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# Exploring the drivers of agricultural carbon emissions using global innovation index: Top-carbon emitting countries

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**Abstract**

This research investigated the total decoupling between CO2 emissions and agricultural growth in Iran, India, Korea, Russia, China, the United States, Japan, Canada, and Germany employing the Tapio decoupling index and Logarithmic Mean Division Index (LMDI) methods The decomposing of the total decoupling index revealed that the energy intensity effect was the main decisive factor for CO2 emissions reduction across all countries while the global innovation efficiency effect was a primary contributor in Korea, Japan, the United States, Germany, China, and Russia specifically in Korea energy intensity and global innovation efficiency were the leading promoters for Canada energy intensity was the most important factor for emissions reduction in China the United States and Germany energy intensity and global innovation efficiency were the main promoters in Russia energy intensity global innovation efficiency and the structure effect all played important roles carbon emissions coefficient was the most critical factor in Iran's decoupling and for India the energy intensity and structure effects were the key promoting factors these findings underscore that strategic measures for sustainable development must aim to decrease energy intensity consumption and that innovations are crucial for mitigating fossil fuel use and reducing emissions the results provide a useful guideline for energy-saving and carbon-reducing policies to foster sustainable economic development in the selected countries.

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## Introduction

Energy is a primary input in the agricultural sector (Mushtaq et al., 2007), used directly in crop and livestock production and indirectly in the production and transport of chemical pesticides and fertilizers (Sebri et al., 2012; Agheli, 2015; Ceylan, 2020; Zaman et al., 2012). The increasing use of energy accelerates environmental degradation, which is immensely worrying given that global warming is a critical global issue (Wang et al., 2013). Carbon dioxide ($CO_2$) is a significant cause of this warming (Myhre et al., 2013), and its annual emissions have been rising since 2019 (Jackson et al., 2019). The agricultural sector itself is a significant contributor, with practices accounting for approximately 20% of carbon emissions (World Bank, 2018), thus playing a major role in global warming (Lynch et al., 2021). Therefore, optimal energy use is a basic necessity to decrease environmental degradation, protect natural resources, and promote agricultural sustainability (De Jonge, 2004; Ghorbani et al., 2011; Yuan and Peng, 2017). Effectively managing these emissions is crucial, as global carbon emissions represent a severe threat to human life (Wu et al., 2019).

The development of low-carbon economy, energy saving and emission reduction has become very important issues for all countries (Meinshausen et al., 2022). The dependence on $CO_2$ emissions and economic growth is a significant issue that needs much attention. To ensure the interdependence between economic growth and $CO_2$ emissions it is necessary to investigate the decoupling index. "*The decoupling index is commonly used to measure the relationships and asynchronous changes between resource consumption, environmental pressure, and economic growth*" (Long and Wang, 2017). The decoupling of the economy growth from $co_2$ emissions is considered as a principle and guide for assessing sustainable economic development (Jorgenson and Clark, 2012; Schandl et al., 2016). In the agricultural policy, research has generally used the absolute decoupling and relative decoupling by The Organization for Economic Cooperation and Development (OECD) (Galko and Jayet, 2011). "*Absolute decoupling shows the stable or declining state of the environmental features associated with economic development. Relative decoupling refers to the increase in environmental pressure and resource consumption, and economic development*".

This paper first measures the agricultural carbon emissions in the top nine $CO_2$ emitters China, Canada, Iran, USA, India, Russia, Japan, Germany, and Korea from 2013 to 2019, then uses the Logarithmic Mean Division Index (LMDI) model to explore the drivers of agricultural carbon emissions, combines the decoupling model to analyze the relationship between agricultural carbon emissions and value added of agricultural sector. Statistics on the top 10 carbon dioxide emissions in 2018 and their global share are represented in Table1. Among the top three emitters, China and India both saw significant increases from Kyoto Protocol 2005.The United States, along with Germany and Japan, have all recorded three-digit declines. For investigating the total decoupling $CO_2$ emissions from agricultural growth, a series of measures have been considered. Firstly, we employed the decoupling method (Tapio, 2005) to explore the decoupling states between $CO_2$ emissions and agricultural growth in the selected countries. Secondly, in order to investigate more factors affecting the carbon emissions of these countries, measuring the decoupling states and driving factors affecting carbon emissions, we combined the extended LMDI and Tapio decoupling methods.

The novelty of this study is in the following aspects:

1) Investigating the decoupling of $CO_2$ emissions from agricultural growth in the nine countries of the top $CO_2$ emitters.
2) Combining the decoupling index (Tapio, 2005) and decomposition index (Kaya).
3) Investigating the impact of the global innovation index on the decoupling of $CO_2$ emissions from agricultural growth.

Although several studies have focused on energy consumption and carbon dioxide emissions, no extant study is devoted to decomposing $CO_2$ emissions and decoupling them from agricultural growth in C9 countries and investigates the impact of the global innovation index on the decoupling of $CO_2$ emissions from agricultural growth. The results of this study are beneficial considering the role of these countries in the global economy and carbon emissions. The global innovation index (GII) is provided metrics about the innovation performance of 131 countries around the world (Wallis, 2012). The Global Innovation Index consists of 81 sub-variables that are divided into two main sub-indices, innovation input and innovation output. The input elements of innovation include institutions - human and research capital - infrastructure - market and business complexity. Innovation output variables also include knowledge and technology output variables and creative outputs (Goodridge et al., 2013).

The rest of this research are arranged as follows: Section 2 investigates the literature related to decoupling index and decomposition method, Section 3 introduces the methodology, Section 4 shows the results and discussion while Section 5 concludes this research based on the research contents.

***Literature review***

Several studies have investigated the decoupling of economic growth and $CO_2$ emissions and energy consumption. Sun et al., (2022) analyzed carbon emissions from agricultural energy consumption using data from the Yangtze River Economic Belt (YEB) between 2000 and 2017. Hossain and Chen (2021) showed that the population, the agricultural energy intensity, and the agricultural economic factor have an important role in increasing $CO_2$ emissions. Peng et al., (2021) used decomposition analysis and showed the electricity sector has the important role in the CO2 emissions. Huo et al., (2021) applied Tapio decoupling index to investigate relation between residential building carbon emissions and residential income in 30 provinces China. Their findings showed that the decoupling state has been changed from weak to strong. Wang and Su (2020) in their study showed that decoupling states of developed countries were stable in weak decoupling. Wang and Jiang (2020) investigated the decoupling of carbon emissions from economic growth. Their findings showed that the decoupling in Russia and, South Africa is better than Brazil, India and China. Zhang et al., (2018) showed that there had an increase in the number of expansive negative decoupling states in China's logistics industry in 2005-2015. Li and Jiang (2020) investigated the effect RandD investment on the decoupling economic growth and $CO_2$ emissions in six carbon dioxide emitters. The results indicated that the decoupling status in the USA, Japan and Germany were better than China, India and Russia. Ahmed and Zeshan (2015), decomposes energy consumption in Pakistan. They showed that agricultural growth can decrease the change in energy consumption. Chontanawat et al., (2020) indicated that the economic structure was decreased $CO_2$ emissions and carbon intensity in the Thailand industrial sector. Gu et al., (2019) applied LMDI method. Their findings showed that the promotion of public transportation and the optimization is helped to decrease Shanghai's $CO_2$ emissions. Engo (2018) used Tapio and LMDI methods for decoupling carbon emissions from economic growth in Cameroon. The findings indicated that Cameroon performed weak decoupling. Zakhan et al., (2019) applied decomposition index to decoupling of manufacturing CO2 emissions in Indonesia. The results showed relative decoupling occurred in 2012-2013. Zhang et al., (2009) investigated energy-related $CO_2$ emissions using analytical analysis. The results of their study showed that economic activity had the most significant positive effect on changes in $CO_2$ emissions for the entire primary economic sector and the Chinese economy as a whole. Wang et al., (2019) performed a comparative analysis between China and, United States in terms of carbon decoupling and decomposition index from economic growth. The results showed that in most years of the study period, China experienced strong and weak decoupling and the United States mostly "weak and strong decoupling. Tunc et al., (2009) investigated $CO_2$ emissions from energy consumption in Turkey using the analysis method and the logarithmic mean division index. Zhao et al., (2015) focused on decoupling $CO_2$ emissions and industrial growth in China. Their findings showed that the most important factor in the decoupling of $CO_2$ and industrial growth was the investment scale. These studies show the importance of using the decoupling index to discover the relationship between carbon emissions and economic growth for the purposes of achieving sustainable development and reducing global carbon emissions. If economic growth occurs alongside a decrease in carbon emissions, strong decoupling takes place.

### *Methodology*

The conceptual model used in this study is shown in Figure 1.

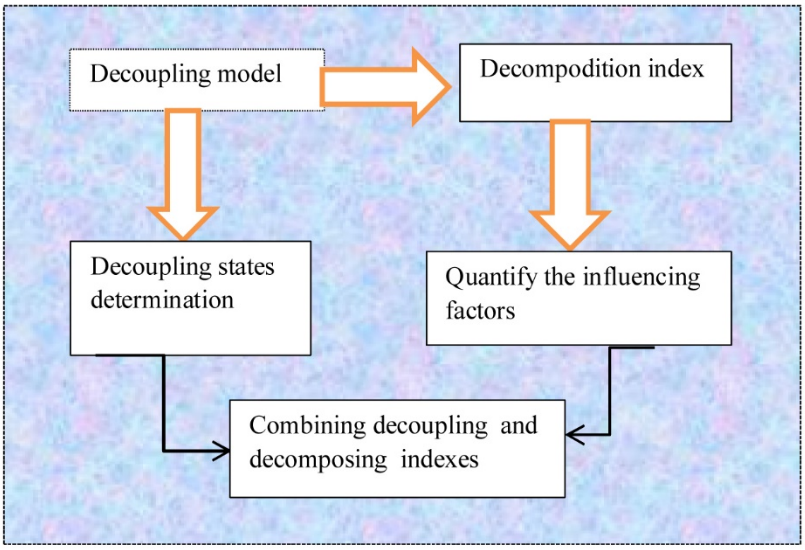


**Figure 1.**The conceptual model used in the study

### *Decoupling Index*

The Decoupling index introduced by Tapio (2005) is shown in Eq (1):

$$DI = \frac{\Delta C}{C_0} / \frac{\Delta AG}{AG_0} \quad (1)$$

where DI indicates the Tapio decoupling elasticity, $\frac{\Delta C}{C_0}$ and $\frac{\Delta AG}{AG_0}$ indicate $CO_2$ emission changes and agricultural value-added changes respectively. Decoupling index can be divided into eight states according to the differences in the elastic coefficient. Table 1 shows the eight states of decoupling index.

**Table 1.** Different states of decoupling index, Tapio, 2005.

| Status | | $\frac{\Delta C}{C_0}$ | $\frac{\Delta AG}{AG_0}$ | Decoupling index |
|---|---|---|---|---|
| Negative Decoupling | Expansive | > 0 | > 0 | DI > 1.2 |
| | Strong | > 0 | < 0 | DI < 0 |
| | Weak | < 0 | < 0 | 0 ≤ DI < 0.8 |
| Decoupling | Weak | > 0 | > 0 | 0 ≤ DI < 0.8 |
| | Strong | < 0 | > 0 | DI < 0 |
| | Recessive | < 0 | < 0 | DI > 1.2 |
| Coupling | Expansive | > 0 | >0 | 0.8 ≤ DI ≤ 0.8 |
| | Recessive | < 0 | < 0 | 0.8 ≤ DI ≤ 0.8 |

***Decomposition model***

Figure 2 shows decomposition techniques. These technics are divided into two methods, structural decomposition analysis (SDA) and index decomposition analysis (IDA) (Jiang et al., 2019). The SDA method needs input-output tables, but the IDA method is better than the SDA method. The IDA method includes the Laspeyres index approach and the Divisia index approach (Fan et al., 2019). The Divisia index approach includes two indexes, Arithmetic Mean Divisia Index (AMDI) and Logarithmic Mean Division Index (LMDI) (Ang, 2015). AMDI has limitations of the residuals and zero value. Therefore, the application of this index is limited (Wang et al., 2018a; Zhang and Da, 2015). LMDI is used to decompose energy consumption and carbon emissions (Wang et al., 2020; Zhang et al., 2019).

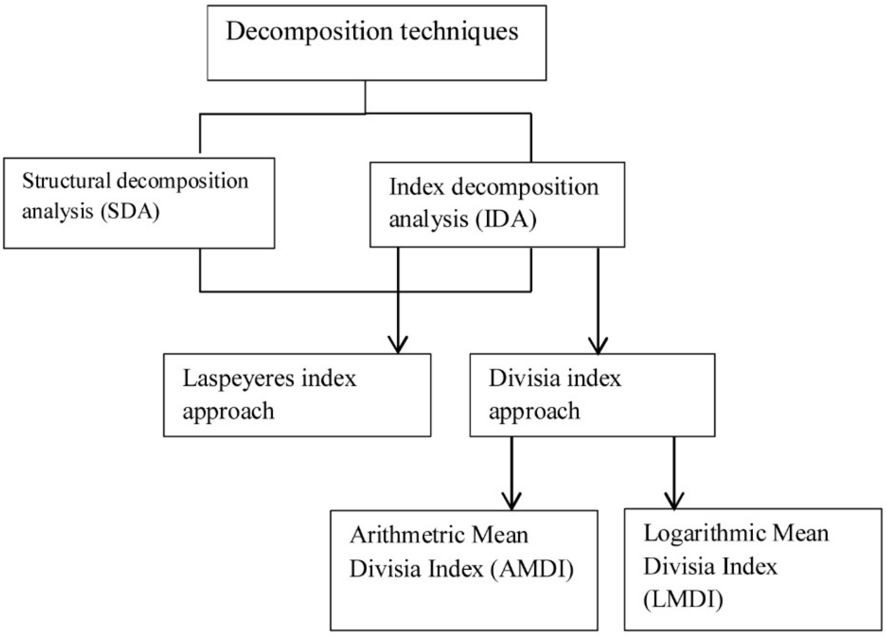


**Figure 2.** Composition of the decomposition techniques

The $CO_2$ emissions can be calculated via Eq. (2), (Kaya, 1990):

$$C = \sum_{i=1}^{2} C_i = \sum_{i=1}^{2} \frac{C_i}{EN_i} \cdot \frac{EN_i}{EN} \cdot \frac{EN}{AG} \cdot \frac{AG}{GII} \cdot GII \quad (2)$$

where i represents i-th energy type in agricultural sector (i=1,2 represents oil and coal in agricultural sector, respectively). Definition of variables are represented in Table 2.

**Table 2.** Definition of variables in Eq (2)

| Variable | Definition |
|---|---|
| $C_i$ | $CO_2$ emissions arising from the i-th energy in agricultural sector |
| $EN_i$ | The i-th energy consumption in agricultural sector |
| EN | Total energy consumption in agricultural sector |
| AG | Value added of agricultural sector |
| GII | Global innovation index |

We can decompose the total of $CO_2$ emissions into four driving forces: the emission coefficient effect, the energy structure effect, the energy intensity effect and the global innovation efficiency effect.

$$\Delta C = C_t - C_0 = \Delta C_{EC} + \Delta C_{ES} + \Delta C_{EI} + \Delta C_{GE} \quad (3)$$

$\Delta C_{EC}, \Delta C_{ES}, \Delta C_{EI}$ and $\Delta C_{GE}$

The decomposition from base year to target year are calculated using eq 4-7:

$$\Delta C_{EC} = \sum_{i=1}^{2} \frac{C_i^t - C_i^0}{Ln(C_i^t) - Ln(C_i^0)} Ln(\frac{EC_i^t}{EC_i^0}) \quad (4)$$

$$\Delta C_{ES} = \sum_{i=1}^{2} \frac{C_i^t - C_i^0}{Ln(C_i^t) - Ln(C_i^0)} Ln(\frac{ES_i^t}{ES_i^0}) \quad (5)$$

$$\Delta C_{EI} = \sum_{i=1}^{2} \frac{C_i^t - C_i^0}{Ln(C_i^t) - Ln(C_i^0)} Ln(\frac{EI_i^t}{EI_i^0}) \quad (6)$$

$$\Delta C_{GE} = \sum_{i=1}^{2} \frac{C_i^t - C_i^0}{Ln(C_i^t) - Ln(C_i^0)} Ln(\frac{GE^t}{GE^0}) \quad (7)$$

In this paper, we combine the Tapio decoupling index with the LMDI decomposition results. The total decoupling index of the agricultural growth and $CO_2$ emissions can be represented in Equation (8): (8)

$$\varepsilon = DI_t = \frac{\Delta C}{C^0} / \frac{\Delta AG}{AG^0} = \frac{\Delta C_{EC}/C^0}{\Delta AG/AG^0} + \frac{\Delta C_{ES}/C^0}{\Delta AG/AG^0} + \frac{\Delta C_{EI}/C^0}{\Delta AG/AG^0} + \frac{\Delta C_{GE}/C^0}{\Delta AG/AG^0} = \varepsilon_{EC} + \varepsilon_{ES} + \varepsilon_{EI} + \varepsilon_{GE}$$

where $DI_t$ represents the total decoupling index, $\frac{\Delta C}{C^0}$ represents the growth rate of CO2; $\frac{\Delta AG}{AG^0}$ represents the growth rate in agricultural sector; $\varepsilon_{EC}$ or $DI_{EC}$ imply emission coefficient decoupling index, $\varepsilon_{ES}$ or $DI_{ES}$ implies energy structure decoupling index; $\varepsilon_{EI}$ or $DI_{EI}$ imply energy intensity decoupling index and $\varepsilon_{GE}$ or $DI_{GE}$ show global innovation decoupling index.

The evaluation of criteria for the influencing effect of the sub-decoupling index on the total decoupling relationship is displayed in Table 3, where $DI_t$ represents the sub-decoupling index.

**Table 3.** The evaluation of the impacts of the sub-decoupling index on the total decoupling relationship

| $\frac{\Delta AG}{AG^0}$ | $\frac{\Delta C}{C^0}$ | Description |
|---|---|---|
| $> 0$ | $> 0$ | $DI_{EC}$ , $DI_{ES}$, $DI_{EI}$, $DI_{GE}$ play an inhibiting role in the decoupling relationship. The higher the value of the sub-decoupling index, the stronger the inhibiting effect of the index on the decoupling relationship. |
| | $< 0$ | $DI_{EC}$ , $DI_{ES}$, $DI_{EI}$, $DI_{GE}$ play a promoting role in the decoupling relationship. The smaller the value of the sub-decoupling index, the stronger the promoting effect of the index on the decoupling relationship. |

Zhang et al (2018)

***Data Sources***

This study examined the period from 2013 to 2019. The data for energy-related $CO_2$ emissions, AG, GII, originate from The World Bank (2019), energy consumptions were derived via the FAOSTAT and Khonema.com.

**Results**

***Decomposition Analysis of CO2 from agricultural sector of countries***

The decomposition results of the $CO_2$ emissions changes from 2013 to 2019 are represented in Table 4.

We concentrated on the results of 2013 and for periods 2014-2019. The results can be seen in Table 4. In 2013, the emission coefficient effect was the reducing contributor to the increase of $CO_2$ emissions in Korea, United States, Germany, Japan, and Russia. The structural effect is the primary driver to the increasing $CO_2$ emissions in Korea, United states, Japan, China, India, Iran, and Russia. The Energy intensity plays a positive role in the total increase of $CO_2$ emissions in the agricultural sector of Japan, China, India, and Iran. The global innovation effect has a positive role in the total increase of $CO_2$ emissions of Canada, United States, Germany, India and Iran.

**Table 4.** The decomposition of CO2 emissions from agricultural sector in the selected countries

| Period | | Korea | Canada | United States | Germany | Japan | China | India | Iran | Russia |
|---|---|---|---|---|---|---|---|---|---|---|
| $\Delta_{EC}$ | 2013 | -0.004 | 0.02 | -0.10 | -0.03 | -0.10 | 0.03 | 0.02 | 0.005 | -1740.45 |
| | 2014 | -0.006 | -0.03 | 0.001 | 0.07 | 0.07 | -0.01 | 0.55 | 0.01 | -291.704 |
| | 2015 | 0.01 | 0.02 | -0.17 | -0.03 | 0.04 | 0.006 | -0.66 | -0.0001 | -67.99 |
| | 2016 | -0.02 | 0.05 | 0.04 | 0.03 | -0.03 | 0.04 | 0.11 | 0.00005 | 231.77 |
| | 2017 | 0.04 | -0.09 | 0.24 | -0.07 | 0.07 | -0.03 | 0.01 | 0.009 | 131.19 |
| | 2018 | -0.05 | 0.08 | 0.05 | 0.04 | -0.09 | 0.0001 | 0.002 | 0.009 | 51.07 |
| | 2019 | -0.51 | -0.05 | -0.10 | -0.04 | -0.01 | 0.059 | -0.02 | -0.02 | 75.63 |
| $\Delta_{ES}$ | 2013 | 5.10 | -0.65 | 9.60 | -2.90 | 5.27 | 0.54 | 293.92 | 4.12 | 3.90 |
| | 2014 | 8.65 | -0.60 | 2.72 | 0.89 | 2.19 | 7.89 | -35.03 | 11.62 | 47.06 |
| | 2015 | -0.29 | 1.16 | -0.13 | 3.44 | 4.35 | 2.81 | -49.48 | 23 | 66.00 |
| | 2016 | 0.05 | -0.19 | -0.15 | 5.39 | 0.50 | -0.53 | -55.49 | 20.06 | -32.61 |
| | 2017 | 1.42 | -0.05 | -1.01 | -0.30 | 4.07 | -2.99 | 114.34 | 16.12 | -34.26 |
| | 2018 | 6.17 | 0.12 | -0.14 | -3.47 | 3.64 | -4.82 | -50.63 | 16.07 | -30.17 |
| | 2019 | 1.36 | 0.26 | -0.41 | 0.86 | 2.39 | -1.22 | -4.57 | 15.47 | -14.42 |
| $\Delta_{EI}$ | 2013 | -32.91 | -15424.2 | -83.90 | -65.73 | 39.38 | 5672.76 | 7953.67 | 5.38 | -167.42 |
| | 2014 | -67.06 | -16702.4 | 14.57 | 31.56 | -5.38 | 5996.77 | -5157.92 | 1.90 | 125.07 |
| | 2015 | 8.50 | -15839.4 | -9.93 | 309.22 | -133.74 | -3248.19 | -4127.18 | 21.51 | -1042.69 |
| | 2016 | 98.59 | -12547.9 | -15.79 | -322.99 | -83.41 | -2403.35 | -3959.25 | 31.57 | -227.80 |
| | 2017 | -80.07 | -11972.9 | -15.77 | -98.49 | 121.37 | -21.94 | -3148.97 | 16.56 | 173.75 |
| | 2018 | 56.42 | -12320.9 | -3.56 | 40.61 | 31.41 | -14047.7 | -1660.10 | 15.84 | 511.86 |
| | 2019 | 45.74 | -11361.8 | -24.95 | -89.85 | 277.08 | -2049.65 | -2610.87 | 19 | -150.98 |
| $\Delta_{GE}$ | 2013 | -30.22 | 74.20 | 46.03 | 75.02 | -24.39 | -3414.21 | 2588.44 | 5.53 | -18.61 |
| | 2014 | -4.13 | -122.76 | -24.92 | -27.86 | -97.31 | -3933.24 | 2264.40 | 9.77 | 247.23 |
| | 2015 | -7.29 | 151.53 | -31.22 | -216.12 | 74.31 | 140.62 | -308.12 | 22.66 | 273.30 |
| | 2016 | -35.40 | 15.30 | -18.63 | 22.60 | 115.15 | 3807.59 | 477.65 | 19.82 | -20.68 |
| | 2017 | 28.96 | 26.71 | 10.80 | 109.97 | 21.10 | 660.89 | 814.74 | 15.86 | -48.17 |
| | 2018 | -18.28 | 1.91 | -15.64 | -107.64 | 47.48 | -406.33 | -344.77 | 15.34 | -30.17 |
| | 2019 | -29.03 | 26.33 | 9.19 | 53.96 | -175.63 | 2624.31 | 732.31 | 19.69 | 158.75 |
| $\Delta C$ | 2013 | -58.03 | -15350.63 | -28.37 | 6.36 | 20.16 | 2259.12 | 10836.05 | 15.03 | -2797.85 |
| | 2014 | -62.54 | -16825.79 | -7.62 | 4.66 | -100.43 | 2071.41 | -2928 | 23.3 | -225.21 |
| | 2015 | 0.93 | -15686.69 | -41.45 | 96.51 | -55.04 | -3104.75 | -4485.44 | 67.17 | 445.06 |
| | 2016 | 63.22 | -12532.74 | -34.53 | -294.97 | 32.21 | 1403.75 | -3536.98 | 71.45 | 690.34 |
| | 2017 | -49.65 | -11946.33 | -5.74 | 11.11 | 146.61 | 635.75 | -2219.88 | 48.55 | -102.22 |
| | 2018 | 44.26 | -12318.79 | -19.29 | -70.46 | 82.44 | -14458.85 | -2055.49 | 47.26 | -9.27 |
| | 2019 | 17.56 | -11335.26 | -16.27 | -35.07 | 103.83 | 573.50 | -1883.15 | 54.14 | 219.96 |

**Table 5.** The decoupling of agricultural growth in the selected countries.

| Period | Korea | Iran | Russia | India | Canada | China | Japan | Germany | United states |
|---|---|---|---|---|---|---|---|---|---|
| 2013 | RD | SD | SD | END | EC | SND | SND | WD | SD |
| 2014 | SD | END | END | SD | SND | SND | RC | SND | WND |
| 2015 | END | END | SD | SD | SD | WD | SD | SND | RD |
| 2016 | SND | SD | RD | SD | SD | WD | WD | SD | RD |
| 2017 | SD | SD | SND | SD | END | EC | END | WD | SD |
| 2018 | SND | WND | SND | RD | SD | SD | END | WND | RD |
| 2019 | SND | SD | SD | SD | SD | SD | SND | SD | SD |

***Investigating the Decoupling index***

Table 5 shows the decoupling states between $CO_2$ emissions and agricultural growth in C9 countries during 2013-2019. We concentrated on strong decoupling and strong negative decoupling. In year 2013, the decoupling state of Russia, Iran and United states was strong decoupling. Therefore, value added of agricultural increases faster than $CO_2$ emissions in these countries. The decoupling state of China and Japan was strong negative decoupling. This state is a worse state. $CO_2$ emissions increases faster than value added of agricultural sector in these countries. In year 2014, the decoupling state of Korea and India and was strong decoupling. The decoupling state of Canada and China was strong negative decoupling. In the year 2015, India, Russia, Canada and Japan are characterized by strong decoupling and Germany is characterized by strong negative decoupling. In the year 2016, India, Russia, Canada, Iran, and Germany are characterized by strong decoupling and Korea is characterized by strong negative decoupling. In the year 2017, the decoupling state of Korea, Iran, India and United states was strong decoupling and the decoupling state in Russia was strong negative decoupling. In 2018, Strong decoupling occurred in China and Canada and strong negative decoupling occurred in Kore. In 2019, Iran, Russia, India, Canada, China, Germany, and United States experienced strong decoupling and Korea and Japan experienced strong negative decoupling.

In the period 2013- 2019, the decoupling state in Korea changed from recessive decoupling to strong negative decoupling. Iran, Russia and United state experienced the decoupling state strong decoupling and were stable in this status. The decoupling state in India has changed from expansive negative decoupling to strong decoupling, China has strong decoupling in 2019 while Japan was stable in strong negative decoupling in this period and the decoupling state of Germany has changed from weak decoupling to strong decoupling.

***Decomposition results of decoupling indicators***

Corresponding to the above decoupling analysis, the driving forces of C9 countries' decoupling were quantified for the periods 2013-2019, see Tables 6-15. The total decoupling index between $CO_2$ emissions and agricultural growth and the influence of the emission coefficient effect, the energy structure effect, the energy intensity effect, the global innovation efficiency effect on the decoupling progress are shown in Tables 6-15.

Table 6 shows that the total decoupling index for Korea was 9.153 and -8.795 in 2013 and 2014, respectively. It can be seen that the energy intensity effect on $CO_2$ emissions appears more than other factors effect in 2013, 2014 and 2017. Also, the total decoupling index was 0.927 in 2015. Therefore, there is no decoupling effect in 2015. The Global innovation efficiency effect appears more than other factors effect in 2018 and 2019, this shows that the economic growth rate caused by the global innovation efficiency effect increase and the carbon emission growth rate decrease. Figure 3 compares the decoupling index and the influence of the emission coefficient effect, the energy structure effect, the energy intensity effect, the global innovation efficiency effect changes on the decoupling progress in Korea.

**Table 6**. The total decoupling between $CO_2$ emissions and agricultural growth, Korea

| Period | $\varepsilon_{EC}$ | $\varepsilon_{ES}$ | $\varepsilon_{EI}$ | $\varepsilon_{GE}$ | Decoupling index | State |
|---|---|---|---|---|---|---|
| 2013 | 0.0007 | -0.805 | 5.191 | 4.766 | 9.153 | RD |
| 2014 | -0.0009 | 1.217 | -9.430 | -0.581 | -8.795 | SD |
| 2015 | 0.016 | -0.298 | 8.504 | -7.295 | 0.927 | EC |
| 2016 | 0.0009 | -0.002 | -3.698 | 1.328 | -2.371 | SND |
| 2017 | 0.002 | 0.079 | -4.474 | 1.618 | -2.773 | SD |
| 2018 | 0.003 | -0.354 | -3.244 | 1.051 | -2.544 | SND |
| 2019 | 0.015 | -0.040 | -1.362 | 0.864 | 0.523 | SND |

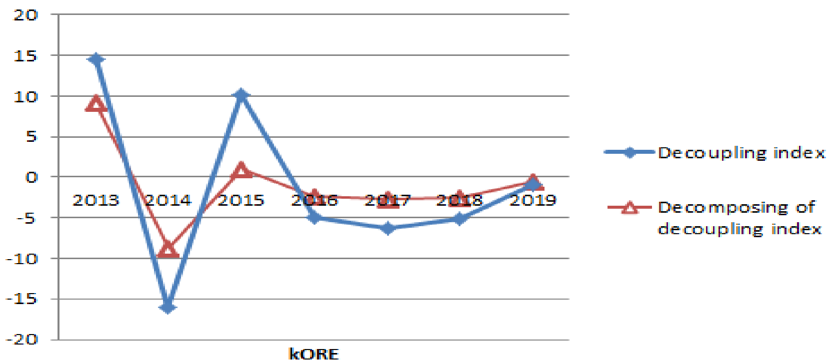


**Figure 3.** The total decoupling trend in Korea

Table 7 shows the decoupling progress in Canada where the emergence of strong decoupling was primarily driven by the energy intensity effect this indicates that the rate of economic growth surpassed the rate of carbon emissions leading to a decrease in carbon emissions alongside an increase in agricultural production. Figure 4 illustrates the decoupling index and the influence of changes in the emission coefficient effect energy structure effect energy intensity effect and global innovation efficiency effect on the decoupling progress in Canada

**Table 7**. The total decoupling between $CO_2$ emissions and agricultural growth, Canada

| Period | $\varepsilon_{EC}$ | $\varepsilon_{ES}$ | $\varepsilon_{EI}$ | $\varepsilon_{GE}$ | Decoupling index | State |
|---|---|---|---|---|---|---|
| 2013 | 0.0004 | -0.012 | -287.25 | 1.382 | -285.88 | SD |
| 2014 | 0.0003 | 0.005 | 148.82 | 1.093 | 149.92 | RD |
| 2015 | 0.0001 | 0.006 | -92.09 | 0.881 | -91.20 | SD |
| 2016 | 0.012 | -0.046 | -3071.11 | 3.745 | -3067.4 | SD |
| 2017 | -0.005 | -0.002 | -662.92 | 1.478 | -661.45 | SD |
| 2018 | 0.006 | 0.009 | -961.12 | 0.149 | -961.13 | SD |
| 2019 | -0.005 | 0.026 | -1145.91 | 2.656 | -1143.23 | SD |

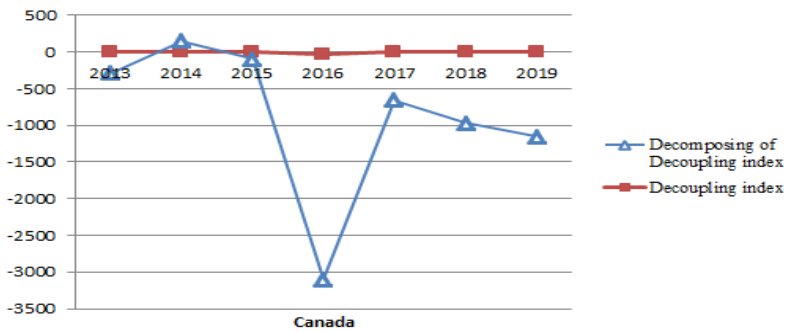


**Figure 4**. The total a decoupling trend in Canada

The global innovation efficiency plays a promoting role as can be seen for the years 2013, 2017, and 2019 when energy intensity effect was promoting in the decoupling relationship. Figure 5 shows the decoupling index and the influence of the emission coefficient effect, the energy structure effect, the energy intensity effect, and the global efficiency effect changes on the decoupling progress in the United States.

It should be noted that in the years 2014, 2015 and 2018 between the emission coefficient effect, the energy structure effect, the energy intensity effect, the global innovation efficiency effect, and the global innovation efficiency effect play a promoting role in the decoupling relationship (Table 8). Also, in 2013, 2016, 2017 and 2019 the energy intensity effect has a positive role in $CO_2$ emissions reduction. Figure 6 shows the decoupling index and the influence of the emission coefficient effect, the energy structure effect, the energy intensity effect, the global innovation efficiency effect changes on the decoupling progress in Germany (Table 9). According to the results of Table 10, in 2013, 2014 and 2019 the global innovation efficiency effect, in 2017 and 2018 emission coefficient effect and in 2015-2016 energy intensity effect have a promoting role in the decoupling state of agricultural growth from the $CO_2$ emissions in Japan. In Figure 7, the decoupling trend is shown for Japan.

**Table 8.** The total decoupling between $CO_2$ emissions and agricultural growth, the United States

| Period | $\varepsilon_{EC}$ | $\varepsilon_{ES}$ | $\varepsilon_{EI}$ | $\varepsilon_{GE}$ | Decoupling index | State |
|---|---|---|---|---|---|---|
| 2013 | -0.002 | 0.184 | -1.610 | 0.883 | -0.544 | SD |
| 2014 | -0.00006 | -0.112 | -0.601 | 1.028 | 0.314 | WND |
| 2015 | 0.006 | 0.005 | 0.375 | 1.180 | 1.568 | RD |
| 2016 | -0.002 | 0.007 | 0.817 | 0.963 | 1.786 | RD |
| 2017 | 0.04 | -0.167 | -2.604 | 1.783 | -0.948 | SD |
| 2018 | -0.005 | 0.014 | 0.350 | 1.535 | 1.894 | RD |
| 2019 | -0.016 | -0.061 | -3.665 | 1.350 | -2.392 | SD |

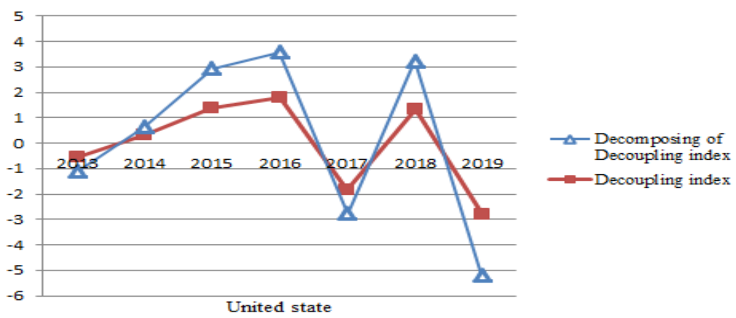


**Figure 5.** The total decoupling trend in the Unites States

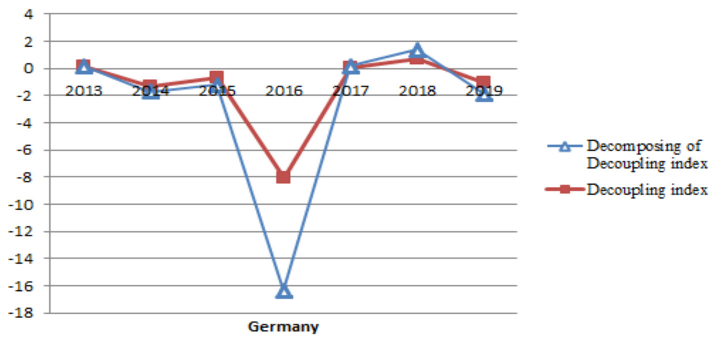


**Figure 6.** The total decoupling trend in Germany

**Table 9.** The total decoupling between $CO_2$ emissions and agricultural growth, Germany

| Period | $\varepsilon_{EC}$ | $\varepsilon_{ES}$ | $\varepsilon_{EI}$ | $\varepsilon_{GE}$ | Decoupling index | State |
|---|---|---|---|---|---|---|
| 2013 | -0.0003 | -0.035 | -0.806 | 0.920 | 0.077 | WD |
| 2014 | -0.005 | -0.065 | -2.320 | 2.048 | -0.343 | SND |
| 2015 | 0.0002 | -0.020 | -1.836 | 1.283 | -0.573 | SND |
| 2016 | 0.0008 | 0.151 | -9.046 | 0.633 | -8.261 | SD |
| 2017 | 0.0006 | -0.002 | -0.846 | 0.944 | 0.095 | WD |
| 2018 | -0.0004 | 0.034 | -0.396 | 1.052 | 0.688 | WND |
| 2019 | -0.001 | 0.019 | -2.020 | 1.213 | -0.788 | SD |

**Table 10.** The total decoupling between $CO_2$ emissions and agricultural growth, Japan

| Period | $\varepsilon_{EC}$ | $\varepsilon_{ES}$ | $\varepsilon_{EI}$ | $\varepsilon_{GE}$ | Decoupling index | State |
|---|---|---|---|---|---|---|
| 2013 | 0.005 | -0.281 | -2.098 | 1.299 | -1.074 | SND |
| 2014 | -0.001 | 0.039 | 0.096 | 1.738 | 1.794 | RC |
| 2015 | 0.0005 | 0.048 | -1.471 | 0.817 | -0.605 | SD |
| 2016 | -0.0002 | 0.004 | -0.673 | 0.929 | 0.260 | WD |
| 2017 | 0.002 | 0.147 | 4.399 | 0.764 | 5.314 | END |
| 2018 | -0.002 | 0.094 | 0.812 | 1.228 | 2.132 | END |
| 2019 | 0.00004 | -0.011 | -1.286 | 0.815 | -0.482 | SND |

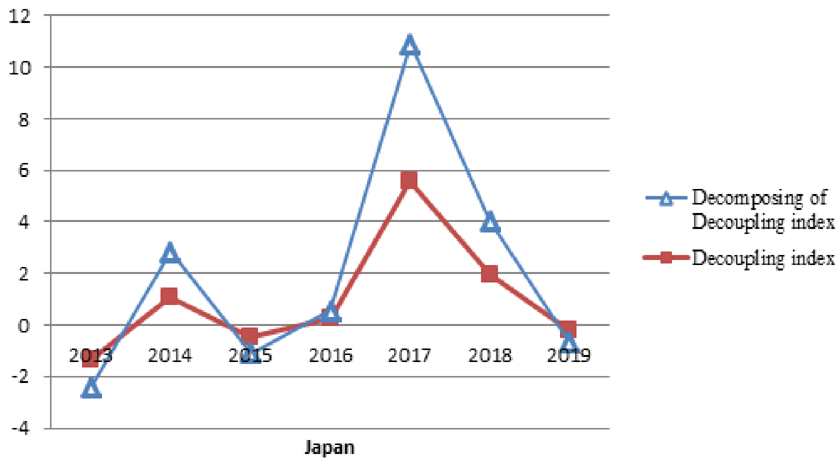


**Figure 7.** The total decoupling trend in Japan

The results in Table 11 show that in China the decoupling index state changed from weak to strong decoupling over the period 2015-2019 during which the energy intensity effect played a promoting role in this progress additionally from 2013 to 2014 the state changed from expansive coupling to weak decoupling indicating the global innovation effect also played a promoting role in the decoupling index with the overall decoupling trend for China illustrated in Figure 8 for India the energy structure effect in 2013 and the energy intensity effect from 2014 to 2018 had promoting roles in the decoupling index respectively as shown by the decoupling index progress in Figure 9 and Table 12

**Table 11.** The total decoupling between $CO_2$ emissions and agricultural growth, China

| Period | $\varepsilon_{EC}$ | $\varepsilon_{ES}$ | $\varepsilon_{EI}$ | $\varepsilon_{GE}$ | Decoupling index | State |
|---|---|---|---|---|---|---|
| 2013 | -0.00004 | -0.0006 | -7.03 | 4.23 | -2.80 | SND |
| 2014 | 0.000006 | -0.003 | -2.34 | 1.54 | -0.81 | SND |
| 2015 | 0.000001 | 0.0006 | -0.71 | 0.03 | -0.68 | SD |
| 2016 | 0.000006 | -0.00008 | -0.36 | 0.58 | 0.21 | WD |
| 2017 | -0.00002 | -0.002 | -0.01 | 0.44 | 0.42 | WD |
| 2018 | 0.00000009 | -0.002 | -7.32 | -0.21 | -7.54 | SD |
| 2019 | 0.00006 | -0.001 | -2.18 | 2.79 | 0.61 | WD |

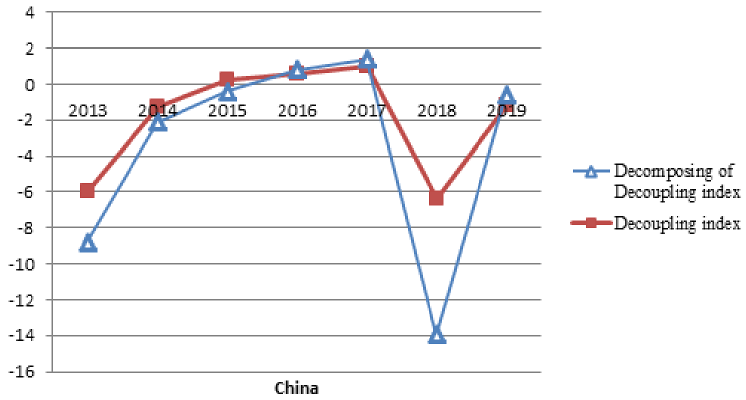


**Figure 8.** The total decoupling trend in China

**Table 12**. The total decoupling between $CO_2$ emissions and agricultural growth, India

| Period | $\varepsilon_{EC}$ | $\varepsilon_{ES}$ | $\varepsilon_{EI}$ | $\varepsilon_{GE}$ | Decoupling index | State |
|---|---|---|---|---|---|---|
| 2013 | 0.00001 | 0.276 | 7.471 | 2.431 | 10.17 | END |
| 2014 | 0.0004 | -0.030 | -4.440 | 1.949 | -2.520 | SD |
| 2015 | -0.0009 | -0.067 | -5.612 | -0.419 | -6.099 | SD |
| 2016 | 0.00007 | -0.039 | -2.820 | 0.340 | -2.519 | SD |
| 2017 | 0.00002 | 0.136 | -3.767 | 0.974 | -2.655 | SD |
| 2018 | -0.0005 | 10.42 | 341.79 | 70.98 | 423.20 | RD |
| 2019 | -0.00003 | -0.007 | -3.980 | 1.116 | -2.871 | SD |

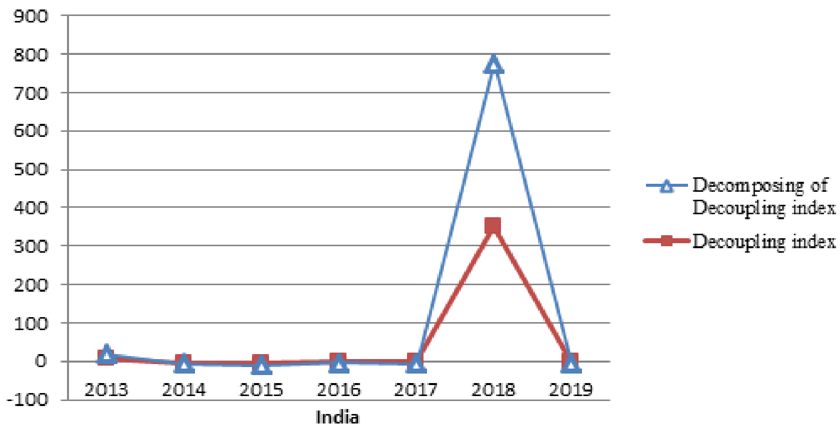


**Figure 9.** The total a decoupling trend in India

The results in Table 13 show that from 2013 to 2019, with the exception of 2018, the decoupling state in Iran was expansive negative decoupling. A comparison with the previous status of the decoupling index in Table 3 indicates that the global innovation efficiency effect played an inhibiting role in 2013 and 2019, while the energy intensity effect was inhibiting in 2016 and 2017. Throughout the entire 2013-2019 period, the coefficient effect consistently played a promoting role in the decoupling index. The total decoupling index for Iran is presented in Figure 10.

**Table 13.** The total decoupling between $CO_2$ emissions and agricultural growth, Iran

| Period | $\varepsilon_{EC}$ | $\varepsilon_{ES}$ | $\varepsilon_{EI}$ | $\varepsilon_{GE}$ | Decoupling index | State |
|---|---|---|---|---|---|---|
| 2013 | 0.004 | 3.552 | 4.633 | 4.763 | 12.954 | END |
| 2014 | -0.080 | 57.75 | 9.435 | 48.57 | 115.68 | END |
| 2015 | -0.00009 | 18.41 | 17.223 | 18.145 | 53.785 | END |
| 2016 | 0.00005 | 19.34 | 30.527 | 19.171 | 69.09 | END |
| 2017 | 0.027 | 43.85 | 45.055 | 43.132 | 132.06 | END |
| 2018 | -0.036 | -58.46 | -57.646 | -55.827 | -171.97 | SND |
| 2019 | -0.008 | 6.745 | 8.285 | 8.585 | 23.60 | END |

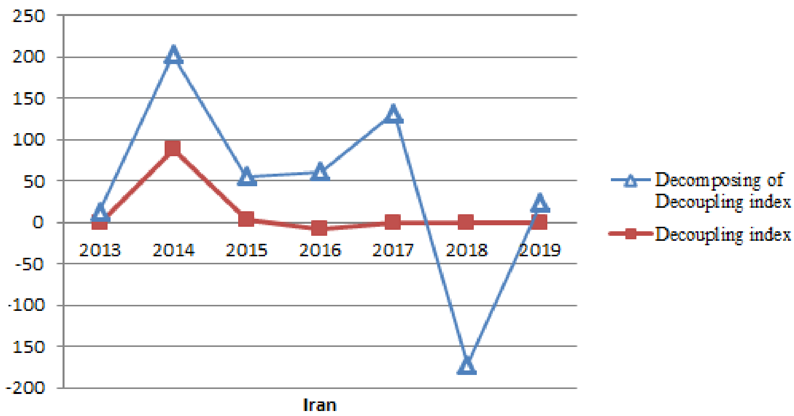


**Figure 10.** The total decoupling trend in Iran

According to the results in Table 14, the decoupling state in Russia shifted from expansive negative decoupling to weak decoupling in 2014, indicating that the coefficient effect played a promoting role in the decoupling index for both 2013 and 2014. An expansive coupling state was observed in 2019, which signifies no discernible relationship between carbon dioxide emissions and agricultural growth. The energy intensity effect played a promoting role in decoupling during 2015-2016, while the global innovation efficiency effect was the promoting factor during 2017-2018. The trend of the decoupling index for Russia is illustrated in Figure 11.

**Table 14.** The total decoupling between $CO_2$ emissions and agricultural growth, Russia

| Period | $\varepsilon_{EC}$ | $\varepsilon_{ES}$ | $\varepsilon_{EI}$ | $\varepsilon_{GE}$ | Decoupling index | State |
|---|---|---|---|---|---|---|
| 2013 | -21.306 | -0.047 | -2.049 | -0.227 | -23.631 | SD |
| 2014 | -1.175 | 0.189 | 0.503 | 0.996 | 0.514 | WD |
| 2015 | -0.225 | 0.218 | -3.453 | 0.905 | -2.554 | SD |
| 2016 | -22.268 | 3.133 | 21.886 | 1.987 | 4.738 | RD |
| 2017 | -1.729 | 0.451 | -2.290 | 0.634 | -2.933 | SND |
| 2018 | -1.381 | 0.816 | -13.842 | 0.825 | -13.581 | SND |
| 2019 | 1.152 | -0.219 | -2.300 | 2.418 | 1.051 | EC |

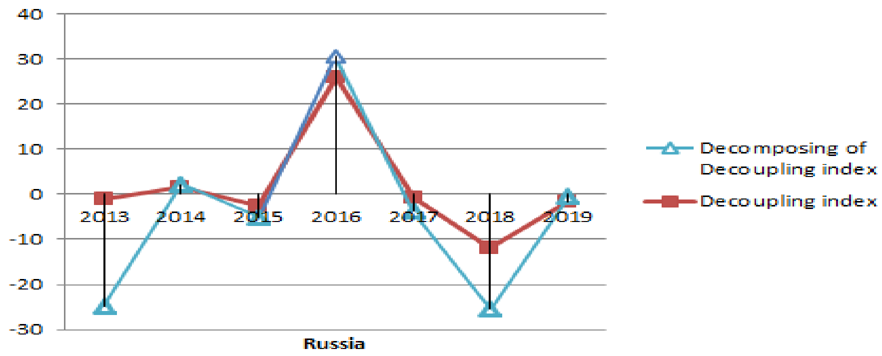


**Figure 11.** The total a decoupling trend in Russia

## Conclusion

This paper compares the decoupling of CO2 emissions from agricultural growth in the top nine CO2-emitting countries from 2013 to 2019 using an extended LMDI model to decompose the decoupling index into four drivers the carbon emission coefficient energy intensity global innovation efficiency effect and structural effect The results showed that from 2013 to 2019 Korea's decoupling state shifted from recessive decoupling to strong negative decoupling while Iran Russia and the United States maintained a stable strong decoupling India's decoupling state progressed from expansive negative decoupling to strong decoupling China achieved strong decoupling in 2019 Japan remained in a state of strong negative decoupling and Germany transitioned from weak decoupling to strong decoupling Decomposition of the total decoupling index revealed that the energy intensity and global innovation efficiency effects were the main promoters of decoupling in Korea China the United States and Germany while in Canada the energy intensity effect was the most critical factor for reducing carbon emissions In Russia the energy intensity global innovation efficiency and structure effects collectively drove the carbon emission reduction rate to exceed the economic growth rate The carbon emission coefficient was the most important factor in Iran's decoupling and the energy intensity and structure effects promoted decoupling in India The global innovation efficiency effect was also a main contributor to emissions reduction in Korea Japan the United States Germany and China Therefore governments are advised to strategically leverage both the energy intensity and global innovation efficiency factors to effectively reduce agricultural CO2 emissions.

## Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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