Dynamic impacts of energy use, agricultural land expansion, and deforestation on CO_2 emissions in Malaysia

Asif Raihan[1] · Rawshan Ara Begum[2] · Mohd Nizam[1] · Mohd Said[1,3] ·
Joy Jacqueline Pereira[4]

Abstract

This study empirically investigates the nexus among energy use, agricultural land expansion, deforestation, and carbon dioxide (CO_2) emissions in Malaysia. Time series data from 1990 to 2019 were utilized using the bounds testing (ARDL) approach followed by the Dynamic Ordinary Least Squares (DOLS) method. The DOLS estimate findings show that the energy usage coefficient is positive and significant with CO_2 emissions, indicating a 1% increase in energy consumption is related to a 0.91% rise in CO_2 emissions. In addition, the coefficient of agricultural land is positive, which indicates that agricultural land expansion by 1% is associated with an increase in CO_2 emissions by 0.84% in the long run. Furthermore, the forested area coefficient is negative, which means that decreasing 1% of the wooded area (i.e., deforestation) has a long-term effect of 5.41% increased CO_2 emissions. Moreover, the pairwise Granger causality test results show bidirectional causality between deforestation and energy use; and unidirectional causality from energy use to CO_2 emissions, agricultural land expansion to CO_2 emissions, deforestation to CO_2 emissions, agricultural land expansion to energy use, and deforestation to agricultural land expansion in Malaysia. The empirical findings reveal that increased energy use, agricultural land expansion, and deforestation have a negative impact on environmental quality in Malaysia. Thus, the effective implementation of policy measures to promote renewable energy, climate-smart agriculture, and sustainable management of forest ecosystems could be useful for reducing environmental degradation in Malaysia.

Keywords Climate change · CO_2 emissions · Energy use · Agriculture · Forest · Malaysia

Communicated by Luiz Duczmal.

Extended author information available on the last page of the article

1 Introduction

Global climate change is a burning issue due to the atmospheric concentrations of greenhouse gases (GHGs) dominated by CO_2 which is largely emitted from human induced activities like the combustion of fossil fuels and deforestation (IPCC 2014; Begum et al. 2020; Uddin 2021; Çıtak et al. 2021). The continuous increase in CO_2 emissions is projected to have tremendous effects on the global climate system resulting in catastrophic consequences that will impact all aspects of society (Seriño 2018). Therefore, reducing CO_2 emissions and increasing the environmental quality became a global concern to secure sustainable development as well as to minimize the climate change detrimental effects (Begum et al. 2015). Within this framework, determining the factors affecting CO_2 emissions is important for selecting appropriate strategies to increase environmental quality (Inekwe et al. 2020). If the functional connection between natural resources and contemporary development processes cannot be avoided, environmental damage is unavoidable. Such issues are greater in nations like Malaysia, where energy security and environmental sustainability are concurrently essential (Begum et al. 2015; Zhang et al. 2021). In Malaysia, the government established a voluntary goal to decrease carbon emissions by 45% by 2030 (MESTECC 2018). Overall knowledge of Malaysia's vulnerability to climate change is increasingly essential for policymakers to strike a balance between policies aimed at mitigating climate change and achieving sustainable development and executing both. The biggest difficulty facing this dual objective is the trade-off between pollution and development. Thus, a significant concern is whether the objectives of sustainable growth and better environmental quality (emission reduction) are mutually incompatible. A major issue emerging is how Malaysia can reduce CO_2 emissions, and this issue may be handled by examining the country's primary CO_2 sources.

However, energy, ecology, and environmental problems are strongly linked in the networks of human and natural systems, usually deconstructed into three distinct elements of reductionist thinking, despite the transdisciplinary inherent in basic and applied research (Chen 2016). Efforts in one subject, without understanding broader connections and effects, are frequently invalid in improving sustainability. For example, increasing energy consumption may lead to possible environmental contamination and ecological deterioration. Such trade-offs require comprehensive analysis and balanced solutions (Chen 2016). Energy demand in Southeast Asia grew quickly owing to rapid population expansion and economic development. Energy is important for meeting domestic requirements, enabling industry and commerce (Pratiwi and Juerges 2020). However, the Malaysian economy subsidizes petroleum prices (Abdullah et al. 2009) which alternatively encourages additional energy use by accelerating economic growth. Zhang et al. (2021) reported that energy-using CO_2 emissions in Malaysia increased by 2% in 2018, the fastest rise in seven years. In 2018, Malaysia's CO_2 emissions were 250.3 million tons, up from 241.6 million tons in 2017. Gan and Li (2008) predicted a 4.3% rise in energy consumption in Malaysia in 2030. Nevertheless, the transport and industrial sectors in Malaysia are the major energy users that have combined used 80% of the total energy consumption (MNRE, 2018). Malaysia has been facing an increasing demand for energy

consumption over the past years due to urbanization and industrial development (Begum et al. 2017). In line with energy demand, Malaysia has also experienced an increasing trend of CO_2 emissions. Therefore, the country is highly concerned about the growing emission intensity, especially from the energy sector. Therefore, it is crucial to analyze the nexus between energy demand and CO_2 emission that would indicate policy options.

Moreover, CO_2 emissions and climate change were connected to agriculture, one of the main drivers of environmental deterioration, and deemed ultrasensitive to climate change (Seo 2016; Naseem et al. 2020). The Agriculture, Forestry and Other Land Use (AFOLU) sector are responsible for about one-fifth of the global annual CO_2 emissions, which is the second-largest CO_2 emission source and is a major contributor to global climate change (IPCC 2014). Agricultural GHG emissions are mainly generated by deforestation, livestock emissions, soil, nutrition management of fossil-fuel-based fertilizer, fossil-fuel-driven agricultural equipment, and bush-burning operations as well as the burning of biomass fuel (Balsalobre-Lorente et al. 2019). Agricultural GHG emissions are a particularly difficult issue in emerging nations like Malaysia because agricultural change is linked with industrialization. Agriculture in Malaysia is dominated by oil palm and rubber production, which plays a major role in economic development. Malaysia is the world's largest exporter and second-largest oil palm producer, contributing 37.7% to agricultural GDP (DOSM 2020). The oil palm business is also a major source of employment, with a total workforce of 1.16 million people, representing 40.45% of the agricultural jobs in Malaysia (MPOC 2014; Sarkar et al. 2020). In addition, Malaysia is the world's fifth-biggest rubber producer (Yusoff et al. 2019). However, the oil palm and rubber sectors have been linked with major environmental problems, such as deforestation, peatland exploitation, and biomass burning that contribute to climate change by releasing CO_2 into the atmosphere (Uning et al. 2020).

The increasing population and growing need for food, transportation, and other infrastructure impose a strain on forest ecosystems in Malaysia (MNRE 2018). Since the agricultural industry revolution, CO_2 emissions from deforestation and forest degradation have grown fast. Global forest cover has changed quickly in recent decades, with the tropical forest cover substantially decreased by an annual loss of 2101 square kilometers (Hansen et al. 2013). Among the many types of environmental degradation, tropical deforestation is said to be one of the main problems to be handled seriously, especially to ensure the sustainability of the global ecosystem (Murshed et al. 2021). Due to high CO_2 emissions from deforestation, significant effects from climate change have occurred in Malaysia, which is also one of South-East Asia's top CO_2 emitters (Begum et al. 2020). Peninsular Malaysia has lost more than half of its natural forests due to industrialization, urbanization, settlements, mining, farming, agricultural fires, clearing forests for oil-palm plantation, and other forms of agriculture (Raihan et al. 2018; Jaafar et al. 2020; Begum et al. 2020). However, forest ecosystems function as both sources and sinks of carbon through which they have a crucial influence on the global climate system (Matthew et al. 2018). Forests play a significant role in climate change mitigation by absorbing the atmospheric CO_2 and storing it in tree biomass, which is called carbon sequestration (Raihan et al. 2019). About 300 billion tons of CO_2 emissions from the atmosphere are yearly absorbed

by the global forest ecosystems, and about three billion tons of it is anticipated to leak into the environment annually due to deforestation (Aziz et al. 2020). Deforestation causes long-term ecological problems by accelerating the effects of climate change, thus attributing to desertification, flooding, soil erosion, and loss of natural habitats (Murshed et al. 2021). With temperatures anticipated to rise 1.5ºC above pre-industrial levels between 2030 and 2052 under the current global warming and climate change scenario, the role of forest ecosystems in absorbing carbon from the atmosphere is becoming increasingly important (IPCC 2018). Therefore, it is crucial to investigate the impact of forest ecosystems on CO_2 emissions in Malaysia.

Over the last decade, the nexus approach to energy, ecology, and the environment has gained traction, and it is projected to discover more information on the widening challenges of climate change, energy consumption, agricultural land expansion, and deforestation (Chen 2016; Ahmad et al. 2020). The IPCC (2014) reported that population size, economic activity, lifestyle, energy use, land use patterns, technology, and inadequate climate policy are the primary drivers of GHG emissions. As a result, several studies examined the relationship between environmental pollution indicators such as CO_2 emissions and economic growth using time series data for Malaysia (Azlina and Mustapha 2012; Saboori et al. 2012; Begum et al. 2015; Begum et al. 2020; Zhang et al. 2021). However, there is a research gap in investigating the dynamic impacts between CO_2 emission and other variables by utilizing econometric approaches. A limited study explores the dynamic impacts of energy use, agricultural land expansion, and deforestation on CO_2 emissions in Malaysia. Therefore, the present study aims to fill this literature gap by using the Dynamic Ordinary Least Squares (DOLS) approach to investigate the dynamic interaction of energy use, agricultural land expansion, and deforestation on CO_2 emission in Malaysia. This study is expected to contribute to the recent literature and policymaking in Malaysia in five ways. Firstly, this investigation establishes a relationship between agricultural land expansion and CO_2 emissions, which is a pioneering attempt to reveal the impact of agricultural land expansion on CO_2 emissions in Malaysia. Secondly, this research portrays the special role of the forest ecosystems, which is commonly neglected when explaining the determinants of CO_2 emissions. Thirdly, this study creates a link between deforestation and agricultural land expansion in Malaysia which is a ground-breaking effort to reveal the nexus between deforestation, agricultural land expansion, and related CO_2 emissions in Malaysia. Next, several unit root tests, cointegration tests, and diagnostic tests are employed to verify the precision of the results. Finally, the study's outcomes would provide further comprehensive and valuable insights to policymakers for designing effective policies related to cleaner energy, climate-smart agriculture, sustainable forest management, and emission reduction in Malaysia.

The rest of the article is structured as follows. The Introduction is followed by Sect. 2 with a brief exposure on the current status of CO_2 emissions, energy use, agricultural land, and forested area in Malaysia. Section 3 exhibits the Literature Review, where relevant research studies have been discussed. The fourth section is the Methodology section, followed by the Empirical Findings in Sect. 5 and Discussion in Sect. 6. Subsequently, Sect. 7 presents the conclusion, policy implications, recommendations, limitations, and future research opportunities.

2 Current status of CO_2 emissions, energy use, agricultural land, and forested area in Malaysia

Malaysia is one of the few developing nations in the world that has transitioned from a resource-based economy in the 1970s to a multi-sector economy in the 1990s, with a focus on manufacturing and services (Begum et al. 2015). Positive economic development, driven mostly by the export of manufactured goods, fostered this change. As a result of the misuse or misallocation of non-renewable energy sources, quicker economic expansion leads to higher urbanization and energy usage, which in turn promotes CO_2 emissions. Malaysia has been facing an increasing demand for energy consumption over the past years (Begum et al. 2017). In line with energy demand, Malaysia has also experienced an increasing trend of CO_2 emissions. Figure 1 presents the annual trend of CO_2 emissions in Malaysia. Total CO_2 emissions in 1960 were about 3,568 kt which increased gradually to 56,190 kt in 1990. Due to rapid industrialization, total CO_2 emissions in Malaysia increased drastically to 239,620 kt in 2018. From 1990 to 2018, Malaysia's average yearly increase rate of CO_2 emissions was approximately 11.66%. Consequently, lowering CO_2 emissions has become a key priority in Malaysia to preserve environmental sustainability and mitigate the harmful effects of climate change.

Malaysia is the world's 26th greatest emitter of energy-related CO_2; its contribution amounts to 0.66% of the world's total emissions (Chik and Rahim 2014). Malaysia's total GHG emissions in 2014 were 248,195 Gg CO_2eq, with the energy

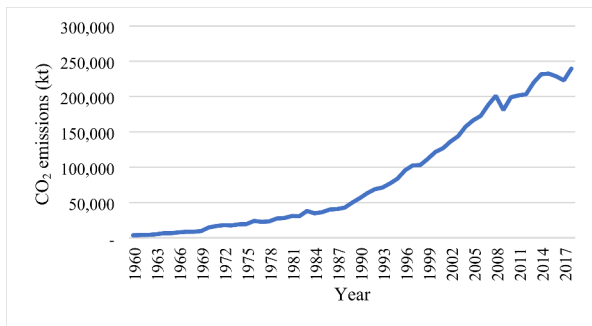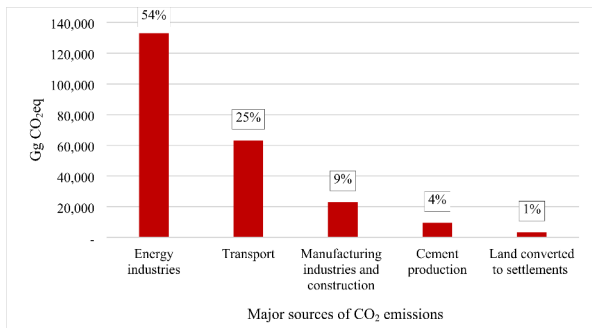**Fig. 1** Annual trend of CO_2 emissions in Malaysia. Source: World Bank (2021)

Fig. 2 The major sources of CO_2 emissions in Malaysia for 2014. Source: MNRE (2018)

sector accounting for 80% of those emissions (MNRE 2018). Therefore, the country is highly concerned about the growing emission intensity, especially from the energy sector. Figure 2 depicts the major sources of CO_2 emissions in Malaysia for 2014. Energy industries are the main culprit of CO_2 emissions in Malaysia, followed by transport, manufacturing industries, and cement production. From 1990 to 2014, the energy sector's emissions rose at an annual rate of 5.8% on average. Between 2005 and 2014, the energy sector's emissions increased by 28% (MNRE 2018). The annual trend of energy use in Malaysia is presented in Fig. 3. Energy use per capita in 1971 was 547 kg which increased to 3,003 kg per capita in 2014. In Malaysia, primary energy supply and energy demand have increased in lockstep with population and economic growth, and this pattern is anticipated to continue. As a result, it is necessary to ensure that the economy has access to reliable and affordable energy while avoiding negative environmental impacts and ensuring long-term energy security. (MNRE 2018).

Moreover, agricultural production is responsible for approximately 20% of global GHG emissions (FAO 2020) and 8.22% of Malaysia's GHG emissions in 2016 (Ridzuan et al. 2020). Agriculture activities in Malaysia that contribute to the CO_2 emission are mainly oil palm plantation, rubber plantation, and other agricultural crops (Omar et al. 2016). Malaysian agriculture has been linked to various unsustainable practices and land clearing, both of which contribute to the country's significant CO_2 emissions. Furthermore, increasing agricultural production to ensure food security necessitates increased energy consumption, which leads to increased emissions. (Zhang et al. 2019). However, Malaysia's agriculture industry has remained one of the top three contributors to the country's gross domestic product (GDP), accounting for 8.2% of GDP in 2020 (World Bank 2021). Malaysia's agriculture is mainly dominated by oil palm cultivation, which accounts for 37.7% of the country's GDP. While oil palm cultivation is important to Malaysia's economic development, it is also responsible for the extinction of several species-rich forest ecosystems, and ongoing unsustainable farming methods are endangering these delicate and fragile ecosystems. Malaysia's oil palm plantations cover about 5.2 million hectares that occupy almost 16% of the total land area and nearly 61% of the total agricultural land (Yamada et al. 2016). Figure 4 presents the annual trend of agricultural land in Malaysia. Total agricultural land in Malaysia increased drastically from 30,847 square km in 1961 to 67,217 square km in 1989. Never-

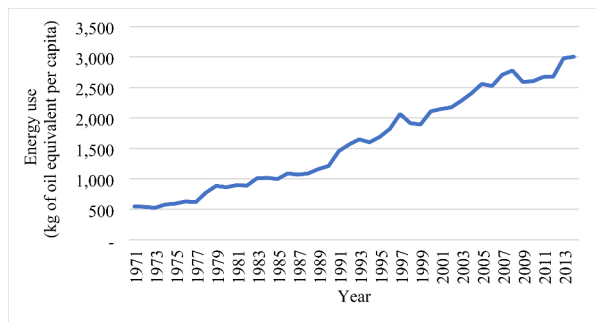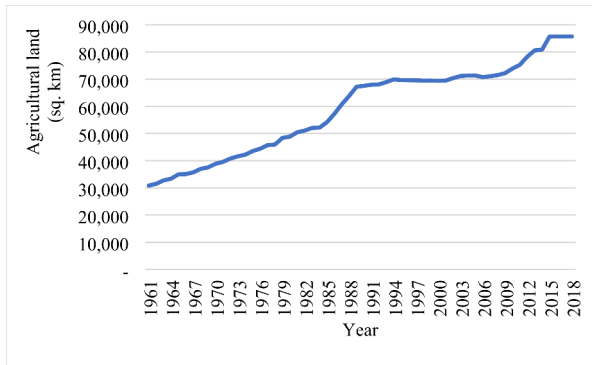Fig. 3 Annual trend of energy use in Malaysia. Source: World Bank (2021)

Fig. 4 Annual trend of agricultural land in Malaysia. Source: World Bank (2021)

theless, agricultural land increased gradually after 1990, and it turned into 85,710 square km in 2018.

Furthermore, forest ecosystems have a crucial role in sustaining the equilibrium of the global climate system by absorbing and storing atmospheric carbon, managing hydrological systems, protecting biodiversity, and providing habitats for wildlife (Begum et al. 2020). Malaysia has forest land, approximately 67% of the total land area (World Bank 2021), which helps mitigate climate change by absorbing atmospheric CO_2 and improving the national carbon sink. However, Malaysia has faced environmental degradation, biodiversity loss, and the destruction of wildlife habitat because of the forest cover changes during the previous few decades due to extensive deforestation. Deforestation and forest degradation have led to global anthropogenic CO_2 emissions, as well as severely affecting tropical forest ecosystems and natural carbon sequestration (Begum et al. 2020). The annual trend of forested area in Malaysia is presented in Fig. 5. Between 1990 and 2010, Malaysia experienced a high rate of deforestation, losing approximately 8.6% of its forest cover. This could be due to a variety of factors, including industrialization, urbanization, settlements, mining, farming, agricultural fires, forest clearing for oil palm and rubber plantations, and other types of agriculture (Begum et al. 2020). In 1990, the total forested area was nearly 206,185 square km which reduced to approximately 189,477 square km in 2010. However, the forested area has been on an upward trend since 2010 due to

Fig. 5 Annual trend of forested area in Malaysia. Source: World Bank (2021)
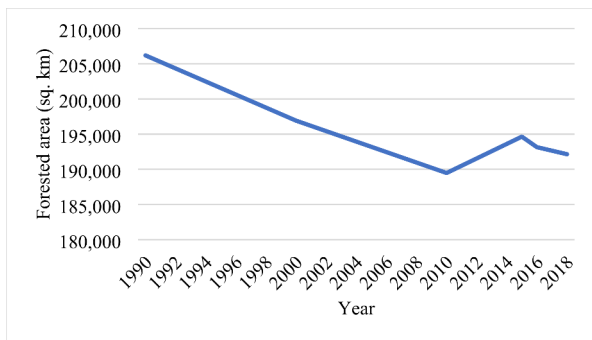
afforestation, reforestation, forest protection, and conservation. The forested area in Malaysia was reported as about 192,143 square km in 2018.

3 Literature Review

Several studies around the world have established the positive relationship between energy use and CO_2 emissions by using numerous econometric approaches. Adebayo and Kalmaz (2021) used ARDL, FMOLS, and DOLS estimators to uncover a positive and significant interaction between energy usage and CO_2 emissions in Egypt by utilizing the data covering the years from 1971 to 2014. Kirikkaleli and Kalmaz (2020) found a long-run positive effect of energy consumption on CO_2 emissions in Turkey throughout 1960–2016 by utilizing FMOLS and DOLS techniques. Odugbesan and Adebayo (2020) investigated the symmetric and asymmetric effects of energy consumption on CO_2 emissions towards environmental sustainability in Nigeria by utilizing the yearly data spanning from 1981 to 2016 employing ARDL, FMOLS, and DOLS techniques. The findings from Odugbesan and Adebayo (2020) showed that energy consumption has a long-run linear relationship with CO_2 in Nigeria. Moreover, by applying ARDL, FMOLS, and DOLS estimators to examine the long-run and causal effects of energy usage on CO_2 emissions in Mexico using the yearly data spanning between 1971 and 2016, Adebayo (2020) found that energy usage impacts CO_2 emissions positively. In addition, he revealed unidirectional causality from CO_2 emissions to energy usage. Furthermore, by employing an ARDL estimator using yearly data between 1980 and 2016, Adebayo (2021) revealed that energy usage positively triggers CO_2 emissions in Indonesia. Using the ARDL estimator for Kazakhstan spanning 1980–2011, Akbota and Baek (2018) found that energy consumption increases CO_2 emissions. By employing the ARDL approach, Nondo and Kahsai (2020) revealed a positive relationship between energy intensity and CO_2 emissions in South Africa from 1970 to 2016.

Furthermore, a number of studies reported the positive association between energy use and CO_2 emissions from a group of countries. By utilizing FMOLS and DOLS estimators using the time series data from 1971 to 2014, Vo et al. (2019) revealed that the level of CO_2 emissions is positively associated with energy consumption in five ASEAN countries (Indonesia, Myanmar, Malaysia, the Philippines, and Thailand). In addition, Vo et al. (2019) found unidirectional causality from energy consumption to CO_2 emissions. Irfan and Shaw (2017) investigated the relationship between energy consumption and CO_2 emissions in South Asian countries over 1978–2011 by employing a nonparametric additive model. Irfan and Shaw (2017) discovered that energy consumption positively impacts CO_2 emissions in the panel of countries. Adebayo et al. (2020) found a positive interconnection between CO_2 emissions and energy usage by utilizing the ARDL model for MINT countries using the time coverage from 1980 to 2018. Zmami and Ben-Salha (2020) investigated the effects of energy consumption on CO_2 emissions in Gulf Cooperation Council (GCC) countries between 1980 and 2017 using the STIRPAT model and the ARDL approach. Zmami and Ben-Salha (2020) reported that energy consumption has a positive and significant impact on CO_2 emissions in the long run.

In Malaysia, Ang (2008) exposed that energy consumption and environmental pollution are positively associated in the long run. By applying the cointegration and vector error correction model for Malaysia over the period 1970–2010, Azlina and Mustapha (2012) reported unidirectional causality running from CO_2 emissions to energy consumption. Using the time series data for the newly industrialized countries spanning 1971–2007, Hossain (2011) found that higher energy consumption increases CO_2 emissions over time. Begum et al. (2015) investigated the dynamic impacts of energy consumption on CO_2 emissions using the ARDL bounds testing approach and DOLS technique for Malaysia by using the data over 1970–2009. Begum et al. (2015) demonstrated that per capita energy consumption has a long-term positive impact on carbon emissions. Using time-series data from 1980 to 2016, Sarkar et al. (2019) revealed unidirectional causality of energy demand with carbon emissions in Malaysia.

However, the agriculture sector is the primary cause of environmental degradation due to its extensive use of fossil fuels and nitrogen-rich fertilizers (Aziz et al. 2020). According to Reynolds and Wenzlau (2012), the agriculture sector uses a lot of fossil fuel for pumping water, irrigation, and nitrogen-rich fertilizer, which accounts for 14–30% of total GHG emissions. Holly (2015) reported that one of the major sources of CO_2 emissions in agriculture is nitrous oxide and methane from livestock practices and soil management. Thus, reducing emissions from the agriculture sector has become a critical issue for sustainable development. Over the last few years, the impact of agriculture on environmental pollution has been a recurring topic of discussion. Recent studies have been performed with various econometric methods to investigate the effects of agriculture on environmental degradation. Doğan (2018) utilized ARDL, FMOLS, DOLS, and CCR techniques to explore the relationship between agricultural production and CO_2 emissions in China by using annual data covering1971-2010. The findings from Doğan (2018) revealed that agriculture increases a country's long term CO_2 emissions. By performing the ARDL approach and Bayer-Hanck cointegration test for Nigeria using annual time series data from 1981 to 2014, Agboola and Bekun (2019) found that agricultural production has a positive but insignificant impact on CO_2 emissions. Using the ARDL method for the period 1990–2016, Burakov (2019) found that the agricultural sector is a statistically significant determinant of carbon emission in Russia. In addition, the pairwise Granger causality test by Burakov (2019) revealed unidirectional causality running from agriculture to CO_2 emissions.

Gokmenoglu et al. (2019) investigated the long-run equilibrium relationship between CO_2 emissions and agriculture in the case of China for the period of 1971–2014. Using the ARDL approach, Gokmenoglu et al. (2019) reported that agricultural development is positively associated with CO_2 emissions. Using the Johansen-Juselius cointegration test and VECM model for Tunisia spanning 1980–2011, Jebli and Youssef (2017a) showed that an increase in agricultural value-added increases CO_2 emissions. By applying the ARDL model for data from 1961 to 2012, Sarkodie and Owusu (2016) found that agricultural production leads to increased CO_2 emissions in Ghana. By performing FMOLS, Maki cointegration, and Toda-Yamamoto causality tests for Pakistan from 1971 to 2014, Gokmenoglu and Taspinar (2018) reported that agriculture deteriorates environmental quality, and there is bidirectional causality

between agriculture and CO_2 emissions. Naseem et al. (2020) examined the asymmetrical impact of agriculture on CO_2 emissions in Pakistan from 1969 to 2018 by utilizing the NARDL approach. The findings by Naseem et al. (2020) revealed that agriculture value-added has a significant positive impact on the CO_2 emissions in Pakistan. In addition, Naseem et al. (2020) found unidirectional causality running from agriculture to CO_2 emissions. Ullah et al. (2018) performed ARDL, Johansen-cointegration test, and Granger causality test by using the data from 1972 to 2014. Ullah et al. (2018) found that six different types of agricultural activities increase CO_2 emissions in Pakistan. They also revealed a bidirectional causality between agriculture and CO_2 emissions.

Furthermore, several studies have uncovered a relationship between agriculture and CO_2 emissions in a set of countries. By utilizing panel cointegration tests, FMOLS, and DOLS techniques in a 1992–2013 sample of BRICS countries, Liu et al. (2017) testified that agricultural production generates environmental pollution. Using the Pedroni cointegration test, FMOLS, DOLS, and VECM for a panel of E7 countries spanning 1990–2014, Aydoğan and Vardar (2020) reported that agriculture has a positive relationship with environmental degradation. Balsalobre-Lorente et al. (2019) employed DOLS and FMOLS methods to investigate the long-run effects of agricultural activities on carbon emissions for Brazil, Russia, India, China, and South Africa (BRICS) over the period 1990–2014. Empirical evidence confirmed that agriculture exerts a negative impact on the environment in BRICS countries. By employing the FMOLS and VECM approach using the data from 1990 to 2014, Qiao et al. (2019) found that agriculture significantly increases CO_2 emissions in G20 countries. Applying the Emirmahmutoglu-Kose panel causality test and augmented, pooled, and mean group estimators for eleven developing countries in the Central and West African regions, Olanipekun et al. (2019) reported that agriculture has a positive impact on environmental pressure. By utilizing the ADL cointegration test for BRIC countries using annual time series data from 1971 to 2016, Pata (2021) found that the impact of agricultural value-added on environmental pollution is positive but statistically insignificant. In addition, the bidirectional causality relationship showed that agriculture is an important factor in environmental pollution and that agricultural activities are affected by environmental problems.

The influence of agriculture on environmental degradation has been a frequent issue of controversy throughout the previous decade. Several studies reported the negative impact of agriculture on environmental deterioration. By utilizing the ARDL approach using data from 1968 to 2010, Dogan (2016) reported that CO_2 emissions in Turkey are negatively associated with agricultural production. Prastiyo et al. (2020) found negative impacts of agriculture value-added on CO_2 emissions utilizing the ARDL technique for Indonesia using the data over 1970–2015. Liu et al. (2017) employed the ARDL model to uncover a negative influence of agricultural value added on CO_2 emissions in ASEAN countries using data over the span time of 1970–2013. Jebli and Youssef (2017b) reported that an increase in agricultural value added decreases CO_2 emissions in North African countries throughout 1980–2011 by utilizing OLS, FMOLS, and DOLS techniques. By employing the ARDL model using the data from 1996 to 2017, Wang et al. (2020) found that agriculture value-added decreases CO_2

emissions in G7 countries. By using panel data from 1982 to 2015, Anwar et al. (2019) found that higher agricultural value added has an inverse association with CO_2 emissions in low- and lower-middle-income nations. Rafiq et al. (2016) found that agricultural value added has a key impact in decreasing emissions using the STIRPAT model and yearly data from 1980 to 2010 for a set of 53 nations.

Moreover, using country-specific panel data from 1990 to 2014 for 86 different countries, Parajuli et al. (2019) established a negative association between forested area and CO2 emissions and a positive relationship between agricultural land and CO_2 emissions. Aziz et al. (2020) investigated the role of forestry and agriculture in testing EKC in Pakistan by employing the Quantile ARDL approach using the data from 1990 to 2018. Aziz et al. (2020) found a positive link between agricultural production and CO_2 emissions, whereas a negative relationship between forested area and CO_2 emissions. Using the ARDL estimator for Pakistan spanning 1990–2014, Waheed et al. (2018) reported that agriculture increases environmental degradation, whereas CO_2 emission can be reduced by increasing forested area. By employing econometrics approaches using time series data from 1991 to 2010, Islam et al. (2017) found a negative relationship between forested area and CO_2 emissions in Malaysia, Indonesia, and Thailand. Shittu et al. (2018) utilized the ARDL technique on secondary data from 1981 to 2014 and found that deforestation positively influences environmental degradation in Malaysia. Begum et al. (2020) examined the dynamic impacts of forested area on CO_2 emissions in Malaysia by utilizing the DOLS approach using time series data from 1990 to 2016. Begum et al. (2020) revealed a negative and significant coefficient of forested area, which implied that declining one hectare of forested area (i.e., deforestation) has an impact of three kilo tons of CO_2 emissions rise in Malaysia. However, most environmental studies have concentrated on GHG emissions into the atmosphere, leaving agricultural land expansion and deforestation as key determinants of environmental quality, especially in Malaysia. Therefore, this study attempts to explore the dynamic impacts of energy use, agricultural land expansion, and deforestation on CO_2 emissions in Malaysia.

4 Methodology

4.1 Data

This study provides an empirical analysis of the dynamic impacts of energy use, agricultural land expansion, and deforestation on CO_2 emissions in Malaysia by using the dynamic ordinary least squared (DOLS) approach of cointegration by Pesaran and Shin (1999) and Pesaran et al. (2001). Time series data from 1990 to 2019 for Malaysia, were obtained from the World Development Indicator (WDI) dataset. The variables are transmuted into a logarithm to ensure that data are normally distributed. The variables with their logarithmic forms, measurement units, and data sources are presented in Table 1. This research considers CO_2 emissions as the dependent variable while energy use, agricultural land, and forested area as explanatory variables.

Table 1 Variables with their logarithmic forms, units, and data sources

Variables	Description	Logarithmic forms	Units	Sources
CO_2	CO_2 emissions	LCO2	Kilotons (kt)	WDI
EU	Energy use	LEU	Kg of oil equivalent per capita	WDI
AGL	Agricultural land	LAGL	Square Kilometers (Sq. km)	WDI
FA	Forested area	LFA	Square Kilometers (Sq. km)	WDI

4.2 Econometric Model

To examine the long-term effects of energy use, agricultural land expansion, and deforestation on CO_2 emissions in Malaysia, we have derived the following equation (Begum et al. 2020; Adebayo 2021):

$$CO_{2t} = f(EU_t; AGL_t; FA_t) \tag{1}$$

The following equation depicts the econometric model:

$$CO_{2t} = \tau_0 + \tau_1 EU_t + \tau_2 AGL_t + \tau_3 FA_t \tag{2}$$

Further Eq. (2) can be expended as an econometric model in the following form:

$$CO_{2t} = \tau_0 + \tau_1 EU_t + \tau_2 AGL_t + \tau_3 FA_t + \epsilon_t \tag{3}$$

where τ_0 and ϵ_t stand for intercept and error term, respectively. In addition, τ_1, τ_2, and τ_3 denote the coefficients.

Moreover, the logarithmic arrangement of Eq. (3) can be as follows:

$$LCO2_t = \tau_0 + \tau_1 LEU_t + \tau_{2L} AGL_t + \tau_{3L} FA_t + \epsilon_t \tag{4}$$

4.3 Stationarity techniques for data

Conducting a unit root test is essential in avoiding spurious regression. It verifies that variables included in regression are stationary by differencing them and estimating the equation of interest using the stationary processes (Mahadeva and Robinson 2004). The obligation to determine the order of integration before investigating cointegration amongst the variables is recognized in the empirical literature. Several researchers have suggested that owing to the power difference of unit root tests regarding the size of the sample, it is vital to utilize more than one unit root test

to evaluate the integration order of the series (Saboori et al. 2017; Adebayo et al. 2021). Therefore, we applied the Augmented Dickey-Fuller (ADF) test introduced by Dickey and Fuller (1979), and Dickey-Fuller generalized least squares (DF-GLS) test proposed by Elliott et al. (1996) to detect the autoregressive unit root. This study did the unit root test to confirm that no variable exceeded the order of integration.

4.4 ARDL bounds test for cointegration

We applied the ARDL bounds test proposed by Pesaran et al. (2001) to capture the cointegration amongst the series. The ARDL bounds test for cointegration valuation has many advantages over the other one-time integer methods (Sam et al. 2019; Sarker and Khan 2020; Tong et al. 2020; Adebayo and Akinsola 2021). Firstly, it can be utilized when series have a mixed order of integration as the ARDL bounds test does not have obligatory assumptions. Secondly, it is significantly more reliable, particularly for a small sample size. Thirdly, it offers an accurate estimation of the long-term model (Adebayo and Akinsola 2021). Therefore, the ARDL bounds testing approach can be used irrespective of whether the fundamental returning system is in sequence to apart in the I(2), and the cointegration order happens at I(0) or I(1). The ARDL bounds test is depicted as follows in Eq. (5):

$$\Delta LCO2_t = \tau_0 + \tau_1 LCO2_{t-1} + \tau_2 LEU_{t-1} + \tau_3 LAGL_{t-1} + \tau_4 LFA_{t-1} + \sum_{i=1}^{q} \gamma_1 \Delta LCO2_{t-i} +$$
$$\sum_{i=1}^{q} \gamma_2 \Delta LEU_{t-i} + \sum_{i=1}^{q} \gamma_3 \Delta LAGL_{t-i} + \sum_{i=1}^{q} \gamma_4 \Delta LFA_{t-i} + \epsilon_t \tag{5}$$

where Δ is the first difference operator and q is the optimum lag length in the above Eq. (5).

The ARDL bounds test follows the F-distribution, and its critical values were proposed by (Pesaran and Timmermann 2005). The estimation procedure begins with Eq. (5) and uses OLS to enable the F-test to determine the joint significance of the coefficient of the lagged variables. The essence of this procedure is to examine the likelihood of any possible long-run relationship among the respective variables. In this regard, the null hypothesis (H_0) states that cointegrating relationships do not exist among the regressors. The F-statistics can be compared against the critical values of the upper and lower bounds, as in Pesaran et al. (2001). If the F-statistics are higher than the upper critical value, the null hypothesis is rejected, which means the existence of a long-run relationship among the respective variables. On the other hand, if the F-statistics are less than the lower critical value, the null hypothesis is accepted. Alternatively, if the F-statistics are observed within the lower and upper critical values, the test is inconclusive.

4.5 DOLS cointegration test

This study employed DOLS, an extended equation of ordinary least squares estimation to analyze the time series data. DOLS cointegration test contains explanatory

factors as well as leads and lags of their initial difference terms to regulate endogeneity and to calculate the standard deviations using a covariance matrix of errors which is resistant to serial correlation. The inclusion of the different terms' leads and lags confirms that the error term is orthogonalized. The standard deviations of the DOLS estimators provide a valid test for the statistical significance of the variables because they have a normal asymptotic distribution (Wang 2012). When a mixed order of integration occurs, the DOLS approach is effective at allowing individual variables in the cointegrated outline to be integrated by estimating the dependent variable on explanatory variables in levels, leads, and lags.

The DOLS estimation's main advantage, however, is the presence of mixed order integration of individual variables in the cointegrated outline. For example, in DOLS estimation, one of I(1) variables was regressed against other variables, some of which were I(1) variables with leads (p) and lags (-p) of the first difference, while others were I(0) variables with a constant term (Alcántara and Padilla, 2009). As a result of aggregating the leads and lags among explanatory variables, this estimate solves small sample bias, endogeneity, and auto correlation issues (Stock and Watson, 1993). However, after confirming cointegration among the variables, the study proceeds with the DOLS estimation of the long-run coefficient by using Eq. (5).

4.6 Cointegration regression to check the robustness of DOLS estimation

This study utilized the fully modified OLS (FMOLS) and Canonical Cointegrating Regression (CCR) to check the robustness of DOLS outcomes. The FMOLS regression was developed by Hansen and Phillips (1990) to incorporate optimum estimates of cointegrating regression. The FMOLS method alters least squares to account for the serial correlation consequences and the endogeneity in the independent variables that arise from the interaction of cointegrating. It facilitated polynomial regression of deterministic variables, stationary error, and integrated procedures. The errors can serially be associated, and the regressors can be endogenous (Hong and Wagner 2011). The FMOLS method is capable of estimating nonstationary I(1) data where it can use standard regression techniques (OLS) of the nonstationary (unit root) data to add to the problem of spurious regressions. Moreover, Park (1992) first introduced the CCR procedure that involves data transformation that uses only the stationary component of a cointegrating model. A cointegrating relationship supported by the cointegrating model would remain unchanged after such data transformation. The CCR transformation makes the error term in a cointegrating model uncorrelated at the zero frequency with regressors. Consequently, the CCR procedure yields asymptotically efficient estimators and provides asymptotic chi-square tests that are free from nuisance parameters. FMOLS and CCR techniques allow asymptotic coherence to be acquired by evaluating the influence of serial correlation. Therefore, long-term elasticity is evaluated in this research by utilizing FMOLS and CCR estimators using Eq. (5).

4.7 Pairwise Granger causality test

The present research intends to capture the causal effects between the variables. Therefore, we utilize the pairwise linear Granger-causality test proposed by Granger

(1969) to examine if there is a causal association between the variables. Granger causality is a 'statistical concept of causality based on prediction' which has a number of advantages over other time-series analysis methods (Winterhalder et al. 2005) and hence is adopted in the present study. If one-time series Y can help predict the future of another time series X, then Y "Granger-causes" X. The time series of these two variables have data length T, denoting their values at time t by X_t and Y_t (t = 1,2, …,T), respectively. However, X_t and Y_t can be modeled by a bivariate autoregressive model:

$$X_t \sum_{l=1}^{p} (a_{11,l}X_{t-l} + a_{12,l}Y_{t-l}) + \epsilon_t \tag{6}$$

$$Y_t \sum_{l=1}^{p} (a_{21,l}X_{t-l} + a_{22,l}Y_{t-l}) + \xi_t \tag{7}$$

where p is the model order, $a_{ij,l}$ (i,j = 1,2) are coefficients of the model, and ϵ_t and ξ_t represent residuals. The coefficients can be estimated by ordinary least squares, and the Granger causality between X and Y can be detected by F tests (Tam et al. 2013).

5 Empirical Findings

5.1 Summary statistic of data

The outcomes of the summary measures amid variables are shown in Table 2 with the statistical values of different normality tests (skewness, probability, kurtosis, and Jarque-Bera) used. Each variable includes 30 observations of time series data from 1990 to 2019 for Malaysia. The negative values of skewness by the variables imply

Table 2 Summary statistics of the variables

Variables	LCO2	LEU	LAGL	LFA
Mean	11.95756	7.737049	11.20678	12.18510
Median	12.07793	7.809222	11.17208	12.17711
Maximum	12.52166	8.114216	11.35872	12.23653
Minimum	10.94364	7.099175	11.12086	12.15202
Std. Dev.	0.432933	0.270180	0.171794	0.025007
Skewness	-0.620361	-0.517288	-0.984275	-0.612215
Kurtosis	2.462901	2.363809	2.395028	2.171672
Jarque-Bera	2.284834	1.843859	2.014041	2.736973
Probability	0.319047	0.397751	0.365306	0.220570
Observations	30	30	30	30

that all the variables adhere to normality. Furthermore, the research employed kurtosis to evaluate if the series is light-tailed or heavy-tailed relative to normal distribution. The empirical findings indicate that all the series are platykurtic as their values are less than 3. In addition, the results of the Jarque-Bera probability reveal that all of the parameters are normal. The unit root test for stationarity of the variables, as well as further analysis of the DOLS estimation, are based on these statistics.

5.2 Correlation between the variables

Correlation analysis to test for linear relationships between the variables is presented in Table 3. The findings reveal that all the variables are correlated to one another. LCO2, LEU, and LAGL indicate a very strong and positive correlation with each other which implies that when the value of one variable increases, the value of the other variable also tends to increase and vice versa. Nevertheless, LFA shows a negative correlation with all the other variables, which reveals that when the value of the forested area increases, the value of the other variable tends to decrease and vice versa. The correlation analysis led us to proceed with the unit root tests for the stationarity of the variables.

5.3 Results of unit root tests

We used unit root tests to check for integration orders. To find the autoregressive unit root, we used the augmented Dickey-Fuller (ADF), and Dickey-Fuller generalized least squares (DF-GLS) approaches based on trends and constants. Table 4 presents the findings of unit root testing using ADF and DF-GLS. The ADF test result reveals that LCO2, LEU, and LFA were stationary at the level and stayed stationary after taking the first difference, whereas LAGL was non-stationary at the level but became stationary at the first difference. In addition, the DF-GLS test revealed that LAGL

Table 3 The results of the correlation analysis

	LCO2	LEU	LAGL	LFA
LCO2	1.000000			
LEU	0.983052	1.000000		
LAGL	0.804503	0.815622	1.000000	
LFA	-0.923738	-0.914016	-0.582244	1.000000

Table 4 Results of unit root tests by Augmented Dickey-Fuller (ADF), and Dickey-Fuller generalized least squares (DF-GLS)

Logarithmic form of the variables		LCO2	LEU	LAGL	LFA
ADF	Log levels	-2.802877**	-2.520625**	-1.285469	-1.798854*
	Log first difference	-5.131625***	-5.307505***	-4.143602***	-2.365068**
DF-GLS	Log levels	-0.344846	-0.318733	-2.493059**	-2.203630**
	Log first difference	-4.151906***	-3.603036***	-3.099441***	-2.358648**

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively

and LFA were stationary at the level and stayed stationary after taking the first difference, whereas LCO2 and LEU were found non-stationary at the level but became stationary at the first difference. Hence, the occurrence of mixed orders integration for variables estimated by the ADF and DF-GLS justifies using the ARDL bounds test and DOLS cointegration test.

5.4 Results of ARDL bounds test

After the stationarity characteristics of the series are affirmed, we proceed to conduct the ARDL bounds test for cointegration valuation. This analysis chose a reasonable lag period to measure the F-statistic constructed on the minimum values of the Akaike Information Criterion (AIC) proposed by Akaike (1987). Table 5 depicts the ARDL bounds test results to explore the cointegration link among the variables. The outcomes are presented in such a manner that the existence of a long-run association between the parameters is verified if the estimated value of the F-test is greater than the values of both limits (lower and upper bound). The findings reveal that the estimated F-statistic value 5.243503 is higher than 10%, 5%, 2.5%, and 1% of the crucial upper limit in the order zero and one, which rejects the null hypothesis by indicating that long-run relationship exists among the respective variables.

5.5 DOLS outcomes

The outcomes of the DOLS estimated by using Eq. (5) are presented in Table 6. The estimated coefficient of LEU is positive and significant at a 1% level, which implies that a 1% increase in energy use will lead to a 0.91% increase in CO_2 emissions when other indicators are held constant. The finding reveals that energy use triggers environmental degradation in the long run. Furthermore, the estimated coefficient of agricultural land is positive and significant at a 1% level, which indicates that agricultural land expansion by 1% is associated with an increase in CO_2 emissions by 0.84% in the long run. This reveals that agricultural land expansion deteriorates environmental quality. Finally, the estimated coefficient of forested area is negative and significant at a 1% level, which implies that a 1% reduction of the forested area due to deforestation has an impact of rising 5.41% of CO_2 emissions in Malaysia. The empirical finding suggests that deforestation prompts environmental degradation while increasing forested area improves the environmental quality as the forest ecosystems absorb the atmospheric CO_2 and store it in tree biomass. The result demonstrates that the forest

Table 5 Findings from cointegration with bounds testing

F-bounds test		Null hypothesis: No levels relationship		
Test statistic	Value	Significance	I0	I1
Value of *F*-statistic	5.243503	At 10%	2.37	3.20
K	3	At 5%	2.79	3.67
		At 2.5%	3.15	4.08
		At 1%	3.65	4.66

Table 6 The outcomes of DOLS: dependent variable LCO2

Variables	Coefficient	Standard Error	t-Statistic
LEU	0.908324***	0.190261	4.774095
LAGL	0.844081***	0.287365	2.937312
LFA	-5.408090***	1.301888	-4.154035
C	61.36847***	14.64527	4.190326
R^2	0.974697		
Adjusted R^2	0.971778		
Standard error of the estimate	0.072730		
Long run variance	0.009956		
Mean of dependent variable	11.95756		
F-statistic	333.8539		
Prob (F-statistic)	0.000000		
Root mean square error (RMSE)	0.067708		

*** denotes significance at the 1% level

ecosystems can be utilized as a tool to keep the environment clean by avoiding deforestation and increasing forest protection and conservation in Malaysia.

Moreover, it is notable that the indications of the calculated coefficients are compatible both from the theoretical point of view and practical expectations. In addition, we evaluated our estimated model's goodness of fit using various diagnostic tests. First, the values of R^2 and adjusted R^2 are 0.9747 and 0.9718, respectively, indicating a very excellent fitting of the calculated regression model. This indicates 97% of the variance in the change of dependent variable can be explained by the independent factors. Second, the F- statistic indicates that the calculated DOLS regression is supported by its dependent and independent variables. The p-value of F- statistic is 0.0000, suggesting that the linear relation of the model is statistically significant. Third, the root mean square error (RMSE) offers an accurate estimate of model predictions for multiple periods. The value of RMSE is 0.0677 (near to 0) and non-negative, suggesting the results of the DOLS model was an almost perfect fit to the data

5.6 Robustness check

We utilized the FMOLS and CCR estimators to verify the consistency of DOLS estimation. The FMOLS and CCR estimation results for the model are presented in Tables 7 and 8. The outcomes of FMOLS and CCR provide evidence of the robustness of the DOLS estimation. The FMOLS and CCR results confirmed the coefficient of energy use and agricultural land is positive and significant at a 1% level. The results further validated the inverse relationship between CO_2 emissions and deforestation at a 1% level of significance. Hence, it can be stated that energy use, agricultural land expansion, and deforestation increase CO_2 emissions in Malaysia while increasing forested area helps to reduce CO_2 emissions. The results of the FMOLS and CCR are duly in line with the findings from DOLS outcomes. The R^2 and adjusted R^2 values from FMOLS and CCR estimation reflect the model's goodness of fit, indicating that the independent variables can explain 97% of the variation in the dependent variable's change.

Table 7 The results of FMOLS: dependent variable LCO2

Variables	Coefficient	Standard Error	t-Statistic
LEU	0.899839***	0.188638	4.452905
LAGL	0.846641***	0.300192	2.820328
LFA	-5.285951***	1.335808	-3.957119
C	60.38815***	15.22006	3.967667
R^2	0.969725		
Adjusted R^2	0.966093		
Standard error of the estimate	0.072763		
Long run variance	0.010586		

*** denotes significance at the 1% level

Table 8 The results of CCR: dependent variable LCO2

| Variables	Coefficient	Standard Error	t-Statistic
LEU	0.781404***	0.174014	4.490560
LAGL	0.971810***	0.264011	3.680942
LFA	-6.15107***	1.244684	-4.941874
C	69.97135***	13.95754	5.013159
R^2	0.970837		
Adjusted R^2	0.967337		
Standard error of the estimate	0.071415		
Long run variance	0.001456		

*** denotes significance at the 1% level

5.7 Diagnostic inspection

This study performed normality, heteroscedasticity, and serial correlation analysis to validate the intensity of the cointegration valuation. The diagnostic test results are presented in Table 9. The model indicates normality and nonexistence of autocorrelation and heteroscedasticity. In addition, we employed the cumulative sum of squares of recursive residuals (CUSUM of Squares) test to check the stability of the model. The CUSUM of Squares plot at 5% significance level is presented in Fig. 6. The CUSUM of Squares plot from the recursive estimation of the model indicates that the model was stable as the residuals were within the critical bounds of the 5% significance level, and there is nonexistence of structural break.

Table 9 The results of diagnostic tests

Diagnostic tests	Coefficient	p-value	Decision
Jarque-Bera test	0.875931	0.6452	Residuals are normally distributed
Lagrange Multiplier test	2.760178	0.1162	No serial correlation exits
Breusch-Pagan-Godfrey test	0.764537	0.6867	No heteroscedasticity exists

Fig. 6 Plot of CUSUM of Squares (critical bounds at 5% significance level)
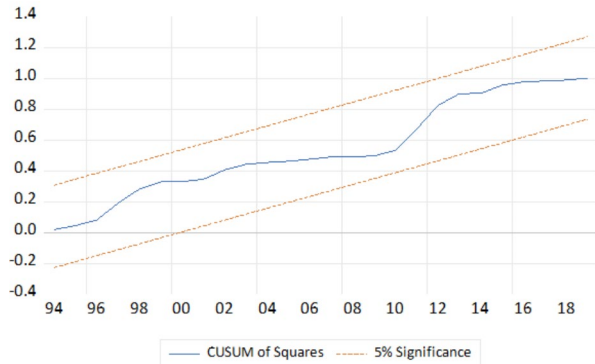
5.8 Results of Pairwise Granger causality test

The relationship between the variables indicates that there is the existence of Granger-causality, which the F-statistic determines. The summary of pairwise Granger causality is presented in Table 10, including the causality direction between the variables, such as left to right ($\rightarrow$), right to left ($\leftarrow$), and bidirectional causality ($\leftrightarrow$) when both variables cause each other. The pairwise Granger causality test results indicate that LEU and LCO2, LAGL and LCO2, LFA and LCO2, LAGL and LEU, LFA and LAGL show unidirectional causality due to statistically significance leading to the rejection of the null hypothesis. This indicates that energy use causes CO_2 emissions, agricultural land expansion causes CO_2 emissions, deforestation causes CO_2 emissions, agricultural land expansion causes energy use, and agricultural land expansion causes deforestation in Malaysia. Furthermore, the pairwise Granger causality test shows bidirectional causality between LFA and LEU, which implies that deforestation causes energy use and energy use causes deforestation.

Table 10 The results of pairwise Granger causality test

Null Hypothesis	F-statistic	Decision on N- Hypothesis	Causality Direction
LEU does not Granger Cause LCO2	0.24487***	Reject	LEU $\rightarrow$ LCO2
LCO2 does not Granger Cause LEU	2.10500	Accept	
LAGL does not Granger Cause LCO2	1.30587**	Reject	LAGL $\rightarrow$ LCO2
LCO2 does not Granger Cause LAGL	1.60623	Accept	
LFA does not Granger Cause LCO2	0.82739**	Reject	LFA $\rightarrow$ LCO2
LCO2 does not Granger Cause LFA	0.79635	Accept	
LAGL does not Granger Cause LEU	3.38347***	Reject	LAGL $\rightarrow$ LEU
LEU does not Granger Cause LAGL	0.95490	Accept	
LFA does not Granger Cause LEU	0.73902**	Reject	LFA $\leftrightarrow$ LEU
LEU does not Granger Cause LFA	1.33240*	Reject	
LFA does not Granger Cause LAGL	1.49809	Accept	LFA $\leftarrow$ LAGL
LAGL does not Granger Cause LFA	0.99517***	Reject	

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively

6 Discussion

The present study investigates the interconnection between energy use and environmental pollution for the case of Malaysia, and the empirical outcomes from the DOLS model illustrate that energy use exerts a positive and significant impact on CO_2 emissions in the long run. The result indicates that an increase in energy usage deteriorates the quality of the environment in Malaysia. Our finding is supported by several studies, such as, Adebayo (2021), Akbota and Baek (2018), Adebayo and Kalmaz (2021), Nondo and Kahsai (2020), Kirikkaleli and Kalmaz (2020), Adebayo (2020), Odugbesan and Adebayo (2020), Vo et al. (2019), Irfan and Shaw (2017), Zmami and Ben-Salha (2020), and Adebayo et al. (2020). Furthermore, our result about the positive association between energy use and CO_2 emissions by the present study is in line with other Malaysian studies by Ang (2008); Azlina and Mustapha (2012); Hossain (2011); Begum et al. (2015); and Sarkar et al. (2019). In addition, we found unidirectional causality from energy use to CO_2 emissions, which is supported by Ang (2008), Hossain (2011), Sarkar et al. (2019), Vo et al. (2019), Adebayo (2020), and Adebayo (2021).

However, energy consumption has a substantial and positive influence on CO_2 emissions, as the electricity, industrial, and transportation sectors account for a large percentage of CO_2 emissions in Malaysia. Begum et al. (2015) reported that technological advancements that increase energy efficiency (e.g., solar, wind, nuclear) are favorable to lowering CO_2 emissions while maintaining economic development. Nevertheless, Southeast Asia's renewable energy development is accelerating due to fast population expansion and limited fossil fuel supply. (Pratiwi and Juerges 2020). With the impending threat of climate change, renewable energy is viewed as a viable alternative option for sustainable development as well as climate change mitigation (Seriño 2018; Pratiwi and Juerges 2020). Renewable energy delivers significant economic advantages in addition to decreasing carbon emissions, such as increased energy availability, improved energy security, and the use of local renewable resources (Seriño 2018). As a result of the growing global environmental consciousness, it is important to shift Malaysia's energy balance to renewables in order to enable the use of sustainable energy sources and build an environmentally sustainable ecosystem.

Moreover, this research uncovers a positive link between agriculture and CO_2 emissions, implying that agricultural land expansion leads to environmental degradation. The outcome indicates that the agriculture sector is a major source of CO_2 emissions in Malaysia. However, numerous studies established the positive link between agriculture and CO_2 emissions, which supports our finding. For example, Sarkodie and Owusu (2016), Liu et al. (2017), Jebli and Youssef (2017a), Doğan (2018), Gokmenoglu and Taspinar (2018), Waheed et al. (2018), Ullah et al. (2018), Agboola and Bekun (2019), Balsalobre-Lorente et al. (2019), Burakov (2019), Qiao et al. (2019), Gokmenoglu et al. (2019), Aydoğan and Vardar (2020), Olanipekun et al. (2019), Aziz et al. (2020), Naseem et al. (2020) and Pata (2021). In addition, the present study reveals unidirectional causality from agriculture to CO_2 emissions, which is in line with the findings by Burakov (2019) and Naseem et al. (2020).

The outcome of our study suggests that traditional agricultural methods should be replaced by modern technologies, which would increase agricultural production and reduce emissions by reducing the necessity for agricultural land expansion to satisfy

the demand from the growing population. Bayrakcı and Koçar (2012) reported that diversified renewable energy sources could be introduced in agricultural activities to reduce emissions from the agriculture sector. For example, (i) solar energy can be used for lighting, product drying, and irrigation; (ii) biofuels such as bioethanol and biogas, as well as different agricultural wastes, can be utilized as energy sources; (iii) wind energy can be utilized to power generators, irrigate farms, and grind certain crops; (iv) hydropower can be used to generate energy, irrigate crops, and provide drinking water, as well as facilitating the equitable distribution of water among farmers.

Furthermore, the IPCC (2014) reported that achieving the goal of reducing GHGs emissions from the agriculture sector would not only result in a cleaner environment, but it will also provide new sources of income as more farming operations may be carried out. Various international organizations have recently developed a climate-smart agriculture (CSA) method to change agricultural growth in order to mitigate environmental damage (FAO 2019). These projects have a long-term impact on global climate change reduction and mitigation. Ridzuan et al. (2020) reported that the agriculture industry might help to reduce GHGs emissions by using correct farming techniques. Carbon release may be stored by agricultural operations when proper management and technology are used, resulting in a reduction in carbon footprint.

However, our investigation reveals that forested area has a negative impact on CO_2 emissions in Malaysia. Thus, it confirms that reducing the forested area through deforestation increases CO_2 emissions and contributes to global climate change. Instead, forest ecosystems improve the quality of the environment as the forests absorb the atmospheric CO_2 and store it in tree biomass. Our empirical finding indicates that enhancing forest carbon sink by increasing forested area mitigates environmental degradation in the long run. However, Islam et al. (2017), Waheed et al. (2018), Shittu et al. (2018), Parajuli et al. (2019), Aziz et al. (2020), and Begum et al. (2020) established a negative relationship between forested area and CO_2 emissions which validate our result. As the second-biggest source of anthropogenic CO_2 emissions into the atmosphere, forest loss has been considered a driver of environmental deterioration (IPCC 2014). Nordhaus (2006) reported that controlling deforestation is the simplest approach to reduce CO_2 emissions. Raihan et al. (2019) reported that enhancing forest carbon sequestration is the most cost-effective way to reduce environmental degradation and mitigate global climate change.

Reversing forest losses via restoration, enhancement, and conservation is a crucial aim for climate change mitigation, and it is a hot topic in today's climate debate (Matthew et al. 2018). Implementing cost-effective mitigation strategies in the forestry sector to prevent deforestation and forest degradation can reduce global carbon emissions and avert climate change at the lowest cost (Raihan et al. 2018). Furthermore, forestry-based mitigation strategies (forest protection, afforestation, natural regeneration) would serve a multifunctional purpose, including carbon sequestration, biodiversity conservation, ecosystem enhancement, and community outputs of goods and services (Raihan and Said 2021). As the forest carbon sequestration rate in Malaysia is relatively high due to the rapid growth of plants (Raihan et al. 2021), Malaysian forests have a huge potential to mitigate global climate change by reducing CO_2 emissions and increasing forest biomass by enhancing the national carbon sink through the widespread implementation of forestry-based mitigation measures.

Moreover, the pairwise Granger causality test shows bidirectional causality between deforestation and energy use which implies that deforestation causes energy use and energy use causes deforestation. However, deforestation requires machinery for timber harvesting and transportation of harvested timber to wood industries which increases energy consumption. Conversely, increased energy use from urbanization, industrialization, and agricultural production requires more land for settlement, agricultural land, building industries, road, and highways, which lead to deforestation. Furthermore, an interesting result from the pairwise Granger causality test is the significant unidirectional causality from forested area to agricultural land, implying that agricultural land expansion causes deforestation in Malaysia. However, one of the most prevalent causes of deforestation in developing nations is land clearing and conversion for agricultural use (Galinato and Galinato 2016). Agricultural growth can account for two-thirds of the change in tropical forest cover. In tropical areas, encroachment of large-scale agricultural production, small-scale agricultural production, and shifting cultivation account for 32%, 26%, and 15% of forest cover change, respectively (FAO 2010). López (2000) estimated that a one-hectare increase in the cultivated area results in a 4.4-hectare reduction in forest cover because the conversion of forest cover to agricultural land necessitates extra land clearing for human settlement and infrastructure supporting agricultural production.

Nevertheless, the environmental degradation generated by agriculture in Malaysia is linked to CO_2 emissions from deforestation due to agricultural land expansion for oil palm plantations. Uning et al. (2020) reported that oil palm production had transformed large areas of Malaysian forest ecosystems over the last three decades, and it is anticipated to be one of the primary sources of GHG emissions connected to land use. However, oil palm production is the mainstay of Malaysian agriculture that contributes the lion's share in Malaysia's economic growth. Thus, high profit from oil palm production triggers agricultural land expansion for oil palm plantations, leading to deforestation due to the scarcity of available plantation areas. Consequently, shrinkage of forested area deteriorates the quality of the environment by releasing a substantial amount of CO_2 back into the atmosphere, which was once stored in forests. Furthermore, enacting fire-related practices to remove vegetation and forest structure is part of the conversion process from forest to oil palm plantations. Controlled burning has played a key role in CO_2 emissions from oil palm production, as well as the long-term deterioration of tropical forest ecosystems. Hence, preventing forest ecosystems from being deforested for oil palm production has been identified as a major challenge in Malaysia's effort against climate change and environmental degradation.

7 Conclusion and policy implications

This study investigates the dynamic impacts of energy use, agricultural land expansion, and deforestation on CO_2 emissions by using time series data from 1990 to 2019. The current study utilized ADF and DF-GLS unit root tests to capture the integration order of the series. We applied the ARDL bounds test to capture the cointegration amongst the series. The DOLS estimator was employed to capture the long-run impacts of energy use, agricultural land expansion, and deforestation on CO_2 emis-

sions in Malaysia. In addition, We employed the FMOLS and CCR test as a robustness check to the DOLS estimation. Furthermore, the pairwise Granger causality test was utilized to check the causal relation amid study variables. The empirical findings indicate that increased energy use, agricultural land expansion, and deforestation in Malaysia have an adverse effect on environmental degradation in the long run. The policy recommendation is drawn following the study outcomes to promote green energy, climate-smart agriculture, and sustainable management of forest ecosystems that will ensure emission reduction in Malaysia.

This research's outcomes have been recommended in adopting the promotion of energy intensity diversification of Malaysia. Developing and adopting sound policies to moderate Malaysia's energy and manufacturing sector practices will improve the country's sustainable growth. If the government imposes CO_2 emission limitations on businesses and industries, this will continue to manage CO_2 pollution levels. The fear of severe action or hefty taxes for those who violate this regulation will help to reduce pollution. Furthermore, Malaysia should introduce clearer policies toward enhancing energy efficiency and energy usage programs to minimize unnecessary energy waste. To enhance energy efficiency and therefore reduce CO_2 emissions, the government should expand investment in fossil fuel energy cleansing technology. Furthermore, carbon intensity should be reduced by using more renewable energy sources for energy generation, such as hydropower, ocean power, geothermal, wind power, and solar. Government and policymakers should pay more attention to promoting renewable energy in Malaysia. Moreover, government spending on renewable energy infrastructure and scientific advancements should be increased. Malaysia must develop measures to lower the cost of renewable energy and discourage the use of fossil fuels in companies and households since renewable energy use can help to reduce emissions. Research and development of green technology should be undertaken to boost domestic investment and reduce pollution. However, because the ongoing COVID-19 epidemic has had an impact on energy consumption patterns, the government should carefully create policies. In Malaysia, for example, residential energy use has increased while transportation energy consumption has decreased. Hence, authorities should focus on boosting energy-efficient resident electric appliances and more cheap renewable options for the household sector.

However, this study recommends that the Malaysian government exercise caution when designing policies to improve agricultural production, particularly through agricultural land expansion for oil palm and rubber plantations, as this might harm the environmental quality. Increased efforts are needed to boost agricultural productivity by implementing modern agro-based technologies such as high-yield and disease-resistant crop varieties and land management, as well as encouraging farmers to abandon traditional farming practices in pursuit of more advanced agrarian techniques. Moreover, agricultural productivity and value-added component may be improved at a greater level with the help of contemporary agricultural technology and the availability of good seeds and other agricultural inputs. Sustainable agriculture by developing organic and low carbon agriculture systems can reduce emissions and enhance carbon sequestration. To achieve long-term agricultural productivity, the government should encourage more efficient energy infrastructure and support the switch to cleaner, more efficient energy sources in agriculture. Governments should

support the use of renewable energy, particularly clean renewable energy like solar and wind, because it boosts agricultural productivity while also helping to battle global warming and climate change. Subsidies for renewable energy use in agriculture, according to this study, would help the industry become more competitive on worldwide markets while emitting less pollution. For a carbon-neutral environment, irrigation methods can be switched from non-renewable to renewable energy sources. Other important agricultural changes include encouraging farming communities to use solar tube wells for irrigation, organic farming, tunnel farming, changing traditional tillage to no-till, and reducing fertilizer use to decrease environmental impact. These contemporary agriculture technologies can help large farms cut personnel, improve productivity, and cut emissions. For the sake of sustainable agriculture and pollution reduction, excessive use of fertilizers and pesticides must be avoided, and green production must be prioritized. The agriculture industry may have a significant positive impact on the environment by using an organic framework. Furthermore, boosting agricultural investment in Malaysia through improved international collaboration will aid in the reduction of emissions from Malaysia's agriculture sector.

The outcomes of our investigation recommend the policymakers in Malaysia implement effective environmental and climate-resilient policies with more focus on reducing CO_2 emissions by enhancing forest ecosystems. To reduce CO_2 emissions from deforestation, Malaysia's government should boost financial investment and implement robust forest laws and policies. Strong forest conservation policies are essential to protect biodiversity by avoiding deforestation in Malaysian forests, which are rich in species diversity. Forest conservation with the participation of the local community is a novel approach to preserve forest conservation while ensuring the local community's livelihood. Furthermore, Malaysia's forestry sector has enormous tourist potential, and encouraging forest protection through ecotourism might boost the country's economy. Moreover, through the formation of private forest plantation areas, the government should promote private investment in forest development. Malaysia, on the other hand, may improve its climate change mitigation potential by implementing many forestry-based mitigation measures, such as forest conservation, afforestation, reforestation, sustainable forest management, enhanced natural regeneration, agroforestry, urban forestry, and wood-based bioenergy. Finally, the actual implementation of forestry policy could help Malaysia to be an emission-free country by enhancing the national carbon sink while maintaining national green growth and sustainable management of the forest ecosystems.

Moreover, the results also suggest that a higher degree of energy use, agricultural land expansion, and deforestation for oil-palm plantations trigger environmental degradation in the long run, which could be reduced by implementing more structured environmental policy, agriculture policy, renewable energy policy, green technology policy, and forestry policy. Although the current study has produced substantial empirical findings in the instance of Malaysia, our analysis has numerous flaws that might be addressed in future research. One of the critical drawbacks of our analysis is the unavailability of the data related to the forested area beyond the period of study, which limits the power of the econometric techniques used. However, this study has examined the dynamic impacts of energy use, agricultural land expansion, and deforestation on CO_2 emissions in Malaysia. Further studies can explore the

other determinants of CO_2 emissions, such as urbanization, industrialization, tourism, etc. Furthermore, this study utilized CO_2 as an indicator for environmental pollution. Future research should investigate more environmental pollution indicators, such as water pollution and land pollution.

Author contributions Asif Raihan contributed to conceptualization, data curation, writing - original draft, formal analysis, methodology, and visualization. Rawshan Ara Begum contributed to conceptualization, supervision, writing - review & editing, methodology, validation, and visualization. Mohd Nizam Mohd Said and Joy Jacqueline Pereira contributed to supervision, investigation, and validation.

Declarations

Conflict of interest The authors have no conflicts of interest to declare that are relevant to the content of this article.

References

Abdullah AZ, Salamatinia B, Mootabadi H, Bhatia S (2009) Current status and policies on biodiesel industry in Malaysia as the world's leading producer of palm oil. Energy Policy 37(12):5440–5448. https://doi.org/10.1016/j.enpol.2009.08.012

Adebayo TS (2020) Revisiting the EKC hypothesis in an emerging market: an application of ARDL-based bounds and wavelet coherence approaches. SN Appl Sci 2(12):1–15. https://doi.org/10.1007/s42452-020-03705-y

Adebayo TS (2021) Testing the EKC hypothesis in Indonesia: empirical evidence from the ARDL-based bounds and wavelet coherence approaches. Applied Economics Journal 28(1): 78–100. Retrieved from https://so01.tci-thaijo.org/index.php/AEJ/article/view/242922

Adebayo TS, Akinsola GD (2021) Investigating the causal linkage among economic growth, energy consumption and CO_2 emissions in Thailand: an application of the wavelet coherence approach. Int J Renew Energy Dev 10(1):17–26. https://doi.org/10.14710/ijred.2021.32233

Adebayo TS, Kalmaz DB (2021) Determinants of CO_2 emissions: Empirical evidence from Egypt. Environ Ecol Stat 28:239–262. https://doi.org/10.1007/s10651-020-00482-0

Adebayo TS, Awosusi AA, Adeshola I (2020) Determinants of CO_2 Emissions in Emerging Markets: An Empirical Evidence from MINT Economies. Int J Renew Energy Dev 9(3):411–422. https://doi.org/10.14710/ijred.2020.31321

Adebayo TS, Awosusi AA, Kirikkaleli D, Akinsola GD, Mwamba MN (2021) Can CO_2 emissions and energy consumption determine the economic performance of South Korea? A time series analysis. Environ Sci Pollut Res 28:38969–38984. https://doi.org/10.1007/s11356-021-13498-1

Agboola MO, Bekun FV (2019) Does agricultural value added induce environmental degradation? Empirical evidence from an agrarian country. Environ Sci Pollut Res 26(27):27660–27676. https://doi.org/10.1007/s11356-019-05943-z

Ahmad M, Khattak SI, Khan A, Rahman ZU (2020) Innovation, foreign direct investment (FDI), and the energy–pollution–growth nexus in OECD region: a simultaneous equation modeling approach. Environ Ecol Stat 27(2):203–232. https://doi.org/10.1007/s10651-020-00442-8

Akaike H (1987) Factor analysis and AIC. In: Parzen E, Tanabe K, Kitagawa G (eds) Selected papers of hirotugu akaike. Springer, New York, NY, pp 371–386. https://doi.org/10.1007/978-1-4612-1694-0_29

Akbota A, Baek J (2018) The environmental consequences of growth: empirical evidence from the Republic of Kazakhstan. Economies 6(1):19. https://doi.org/10.3390/economies6010019

Alcántara V, Padilla E (2009) Input–output subsystems and pollution: An application to the service sector and CO_2 emissions in Spain. Ecol Econ 68(3):905–914. https://doi.org/10.1016/j.ecolecon.2008.07.010

Ang JB (2008) Economic development, pollutant emissions and energy consumption in Malaysia. J Policy Model 30(2):271–278. https://doi.org/10.1016/j.jpolmod.2007.04.010

Anwar A, Sarwar S, Amin W, Arshed N (2019) Agricultural practices and quality of environment: evidence for global perspective. Environ Sci Pollut Res 26(15):15617–15630. https://doi.org/10.1007/s11356-019-04957-x

Aydoğan B, Vardar G (2020) Evaluating the role of renewable energy, economic growth and agriculture on CO2 emission in E7 countries. Int J Sustain Energ 39(4):335–348. https://doi.org/10.1080/14786451.2019.1686380

Aziz N, Sharif A, Raza A, Rong K (2020) Revisiting the role of forestry, agriculture, and renewable energy in testing environment Kuznets curve in Pakistan: evidence from Quantile ARDL approach. Environ Sci Pollut Res 27(9):10115–10128. https://doi.org/10.1007/s11356-020-07798-1

Azlina AA, Mustapha NN (2012) Energy, economic growth and pollutant emissions nexus: the case of Malaysia. Procedia-Social and Behavioral Sciences 65:1–7. https://doi.org/10.1016/j.sbspro.2012.11.082

Balsalobre-Lorente D, Driha OM, Bekun FV, Osundina OA (2019) Do agricultural activities induce carbon emissions? The BRICS experience. Environ Sci Pollut Res 26(24):25218–25234. https://doi.org/10.1007/s11356-019-05737-3

Bayrakcı AG, Koçar G (2012) Utilization of renewable energies in Turkey's agriculture. Renew Sustain Energy Rev 16(1):618–633. https://doi.org/10.1016/j.rser.2011.08.027

Begum RA, Abdullah SMS, Sarkar M, Kabir S (2017) Time series patterns and relationship of energy consumption and CO_2 emissions in Malaysia. Asian J Water Environ Pollut 14(2):41–49. https://doi.org/10.3233/AJW-170014

Begum RA, Raihan A, Said MNM (2020) Dynamic Impacts of Economic Growth and Forested Area on Carbon Dioxide Emissions in Malaysia. Sustainability 12(22):9375. https://doi.org/10.3390/su12229375

Begum RA, Sohag K, Abdullah SMS, Jaafar M (2015) CO_2 emissions, energy consumption, economic and population growth in Malaysia. Renew Sustain Energy Rev 41:594–601. https://doi.org/10.1016/j.rser.2014.07.205

Burakov D (2019) Does Agriculture Matter for Environmental Kuznets Curve in Russia: Evidence from the ARDL Bounds Tests Approach. AGRIS on-line Papers in Economics and Informatics 11(3):23–34. https://doi.org/10.22004/ag.econ.294162

Chen B (2016) Energy, ecology and environment: a nexus perspective. Energy Ecol Environ 1(1):1–2. https://doi.org/10.1007/s40974-016-0017-8

Chik NA, Rahim KA (2014) Sources of change in CO_2 emissions from energy consumption by industrial sectors in Malaysia. In Proceedings for 9th Malaysian National Economic Conference (PERKEM), Terengganu, Malaysia. Retrieved from http://www.ukm.my/fep/perkem/pdf/perkem2014/PERKEM_2014_1D3.pdf

Çıtak F, Şişman MY, Bağcı B (2021) Nexus between disaggregated electricity consumption and CO_2 emissions in Turkey: new evidence from quantile-on-quantile approach. Environ Ecol Stat 28: 843–860. https://doi.org/10.1007/s10651-021-00504-5

Dickey DA, Fuller WA (1979) Distribution of the estimators for autoregressive time series with a unit root. J Am Stat Assoc 74(366a):427–431. https://doi.org/10.1080/01621459.1979.10482531

Dogan N (2016) Agriculture and Environmental Kuznets Curves in the case of Turkey: evidence from the ARDL and bounds test. Agric Econ 62(12):566–574. https://doi.org/10.17221/112/2015-AGRICECON

Doğan N (2018) The impact of agriculture on CO_2 emissions in China. Panoeconomicus 66(2):257–271. https://doi.org/10.2298/PAN160504030D

DOSM (2020) Selected Agricultural Indicators, Malaysia, 2020. Official Portal of Department of Statistics Malaysia. https://www.dosm.gov.my/

Elliott G, Rothenberg TJ, Stock JH (1996) Efficient tests for an autoregressive unit root (No. t0130). National Bureau of Economic Research

FAO (2010) Global Forest Resources Assessment 2010: Main report (Vol. 163). Food and Agriculture Organization of the United Nations, Rome. Retrieved from http://www.fao.org/3/i1757e/i1757e.pdf

FAO (2016) Food and Agriculture Organization: The State of Food and Agriculture. Retrieved from http://www.fao.org/3/a-i6030e.pdf

FAO (2019) Climate-smart agriculture. Food and Agriculture Organization of the United Nations. Retrieved from http://www.fao.org/climate-smart-agriculture/en/

Galinato GI, Galinato SP (2016) The effects of government spending on deforestation due to agricultural land expansion and CO_2 related emissions. Ecol Econ 122:43–53. https://doi.org/10.1016/j.ecolecon.2015.10.025

Gan PY, Li Z (2008) An econometric study on long-term energy outlook and the implications of renewable energy utilization in Malaysia. Energy Policy 36(2):890–899. https://doi.org/10.1016/j.enpol.2007.11.003

Granger CW (1969) Investigating causal relations by econometric models and cross-spectral methods. Econometrica 37:424–438. https://doi.org/10.2307/1912791

Gokmenoglu KK, Taspinar N (2018) Testing the agriculture-induced EKC hypothesis: the case of Pakistan. Environ Sci Pollut Res 25(23):22829–22841. https://doi.org/10.1007/s11356-018-2330-6

Gokmenoglu KK, Taspinar N, Kaakeh M (2019) Agriculture-induced environmental Kuznets curve: the case of China. Environ Sci Pollut Res 26(36):37137–37151. https://doi.org/10.1007/s11356-019-06685-8

Hansen BE, Phillips PC (1990) Estimation and inference in models of cointegration: A simulation study. Adv econometrics 8:225–248

Hansen MC, Potapov PV, Moore R, Hancher M, Turubanova SA, Tyukavina A, Thau D, Stehman SV, Goetz SJ, Loveland TR, Townshend J (2013) High-resolution global maps of 21st-century forest cover change. Science 342(6160):850–853. https://doi.org/10.1126/science.1244693

Holly R (2015) The complicated relationship between agriculture and climate change. Retrieved from http://investigatemidwest.org/2015/07/09/thecomplicated-relationship-between-agriculture-and-climate-change/

Hong SH, Wagner M (2011) Cointegrating polynomial regressions: fully modified OLS estimation and inference: Reihe Ökonomie, Institut für Höhere Studien. https://doi.org/10.1016/j.enpol.2011.01.025

Hossain MS (2011) Panel estimation for CO_2 emissions, energy consumption, economic growth, trade openness and urbanization of newly industrialized countries. Energy Policy 39(11):6991–6999. https://doi.org/10.1016/j.enpol.2011.07.042

Inekwe J, Maharaj EA, Bhattacharya M (2020) Drivers of carbon dioxide emissions: an empirical investigation using hierarchical and non-hierarchical clustering methods. Environ Ecol Stat 27(1):1–40. https://doi.org/10.1007/s10651-019-00433-4

IPCC (2014) Climate change 2014: Synthesis report. Contribution of working groups I, II and III to the fifth assessment report of the intergovernmental panel on climate change.Core writing team,1–151

IPCC (2018) Summary for Policymakers. Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty. World Meteorological Organization: Geneva, Switzerland, p 32

Irfan M, Shaw K (2017) Modeling the effects of energy consumption and urbanization on environmental pollution in South Asian countries: a nonparametric panel approach. Qual Quant 51(1):65–78. https://doi.org/10.1007/s11135-015-0294-x

Islam R, Abdul Ghani AB, Mahyudin E (2017) Carbon dioxide emission, energy consumption, economic growth, population, poverty and forest area: Evidence from panel data analysis. Int J Energy Econ Policy 7(4):99–106

Jaafar WSWM, Maulud KNA, Kamarulzaman AMM, Raihan A, Sah SM, Ahmad A, Saad SNM, Azmi ATM, Syukri NKAJ, Khan WR (2020) The Influence of Forest Degradation on Land Surface Temperature – A Case Study of Perak and Kedah, Malaysia. Forests 11(6): 670. https://doi.org/10.3390/f11060670

Jebli MB, Youssef SB (2017a) Renewable energy consumption and agriculture: evidence for cointegration and Granger causality for Tunisian economy. Int J Sustainable Dev World Ecol 24(2):149–158. https://doi.org/10.1080/13504509.2016.1196467

Jebli MB, Youssef SB (2017b) The role of renewable energy and agriculture in reducing CO_2 emissions: Evidence for North Africa countries. Ecol Ind 74:295–301. https://doi.org/10.1016/j.ecolind.2016.11.032

Kirikkaleli D, Kalmaz DB (2020) Testing the moderating role of urbanization on the environmental Kuznets curve: empirical evidence from an emerging market. Environ Sci Pollut Res 27(30):38169–38180. https://doi.org/10.1007/s11356-020-09870-2

Liu X, Zhang S, Bae J (2017) The nexus of renewable energy-agriculture-environment in BRICS. Appl Energy 204:489–496. https://doi.org/10.1016/j.apenergy.2017.07.077

Liu X, Zhang S, Bae J (2017) The impact of renewable energy and agriculture on carbon dioxide emissions: investigating the environmental Kuznets curve in four selected ASEAN countries. J Clean Prod 164:1239–1247. https://doi.org/10.1016/j.jclepro.2017.07.086

López R (2000) Trade reform and environmental externalities in general equilibrium: Analysis for an archetype poor tropical country. Environ Dev Econ 5(4):377–404. https://doi.org/10.1017/S1355770X00000243

Mahadeva L, Robinson P (2004) Unit root testing to help model building. Centre for Central Banking Studies, Bank of England, London

Matthew NK, Shuib A, Eusop MEM, Ramachandran S, Afandi SHM, Samdin Z (2018) Carbon stock and sequestration valuation in a mixed dipterocarp forest of Malaysia. Sains Malaysiana 47(3):447–455. https://doi.org/10.17576/jsm-2018-4703-04

MESTECC (2018) Official Portal Ministry of Energy, Science, Technology, Environment and Climate Change Malaysia. Retrieved from https://www.devex.com/organizations/ministry-of-energy-science-technology-environment-climate-change-mestecc-malaysia-128833

MNRE (2018) Malaysia's Third National communication (NC3) and Second Biennial Update Report submitted to the United Nations Framework Convention on Climate Change (UNFCCC) in December 2018. Ministry of Natural Resources and Environment Malaysia

MPOC (2014) Malaysian palm oil industry. Retrieved from Malaysian Palm Oil Council website, Available at: http://www.mpoc.org.my/Malaysian_Palm_Oil_Industry.aspx

Murshed M, Ferdaus J, Rashid S, Tanha MM, Islam MJ (2021) The Environmental Kuznets curve hypothesis for deforestation in Bangladesh: an ARDL analysis with multiple structural breaks. Energy Ecol Environ 6(2):111–132. https://doi.org/10.1007/s40974-020-00188-w

Naseem S, Ji TG, Kashif U (2020) Asymmetrical ARDL correlation between fossil fuel energy, food security, and carbon emission: providing fresh information from Pakistan. Environ Sci Pollut Res 27:31369–31382. https://doi.org/10.1007/s11356-020-09346-3

Nondo C, Kahsai MS (2020) The impact of energy intensity, urbanisation, industrialisation, and income on CO_2 emissions in South Africa: an ARDL bounds testing approach. Afr J Economic Sustainable Dev 7(4):307–330. https://doi.org/10.1504/AJESD.2020.106826

Nordhaus W (2006) The Stern Review on the Economics of Climate Change. HM Treasury, London. https://doi.org/10.3386/w12741

Odugbesan JA, Adebayo TS (2020) The symmetrical and asymmetrical effects of foreign direct investment and financial development on carbon emission: evidence from Nigeria. SN Appl Sci 2(12):1–15. https://doi.org/10.1007/s42452-020-03817-5

Olanipekun IO, Olasehinde-Williams GO, Alao RO (2019) Agriculture and environmental degradation in Africa: The role of income. Sci Total Environ 692:60–67. https://doi.org/10.1016/j.scitotenv.2019.07.129

Omar H, Chuah NMJ, Parlan I, Musa S (2016) Emission of CO_2 resulted from conversion of forests to agricultural landuse in Malaysia. Int J Agric Forestry Plantation 2:192–201

Parajuli R, Joshi O, Maraseni T (2019) Incorporating forests, agriculture, and energy consumption in the framework of the Environmental Kuznets Curve: a dynamic panel data approach. Sustainability 11(9):2688. https://doi.org/10.3390/su11092688

Park JY (1992) Canonical cointegrating regressions. Econometrica: Journal of the Econometric Society 60(1): 119–143. https://doi.org/10.2307/2951679

Pata UK (2021) Linking renewable energy, globalization, agriculture, CO_2 emissions and ecological footprint in BRIC countries: A sustainability perspective. Renewable Energy 173:197–208. https://doi.org/10.1016/j.renene.2021.03.125

Pesaran MH, Shin Y (1999) An autoregressive distributed lag modelling approach to cointegration analysis. In Strom S (Ed.), Econometrics and Economic Theory in the 20th century: The Ragnar Frish Centennial Symposium (pp. 371–413). Cambridge University Press. https://doi.org/10.1017/CCOL521633230.011

Pesaran MH, Shin Y, Smith RJ (2001) Bounds testing approaches to the analysis of level relationships. J Appl Econom 16(3):289–326. https://doi.org/10.1002/jae.616

Pesaran MH, Timmermann A (2005) Small sample properties of forecasts from autoregressive models under structural breaks. J Econ 129(1–2):183–217. https://doi.org/10.1016/j.jeconom.2004.09.007

Prastiyo SE, Irham, Hardyastuti S, Jamhari (2020) How agriculture, manufacture, and urbanization induced carbon emission? The case of Indonesia. Environ Sci Pollut Res 27(33):42092–42103. https://doi.org/10.1007/s11356-020-10148-w

Pratiwi S, Juerges N (2020) Review of the impact of renewable energy development on the environment and nature conservation. Southeast Asia Energy Ecology and Environment 5:221–239. https://doi.org/10.1007/s40974-020-00166-2

Qiao H, Zheng F, Jiang H, Dong K (2019) The greenhouse effect of the agriculture-economic growth-renewable energy nexus: evidence from G20 countries. Sci Total Environ 671:722–731. https://doi.org/10.1016/j.scitotenv.2019.03.336

Raihan A, Begum RA, Said MNM, Abdullah SMS (2019) A Review of emission reduction potential and cost savings through forest carbon sequestration. Asian J Water Environ Pollut 16(3):1–7. https://doi.org/10.3233/AJW190027

Raihan A, Begum RA, Said MNM, Abdullah SMS (2018) Climate change mitigation options in the forestry sector of Malaysia. J Kejuruteraan SI 1(6):89–98. https://doi.org/10.17576/jkukm-2018-si1(6)-11

Raihan A, Begum RA, Said MNM, Pereira JJ (2021) Assessment of carbon stock in forest biomass and emission reduction potential in Malaysia. Forests 12(10):1294. https://doi.org/10.3390/f12101294

Raihan A, Said MNM (2021) Cost–Benefit Analysis of Climate Change Mitigation Measures in the Forestry Sector of Peninsular Malaysia. Earth Syst Environ 5:1–15. https://doi.org/10.1007/s41748-021-00241-6

Rafiq S, Salim R, Apergis N (2016) Agriculture, trade openness and emissions: an empirical analysis and policy options. Australian J Agricultural Resource Econ 60(3):348–365. https://doi.org/10.1111/1467-8489.12131

Reynolds L, Wenzlau S (2012) Climate-Friendly Agriculture and Renewable Energy: Working Hand-in-Hand toward Climate Mitigation. Renewable Energy World. Retrieved from https://www.renewableenergyworld.com/baseload/climate-friendly-agriculture-and-renewable-energy-working-hand-in-hand-toward-climate-mitigation/#gref

Ridzuan NHAM, Marwan NF, Khalid N, Ali MH, Tseng ML (2020) Effects of agriculture, renewable energy, and economic growth on carbon dioxide emissions: Evidence of the environmental Kuznets curve. Resour Conserv Recycl 160:104879. https://doi.org/10.1016/j.resconrec.2020.104879

Saboori B, Sulaiman J, Mohd S (2012) Economic growth and CO_2 emissions in Malaysia: a cointegration analysis of the environmental Kuznets curve. Energy policy 51:184–191. https://doi.org/10.1016/j.enpol.2012.08.065

Saboori B, Rasoulinezhad E, Sung J (2017) The nexus of oil consumption, CO_2 emissions and economic growth in China, Japan and South Korea. Environ Sci Pollut Res 24(8):7436–7455. https://doi.org/10.1007/s11356-017-8428-4

Sam CY, McNown R, Goh SK (2019) An augmented autoregressive distributed lag bounds test for cointegration. Econ Model 80:130–141. https://doi.org/10.1016/j.econmod.2018.11.001

Sarkar MSK, Al-Amin AQ, Mustapa SI, Ahsan MR (2019) Energy consumption, CO_2 emission and economic growth: empirical evidence for Malaysia. Int J Environ Sustain Dev 18(3):318–334. https://doi.org/10.1504/IJESD.2019.101036

Sarkar MSK, Begum RA, Pereira JJ (2020) Impacts of climate change on oil palm production in Malaysia. Environ Sci Pollut Res 27(9):9760–9770. https://doi.org/10.1007/s11356-020-07601-1

Sarker B, Khan F (2020) Nexus between foreign direct investment and economic growth in Bangladesh: an augmented autoregressive distributed lag bounds testing approach. Financial Innov 6(1):1–18. https://doi.org/10.1186/s40854-019-0164-y

Seo SN (2016) Modeling farmer adaptations to climate change in South America: a micro-behavioral economic perspective. Environ Ecol Stat 23(1):1–21. https://doi.org/10.1007/s10651-015-0320-0

Seriño MNV (2018) Diversification of nonhydro renewable energy sources in developing countries. Energy Ecol Environ 3(6):317–329. https://doi.org/10.1007/s40974-018-0106-y

Shittu WO, Musibau H, Hassan S (2018) Revisiting the environmental Kuznets curve in Malaysia: the interactive roles of deforestation and urbanisation. Int J Green Econ 12(3–4):272–293. https://doi.org/10.1504/IJGE.2018.097872

Stock JH, Watson MW (1993) A simple estimator of cointegrating vectors in higher order integrated systems. Econometrica: J Econometric Soc 61(4):783–820. https://doi.org/10.2307/2951763

Tam GHF, Hung YS, Chang C (2013) Meta-analysis on gene regulatory networks discovered by pairwise granger causality. In 7th International Conference on Systems Biology, pp. 123–128

Tong T, Ortiz J, Xu C, Li F (2020) Economic growth, energy consumption, and carbon dioxide emissions in the E7 countries: a bootstrap ARDL bound test. Energy Sustain Soc 10(1):1–17. https://doi.org/10.1186/s13705-020-00253-6

Uddin MMM (2021) Revisiting the impacts of economic growth on environmental degradation: new evidence from 115 countries. Environ Ecol Stat 28(1):153–185. https://doi.org/10.1007/s10651-020-00479-9

Ullah A, Khan D, Khan I, Zheng S (2018) Does agricultural ecosystem cause environmental pollution in Pakistan? Promise and menace. Environ Sci Pollut Res 25(14):13938–13955. https://doi.org/10.1007/s11356-018-1530-4

Uning R, Latif MT, Othman M, Juneng L, Hanif NM, Nadzir MSM, Maulud KNA, Jaafar WSWM, Said NFS, Ahamad F, Takriff MS (2020) A Review of Southeast Asian Oil Palm and Its CO_2 Fluxes. Sustainability 12(12):5077. https://doi.org/10.3390/su12125077

Vo AT, Vo DH, Le QTT (2019) CO_2 emissions, energy consumption, and economic growth: New evidence in the ASEAN countries. J Risk Financial Manage 12(3):145. https://doi.org/10.3390/jrfm12030145

Waheed R, Chang D, Sarwar S, Chen W (2018) Forest, agriculture, renewable energy, and CO_2 emission. J Clean Prod 172:4231–4238. https://doi.org/10.1016/j.jclepro.2017.10.287

Wang KM (2012) Modelling the nonlinear relationship between CO_2 emissions from oil and economic growth. Econ Model 29(5):1537–1547. https://doi.org/10.1016/j.econmod.2012.05.001

Wang L, Vo XV, Shahbaz M, Ak A (2020) Globalization and carbon emissions: Is there any role of agriculture value-added, financial development, and natural resource rent in the aftermath of COP21? J Environ Manage 268:110712. https://doi.org/10.1016/j.jenvman.2020.110712

Winterhalder M, Schelter B, Hesse W, Schwab K, Leistritz L, Klan D, Bauer R, Timmer J, Witte H (2005) Comparison of linear signal processing techniques to infer directed interactions in multivariate neural systems. Sig Process 85(11):2137–2160. https://doi.org/10.1016/j.sigpro.2005.07.011

World Bank (2021) World Development Indicators (WDI), Data series by The World Bank Group, The World Bank: Washington, DC, USA, 2021. Retrieved from https://databank.worldbank.org/source/world-development-indicators

Yamada T, Watanabe K, Okuda T, Sugimoto T, Azlin YN (2016) Growth and survival of trees planted in an oil palm plantation: Implications for restoration of biodiversity. J Trop For Sci 28(1):97–105. https://www.jstor.org/stable/43748083

Yusoff S, Mohamed Z, Ahmad AZ (2019) Environmental impact evaluation of rubber cultivation and industry in Malaysia. Clim Change Agric 20(6):1–14. https://doi.org/10.5772/intechopen.84420

Zhang L, Li Z, Kirikkaleli D, Adebayo TS, Adeshola I, Akinsola GD (2021) Modeling CO_2 emissions in Malaysia: an application of Maki cointegration and wavelet coherence tests. Environ Sci Pollut Res 28:26030–26044. https://doi.org/10.1007/s11356-021-12430-x

Zhang L, Pang J, Chen X, Lu Z (2019) Carbon emissions, energy consumption and economic growth: Evidence from the agricultural sector of China's main grain-producing areas. Sci Total Environ 665:1017–1025. https://doi.org/10.1016/j.scitotenv.2019.02.162

Zmami M, Ben-Salha O (2020) An empirical analysis of the determinants of CO_2 emissions in GCC countries. Int J Sustainable Dev World Ecol 27(5):469–480. https://doi.org/10.1080/13504509.2020.1715508

Authors and Affiliations

Asif Raihan[1] · Rawshan Ara Begum[2] · Mohd Nizam[1] · Mohd Said[1,3] · Joy Jacqueline Pereira[4]

✉ Asif Raihan
  asifraihan666@gmail.com

✉ Joy Jacqueline Pereira
  joy@ukm.edu.my

[1] Institute of Climate Change, Universiti Kebangsaan Malaysia, 43600 Bangi, Selangor, Malaysia

[2] Centre for Corporate Sustainability and Environmental Finance, Macquarie University, 2109 Sydney, Australia

[3] Department of Biological Sciences and Biotechnology, Faculty of Science and Technology, Universiti Kebangsaan Malaysia, 43600 Bangi, Selangor, Malaysia

[4] Southeast Asia Disaster Prevention Research Initiative (SEADPRI), Institute for Environment and Development (LESTARI), Universiti Kebangsaan Malaysia, 43600 Bangi, Selangor, Malaysia