ($\Delta SE < 0$) has the inhibiting power to decrease agrarian carbon emissions in 2015, meaning an insignificant inhibitory effect. However, in time point 2020, all the factors are positive driving factors of the agrarian carbon emissions, which caused for increase in the agricultural carbon emissions, except for the agricultural economic effect.

5. Conclusion

In this paper, we conducted the decoupling and decomposition analysis to examine the inter-relationships between carbon emissions from agriculture and agrarian economic growth in Jharkhand, India during 2005-2022. The decoupling analysis revealed six decoupling states:

recessive decoupling (1 year), strong decoupling (3 years), weak decoupling (7 Years), expansive coupling (2 years), strong coupling (3 years), and weak coupling (1 year). While recessive, strong, and weak decoupling states were frequent, there was no clear pattern of transition from coupling to decoupling. This indicates the pressure and challenges faced by the state as it aims to develop low-carbon agriculture.

Based on the LMDI method, the results indicate that the increase in agricultural carbon emissions is significantly driven by the agricultural economic effect (ΔEE) followed by the agricultural labor force effect (ΔLE). On the other hand, factors such as the agricultural carbon emission intensity effect (ΔCIE) and agricultural structure effect (ΔSE) tend to inhibit agrarian carbon emissions, with the intensity effect of agrarian carbon emissions being the primary inhibiting factor. Furthermore, when combining decoupling with decomposition analysis, it has been observed that the environmental pressure declined with a rise in the agricultural economic structure for 2008, 2009, and 2018. The intensity of agrarian carbon emissions has played a significant role in reducing emissions during these years. It also suggests that agricultural carbon emissions declined in 2010 and 2019 due to recessive decoupling and weak coupling states. Overall, the efforts aimed at reducing carbon emissions from the agriculture sector in Jharkhand are still ineffective.

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