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Wind energy, industrial-economic development and CO_2 emissions nexus: Do droughts matter?

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ABSTRACT

This study empirically explored the nexus of wind energy (with regards to the effect of the drought), industrial-economic development, and emitted CO_2 in 41 World's top countries in wind energy consumption from 1997 to 2018. Cross-sectional augmented distributed lag estimators (CS-DL, CS-ARDL, CCE-P) and newly updated estimation packages to effectively assess the relationships between variables. Our results are the following: First, severe droughts were not a significant matter in wind energy, and consuming wind energy reasonably contributes to reducing emitted CO_2, while industrial and economic development positively promotes CO_2 emissions in sampled countries. Second, industrial development significantly promotes economic growth, while wind energy use has an insignificant positive effect on economic growth. Moreover, wind energy negatively affects industrial development. Third, two-way directional causal relationships were noted between CO_2 and other covariates, this hypothesis was also noted between industrial development and economic growth and wind energy use. We, therefore, suggested policy implications to reduce CO_2 across the globe and country-specific and consider the positive effect of wind energy on growth.

Abbreviations list:

CO_2	Carbon dioxide emissions
CS-DL	Cross-sectional augmented distributed lags
CS-ARDL	cross-sectional augmented Autoregressive distributed lags
CCE-P	common corrected effect pooled
UNFCCC	United Nations Framework Convention on Climate Change
EIA	U.S. Administration Information Agency
OECD	Organization for Economic Cooperation and Development
GDP	Gross Domestic Product
DOLS	dynamic ordinary least square
PARDL	panel Autoregressive distributed lags
MG	mean group
PMG	Pooled Mean Group
UNSD	United Nations Statistics Division database
ID	industrial development
WE	wind energy use
GWh	Gigawatt hours
kWh	Kilo-Watt hours

1. Introduction

Achieving environmental decarbonization policies (low-carbon and net-zero carbon emissions) requires a reasonable offer from governmental officials. For instance, accelerating the global economy through industrial development coupled with intensive natural resources exploration can be applied in terms of depleting carbon emissions towards low-carbon emissions [1], which on the other hand, reduces the growth rate. And yet, as it is a global policy for reaching environmental sustainability, some countries may shrink dependence on traditional economic growth indicators, such as using unfriendly energy consumption. In this respect, practical global CO_2 mitigation strategies have been initiated: (1) in 1992, a policy named "*the United Nations Framework Convention on Climate Change*" (UNFCCC) was proposed; around 1997, the Tokyo protocol was established [2,3]; Copenhagen agreement signed in 2009 [4]; the China-USA convention agreed in 2014, and Paris agreement established in 2015. Through their effective effort, reasonable achievements toward environmental sustainability have been marked [5,6].

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To support the above CO_2 mitigation policies, the green growth policy[1] has been proposed to accelerate emissions reduction strategies, although Hickel and Kallis (2020)[7] argued that this policy is realistically impossible due to it relying on an absolute decoupling[2] strategy. From their estimates, statistical results reveal that a green economy increase can be achieved at a very low growth rate (less than 1% annual rate), however, some countries choose to growingly depend on traditional economic growth tactics for maintaining the growth rate of an economy, while are damaging environment through emitting a massive metric ton of CO_2.

The Advanced global responses to the emissions rely on renewable energy projects, which are gradually replacing non-renewable energy, for instance, renewables (solar, wind, geothermal, and others) are being used for cooking, green transportation, manufacturing, and others [8–13]. Some literature argued that the higher dependence on traditional energy, higher carbon emissions releases, and the situation changes within development categories [14–18]. Like other renewables, Wind energy is at a good stage in developed and developing countries to replace fossil fuel and coal combustion as well as accelerate the advanced CO_2 reduction Agenda. For instance, wind power and hydroelectricity are mostly dominating other renewable energies [19,20], more specifically, wind production reached 837 GW with a 12.4% increment in 2021 [21], which it to be the second most renewable after solar energy (23% growth) due to high wind capacity in several regions and followed by hydropower and geothermal energy [22]. These energy projects lead to positive results in economic determinants, such as industrial development, manufacturing, transportation, and others globally and regionally and country-specific [23,24]. Drought phenomena, on the other hand, eventually influence renewable energy generation in several countries, for instance, Atirah et al. (2021)[25] argued that the drought phenomenon affected renewable energy generation, such as hydro-power and biomass energy, and affects CO_2 in the Association of Southeast Asian Nations (ASEAN). Particularly, the drought phenomenon reduces wind speed and leads to wind energy generation depletion [26,27].

Various studies confirm that consuming renewable energies reasonably contributes to economic increment at the global level as well as in some countries [28,29]. Especially, wind energy has a high dominance in boosting socio-economic development in rural villages in developed countries [30]. In this regard, some countries explored their available renewable energy resources, whereas, wind energy generation and consumption have been promoted globally, and are playing a significant role to reduce CO_2 [31–33]. Unfortunately, the CO_2 reduction due to wind energy utilization is not coinciding with the current global environmental status, whereas, the direct view of wind energy and emissions reveals that as wind energy increase, CO_2 increase, see Fig. 1. In this case, deeply investigating the specific impact of wind energy use on responding to emitted CO_2 across the globe can bring a scientific contribution to environmental sustainability.

Due to energy use being mostly a mixture with the purpose of economic growth, consuming energy while ignoring distinguishing energy proxies (nonrenewable and renewable energies) can lead to an increase in the economy of the country at the cost of the environmental scandal. For instance, some studies indicated that using energy in total (mixed energy types) in the development sector promotes economic growth across countries located in low-, lower-, and upper-middle-income [34,35]. While some studies argued that although some energy types promote economic growth, destroy the environment through increasing CO_2 [15,36]. This scenario is supported by the quick view of simultaneous global increment in wind energy consumption, economic growth, and CO_2, see Figs. 1 and 2. In this context, suitable estimators, which can separately estimate the impact of each energy type on carbon emissions are of importance to accelerating the global decarbonization Agenda, including the transition from low-carbon to net-zero carbon cities[3], and allow environmental policymakers to accordingly establish suitable responses [1].

Criticisms, on the other hand, were raised on economic development dependencies, such as financial development, trade-in terms of export and import, real gross domestic product, and others for their significant share to promote CO_2 across the globe and regions. Available results showed that globalization influences economic development among countries with economic differences and expenditures, and leads to degrading environments in developing and underdeveloped countries [37–39]. Existing studies showed directional causation impact, moving from growth to CO_2 in G7 countries [40], and economic growth promotes inclining trends in CO_2 in China [41]. Besides, Shahbaz et al. (2013)[42] showed that international trade and financial development contribute to compact CO_2. Peters and Hertwich, (2008) [43] showed that the share of international trade in CO_2 was very high in the last two decades, whereas over 5.3 Gt of CO_2 emissions were estimated to be embodied in international trade. The significant increment of CO_2 was noted due to export and imports in the US-China trade [44], and shreds of evidence reveal that China's domestic trade activities promote CO_2 increment [45].

Furthermore, scientific studies highly debated the case of industrial and economic development linkage in developing and developed countries [46,47]. Though their results revealed that industrial development positively affects growth, it invades environmental sustainability in several countries [38]. Shahbaz et al. (2014) found the environmental Kuznets relations between industrial development and carbon emissions, and the causal relationship moves from international trade to industrial development in Bangladesh. Muhammad et al. (2022) argued that industrial development declines environmental efficiency and secondary industry negatively and severely affects environmental sustainability in developing and developed countries. The contradicted results were noted in some literature and reinforced by the global direct view of relative increment between industrial development (Fig. 3C) and economic growth (Fig. 2), which is proportional to CO_2 increment (Fig. 1). However, the influence of consuming wind energy on industrial evolution is not discussed, which may be one of the effective mechanisms for reducing industrial CO_2 across the globe.

Based on the overview of previous literature, our study contributes to the four-fold novel findings: First, this study is the first to simultaneously examine the impact of wind energy, industrial and economic growth on emissions. We noted that analyzing the causal effect between these variables in the World's top-wind energy consumers could bring new understanding into achieving low-carbon emissions and net-zero carbon emissions and a green growth economy. Second, we noted that it is important to detect the presence of drought phenomenon in the panel of considered countries, as some studies argued that drought reduces wind energy. From this, we can investigate if the observed significant peaks in drought coincide with peaks in wind energy. Third, this is the first study conducted to examine the impact of wind energy on industrial and economic growth in the selected countries. Moreover, the

[1] By ***UNEP***, *green growth is "one that simultaneously grows income and improves human well-being, while significantly reducing environmental risks and ecological scarcities". By* ***World Bank***, *it is "economic growth that is efficient in its use of natural resources, clean in that it minimizes pollution and environmental impacts, and resilient in that it accounts for natural hazards and the role of environmental management and natural capital in preventing physical disasters* (World Bank, 2012)*". By* ***OECD***" *fostering economic growth and development while ensuring that natural assets continue to provide the resources and environmental services on which our well-being relies* (OECD, 2011)".

[2] *The ratio of GDP and domestic materials consumption which estimated from relatively decoupling GDP from resource use and carbon emissions* [98–100].

[3] Net-zero carbon cities: In December 2020, around 800 global cities committed to achieving a neutral-carbon cities/climate-neutral cities relying on balancing carbon removal from the atmosphere and completely zero urban carbon emissions.

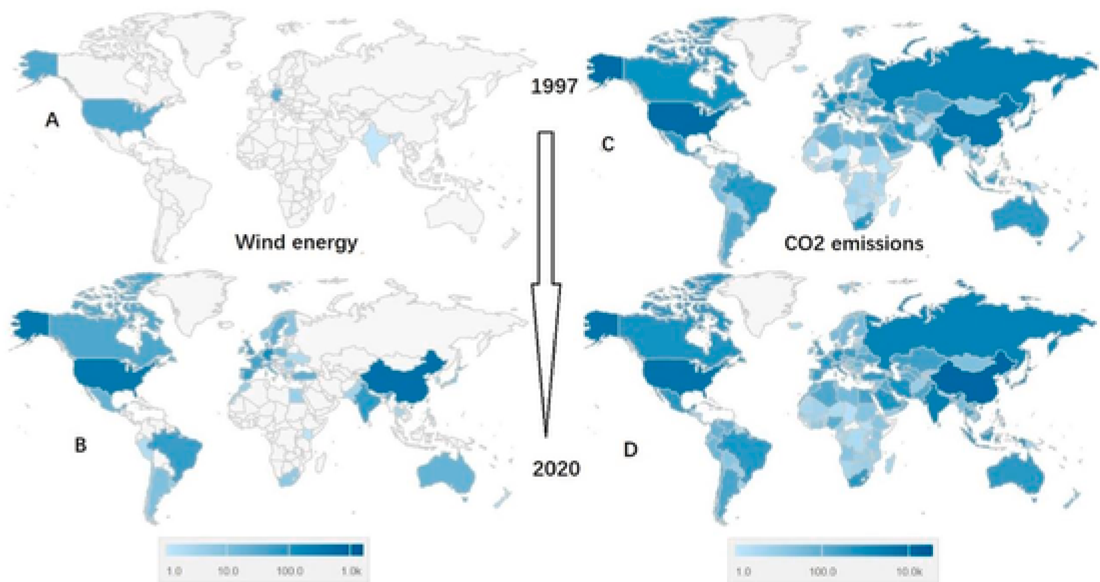

Fig. 1. Wind energy generation and consumption from 1997 (A) to 2020 (B) and CO_2 emissions increment from 1997 (C) and 2020 (D).

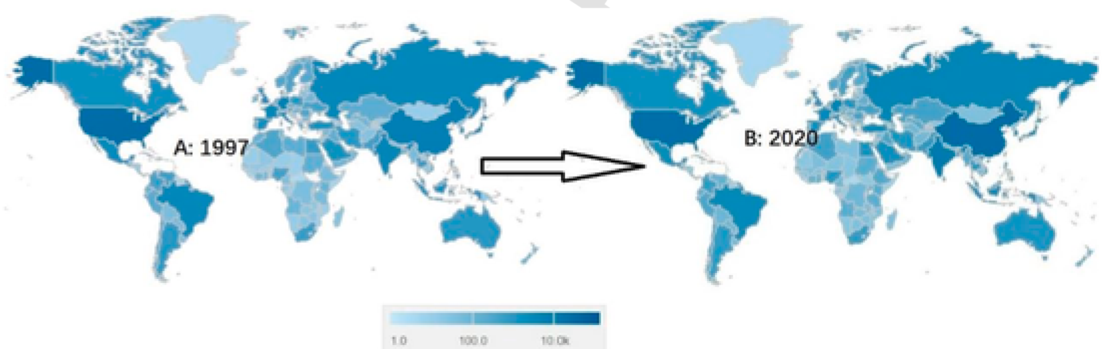

Fig. 2. The global economic growth from 1997 (A) to 2020 (B).

previous studies have used methods, which are restricted to trucking the level of cross-sectionally dependence and ignoring heterogeneities and collinearities among variables. Four, this study contributes to employing the most recent estimators and new estimation codes, that built by Chudik and Peraran [50,51] and updated estimating packages (xtdcce2) proposed by Ditzen, (2021)[52]. The most preferable estimators are cross-sectional augmented distributed lags (CS-DL), cross-sectional Autoregressive distributed lags (CS-ARDL), and common corrected effect pooled (CCE-P). These approaches effectively respond to any strongest level of cross-sectional dependence, to detect the existence of collinearities and heteroscedasticity. The exponent of the cross-sectional dependence test established by Bailey et al. (2016)[53] and the new package (xtcse2) proposed by Ditzen, (2018)[54] have been applied to evaluate the strength of cross-sectional dependence between variables.

In brief, existing studies are unable to show the long-run link between wind energy use, industrial-economic development, and emitted CO_2 in the sampled countries rich in wind energy. However, this paper adds input to the understanding of the contribution of wind energy use, and industrial and economic development in decarbonization strategies. This study, furthermore, examines whether wind energy can respond to both economic growth increment and CO_2 reduction in the World's top countries, which generate and consume wind energy. We focused on the countries which produce a high extent of wind energy across the globe from 1997 to 2018. The most recent estimators coupled with updated estimating packages ought to be employed. The study results are potential for environmental policymakers for establishing suitable strategies toward global net-zero carbon.

The rest of this study is presented as follows: Section 2 is the literature review. Section 3 discusses the methodology and data, section 4 provides the empirical results, discussion and section 5 present the conclusion and policy implications.

2. Overview of related studies

Currently, wind energy generation has considerably increased globally, not only does producing and consuming wind energy have less impact on the environment than other energy sources (EIA, 2022)[55], but also economic input from industrial productivity via jobs creation during wind power sector installation and reducing energy costs for businesses and local communities. For instance, in China, as the top wind energy producer, energy efficiency and its driving forces are the potentials for efficiency improvement and environmental [56,57], and the variability of energy prices affects the stock price of new energy companies [58]. From these facts, a surging number of countries are increasing wind energy resources exploration, such as China, the USA, Germany, the UK, and India are the 2020-top countries in wind energy generation with 30%, 21%, 8%, 5%, and 4% share in World wind energy generation, respectively. Approximately 3.6 billion kWh of wind energy was produced in 16 countries in 1990, 340 billion kWh has been produced by 105 countries in 2020, while in 2022, 1597 billion kWh was generated by 129 countries [59]. It was recently, predicted that

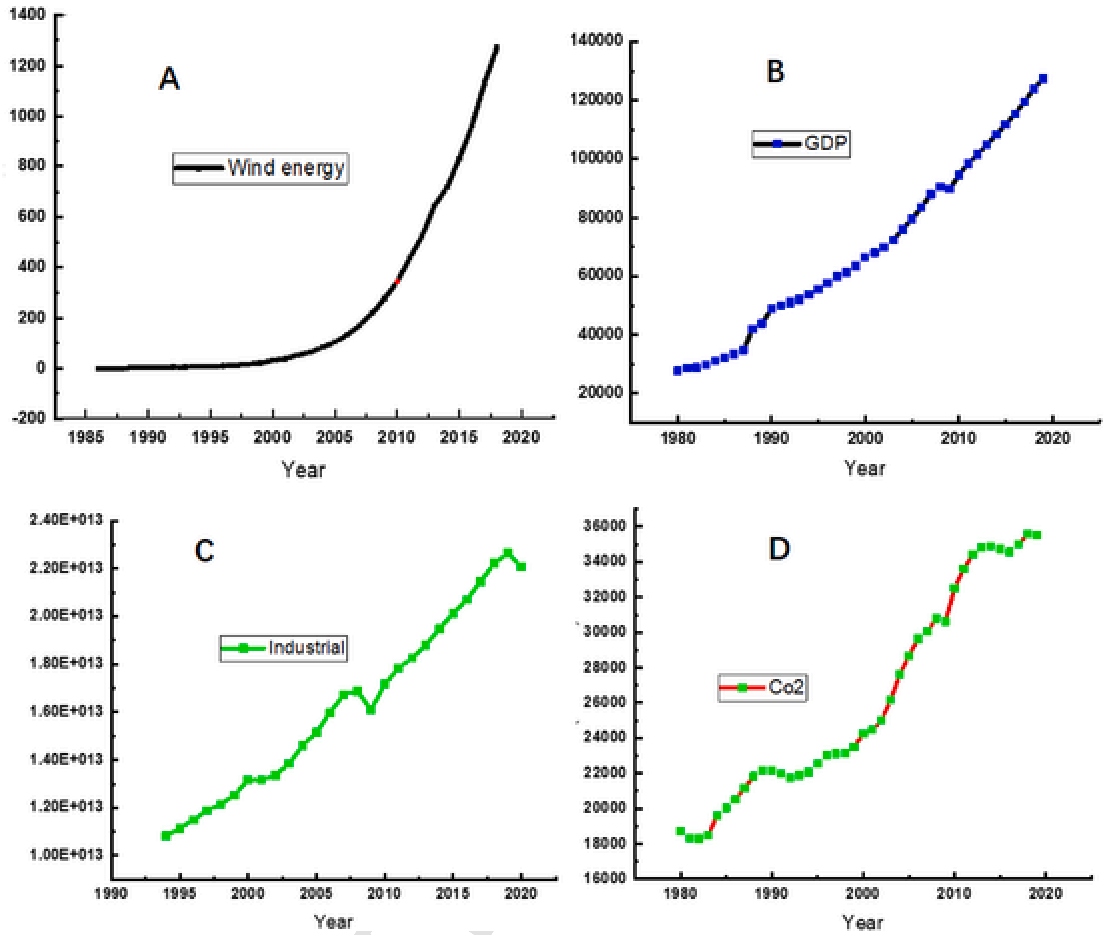

Fig. 3. The global trends in wind energy measured in GW (A), GDP (billions of 2015 US dollars, B), industrial development (2015 US dollars, C), and CO2 emissions (millions of metric tons, D).

wind energy was supposed to have a share of 43.1% of mixed renewable energy resources in European countries by 2020 on the condition that all countries could pay the possible offer to generate wind energy [60,61]. Fig. 3 shows the dramatic increment trends in wind electricity use, economic development, industrial development, and CO_2 from 1997 to 2020 across the globe. Very few studies investigated the impact of the drought phenomenon on wind energy generation, which may indirectly or directly influence the impact of wind energy use on economic growth and CO_2. For example, Urban and Mitchell, (2011) argued that the drought phenomenon reduces wind energy through wind speed reduction.

The nexus of energy proxies and economic growth is reasonably debated for the last three decades, for instance, recent studies showed that consuming energy in the total lead to significant growth in the economy, mostly in developing, and developed countries [62–64]. Yu et al. (2018)[65] showed that the demographic move to small and aging households will increase carbon emissions due to the high consumption of energy in less developed provinces in China, and also improved infrastructure is noted to positively influence air quality [66]. The impact of manufacturing was noted to stimulate growth when it incorporated with energy efficiency, which leads to CO_2 reduction [67]. Some researchers distinguished energy proxies, some focused on renewable energy and the economic growth nexus, their results indicated that consuming renewable energy has a positive contribution to economic growth globally and regionally [28,29,62,68]. The research found, on the other hand, the disturbance of consuming renewable energy to the development of middle and upper-income countries [69]. There is a probability that the positive impact of renewable energy on economic growth implicitly enhances the reasonable contribution of economic growth on CO_2 increments globally. For instance, the inverted-U-shaped impact was noted between economic development and emitted CO_2 [41,70].

However, the wind energy use and economic development nexus was rarely discussed, for instance, one study conducted on the wind energy-growth nexus over 23 developed countries between 2004 and 2016, indicated that wind energy growth leads to a positive impact on economic development [71]. Duarte et al. (2022) investigated the impact of rural development compatibility on environmental goals, results indicated that socio-economic compatibility and environmental aims difficulty can be achieved in rural regions, and wind energy will have a temporal income to boost socio-economic development in developed countries. A typical example is in USA, wind energy installation noted to stimulated the socio-economic development via job creations and boosting the local economy [72]. Similarly, the European Union economy is stimulated by the wind energy industry globalization [73].

Industrial development, is ahead of World economic development, which is strongly correlated to CO_2, and steelmaking is among the most energy and carbon-intensive industries with 7% of global CO_2 in 2020. Referring to the recent EIA report on carbon and energy use in the industries sector, the 2050 predictions reveal that carbon intensity will be reduced by 31%, while renewable energy will be increased by 9% in the OECD, which presents less than 1/10 of World steelmaking. Carbon intensity will be reduced in China (the global largest country in steel production) by 14% in 2050, with an increment in renewable energy generation (EIA, 2022). With the lack of enough literature on wind energy's impact on CO_2, Kuşkaya and Bilgili, (2020) detected the effect of wind energy use on CO_2 and greenhouse gas in the USA from 1981 to 2017, results showed that wind energy utilization negatively and positively affects both greenhouse gas and CO_2 during the different periods. More specifically, the consumption of wind energy reduced CO_2 in 2015–2017, while the results were contrary in 1999–2002.

Industrial development, on the other hand, can implicitly and explicitly contribute to increasing CO_2. The direct link between industrial development and emissions has been noted in industrial activities [75–78]. Precisely, the inverted-U-shaped link was noted between emitted CO_2 and industrial development [48,49]. The positive contribution of industrial development to economic growth can lead to the indirect impact of industrial development on CO_2, due to economic development positively affecting CO_2 [46,47]. Therefore, we noticed that it is interesting to study the effect of wind energy on emitted CO_2 and both the direct and indirect impact of industrial development on emissions in the countries, which produce a high level of wind energy.

Although there is very little literature that investigated the impact of wind energy usage, industrial development, and economic growth on emitted carbon emissions, the above studies have mostly employed first-generation estimators for examining the causal relations between carbon emissions and their determinants. Estimators classified in first-generation, including dynamic ordinary least square (DOLS), panel Autoregressive distributed lags (ARDL), and others, while other estimators located in second-generation estimators, including common corrected effect pooled (CCE-P), mean group (MG), Pooled Mean Group (PMG), and others have rarely employed. For instance, PMG has been used to detect the link between green ecological performance, green innovation, and green finance across 57 developing countries from 2002 to 2016, results revealed the positive side-effect of finance and environmental quality on innovation [79]. Panel autoregressive distributed lag (PARDL) has been employed to detect the effect of fossil fuel combustion and economic growth on CO_2 emissions in some countries in the Asian region. Results indicated the U-shape relationship between emissions and growth, while fossil fuel contributes to increasing CO_2 [80]. Other methods, such as Morlet wavelet coherence analysis have been applied to detect the impact of wind energy on greenhouse gas, results showed that wind energy can negatively and positively affect environmental quality during different periods in the USA [74]. The displacement method was used to estimate the long-run impact of wind energy generation on CO_2 reduction, revealed that the yearly displacement carbon emissions factor by wind energy can be changed from 422 to 741 tons CO_2 per GWh in 2015 to 222. The results show that the annual displacement emission factor by wind energy may vary from about 422 to 741 tons of CO_2 per GWh in 2015 to about 222–515 tons of CO_2 per GWh in 2050. The displacement estimator prediction shows that CO_2 reduction diverges about 6600–13100 metric tons of CO_2 between 2015 and 2050 [31]. A spatial panel approach has been employed to examine the impact of economic globalization on emitted CO_2 across 83 countries [38]. These estimators and among others are from first and second generations estimators characterized by several limitations and restrictions during the estimation, which may lead to biased conclusions, however, using the most recent methods can lead to robust results and conclusions.

3. Methods and data

3.1. Data description

This study has used time-varying data from 1997 to 2018 and has mined from different databases across 41 World's top countries, which are highly produced and consume wind energy, see Appendix A for the selected countries list. wind energy consumption and emitted CO_2 have been extracted from the US Energy Information Administration database (EIA) [59]. The World Bank database has been mined to get the gross domestic product (GDP) [36]. While United Nations Statistics Division database (UNSD) [81] has been used to extract industrial development-related data. The wind energy consumption measured in Quadrillion Btu, GDP per capita (used as economic growth) in constant 2010 US. dollars, industrial development (expressed as the amount of the added value of the industry to GDP), and emitted CO_2 measured in metric tons. All variables have reformed into the natural logarithm, for avoiding possible heteroscedasticity, which leads to robust results. Table 1 presents descriptive statistics of all selected variables, which indicate the normality of data via skewness, kurtosis, and Jarque-Bera coefficients, and stardard deviations and mean lead to the use of parametric tests for estimating regressions between variables.

3.2. Econometric model

This article merely on examining the relationships between wind energy, industrial development, and economic growth, CO_2 emissions in the World's top-wind energy consumers. To efficiently access the impact of regressors on CO_2, some inputs of economic growth, including capital assets, and labor were assumed to be invariant on CO_2. We, furthermore, examine the contribution of wind energy to the growth of the economy by employing labor and capital as regulators. Therefore, for the nation i at the time t, CO_2 emission can be expressed as the function below:

$$CO2_{it} = f\left(WE_{it}, ID_{it}, EG_{it}\right) \tag{1}$$

Where $i = 1, 2, \ldots N$ indicates the sampled nation, $t = 1, 2, \ldots T$ period, $CO2_{it}$ is the CO_2 emission, ID_{it} is industrial development, WE_{it} is wind energy, and EG_{it} is economic growth. To compute the long-run equilibrium quantities, Eq. (1) can be rewritten as follow:

$$lnCO2_{it} = \alpha_{0i} + \alpha_{1i} lnWE_{it} + \alpha_{2i} lnID_{it} + \alpha_{3i} lnEG_{it} + \varepsilon_{it} \tag{2}$$

For α_{0i} is the static impact, $\alpha_1 - \alpha_3$ are coefficients to be estimated, while ε_{it} is the residual.

3.3. The exponent of the cross-sectional dependence test

Pesaran, (2004) built Lagrange Multiplier (LM) and CD[4] cross-sectional dependence tests effective for large panel datasets, and Breusch and Pagan, (1980) established the Breusch-Pagan[5] LM cross-sectional dependence test for examining the cross-sectional dependence in a small panel dataset. Bailey et al. (2016) proposed the exponent of the cross-sectional dependence test to evaluate the strength of the cross-sectional dependence between variables identified by the Pesaran and Breusch tests. The simple consistency estimate of the cross-sectional dependence exponent can be expressed as follow:

$$\alpha = 1 + \frac{1}{2}\frac{\ln\left(\delta_x^2\right)}{\ln(N)} - \frac{\delta_N^2}{2\left[N\ \ln(N)\right]\delta_x^2} \tag{3}$$

Where α and δ_x^2 are the alpha exponent value of cross-sectional dependence and variance of the variable to be tested, respectively, and N is the variable size. Alpha measured in a constant $0 \le \alpha \le 1$, is the strength of features, and based on the boundaries of alpha, [84] proposed four levels of cross-sectional dependence in the variable. These levels are weak ($\alpha = 0$), semi-weak, ($0<\alpha<0.5$), semi-strong ($0.5 \le \alpha<1$), and strong ($\alpha = 1$).

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[4] *Pasaran CD and LM cross-sectional dependence test are potential for large panel data size N and time T, can be estimated from the following equation:* $CD = \left[\frac{2}{n(n-1)}\right]^{1/2} \sum_{i=1}^{n-1}\sum_{j=i+1}^{n} T_{ij}\rho_{ij}^2$ and $LM = \left[\frac{1}{n(n-1)}\right]^{1/2} \sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\left(T_{ij}\rho_{ij}^2 - 1\right)$, *approximately to follow normal distribution,* $N(0,1)$

[5] *Breusch-pagan LM test is potential for small panel data with size N, and time T, and can be estimated as follow:* $BLM = \sum_{i=1}^{n-1}\sum_{j=i+1}^{n} T_{ij}\rho_{ij}^2 \longrightarrow \chi^2\left[\frac{n(n-1)}{2}\right]$

Table 1
Descriptive statistics.

	lnCO2	lnEG	lnID	lnWE
Mean	1.771	9.730	3.275	−0.849
Median	1.987	10.066	3.273	−0.597
Max	3.004	11.430	3.904	5.218
Min	−0.261	6.588	2.616	−8.111
Std. Dev.	0.714	1.144	0.231	2.576
Skewness	−0.852	−0.733	0.1694	−0.283
Kurtosis	3.214	2.545	3.000	2.485
Jarque-Bera	102.402	81.828	3.984	20.331
Observation	833	833	833	833

3.4. Panel unit root test

Among the available panel unit root tests, [85] proposed a CIPS, a second-generation panel unit test, recently Westerlund et al. (2016) derived its asymptotic, which makes it powerful and superior to other panel unit root tests. This CIPS test tolerates the cross-sectional dependence by weighting lag averages and differences for each panel unit. This test depends on the cross-sectional augmented Dickey-Fuller test, and is presented as follows:

$$\Delta x_{it} = \mu_i + \beta_i x_{i,t-1} + \rho_i \bar{x}_{t-1} + \sum_{j=0}^{p} d_{ij}\Delta \bar{x}_{t-j} + \sum_{j=1}^{p} \tau_{ij}\Delta x_{i,t-j} + \varepsilon_{it} \tag{4}$$

For $\bar{x}_{t-1}$ and $\Delta\bar{x}_{t-j}$ are the cross-sectional lags averages, and the 1st difference with ρ_i and d_{ij} factors, respectively. μ and β_i are the constant and drifts, correspondingly, while τ_{ij} is the lead factor. By using cross-sectional augmented Dickey-Fuller (CADF) statistics, CIPS statistics are computed as follows:

$$CIPS\ statistic = N^{-1}\sum_{i=1}^{N} CADF_i \tag{5}$$

3.5. Panel test for cointegration

The error correction panel cointegration test built by Westerlund and Edgerton, (2007)[86] was applied in this study. This test allows dependence for both within and between cross-sectional dependent units due to it applying error correction terms in computation[6]. This test tests a pair of different null hypotheses: (1) no existence of cointegration in the unit of panels, and (2) no existence of cointegration in all panels. In this respect, the estimated adjustment term ϑ_i used to compute the group mean statistics, G_τ and G_α for Westerlund cointegration for first null hypothesis as follows:

$$G_\tau = \frac{1}{N}\sum_{i=1}^{N}\frac{\vartheta_i}{SE(\vartheta_i)} \tag{6}$$

$$G_\alpha = \frac{1}{N}\sum_{i=1}^{N}\frac{T\vartheta_i}{\vartheta_i(1)} \tag{7}$$

On the other hand, the group means statistics for testing the second null hypothesis computed in the following expressions:

$$P_\tau = \frac{\hat{\vartheta}_i}{SE(\hat{\vartheta}_i)} \tag{8}$$

$$P_\alpha = T\hat{\vartheta}_i \tag{9}$$

3.6. Panel estimators

To ensure the robust estimated impact of regressors on regressed variables, this study has used the most recent estimators and compared them with the second-generation estimator. These recent estimators effectively estimate the effect in the presence of cross-sectional dependence among variables by involving average lags to remove cross-sectional effects. Therefore, the estimation framework consists of cross-sectional augmented distributed lags (CS-DL), Autoregressive distributed lags (CS-ARDL), and common corrected Effect pooled mean group (CCE-P).

3.6.1. Cross-sectional augmented distributed lags (CS-DL)

Chudik et al. (2016)[87]; Chudik and Pesaran, (2019)[88] have proposed a panel cross-sectional augmented distributed lagged model (CS-DL) for estimating long-run relationships in the presence of weak and semi-weak cross-sectional dependence among variables. During the estimation process, average lags were added to the model to remove strong cross-sectional dependence. Hence, to effectively estimate the link between selected variables in the CS-DL, CO_2 emissions are represented as y_{it} and x_{it} represents all regressors in the following equation:

$$y_{it} = \alpha_i + \beta_{1i}x_{it} + \sum_{l=0}^{px-1}\delta_{il}\Delta x_{it-l} + \sum_{l=0}^{p\bar{y}}\gamma_{y,il}\bar{y}_{t-l} + \sum_{l=0}^{p\bar{x}}\gamma_{x,il}\bar{x}_{t-l} + \varepsilon_{it} \tag{10}$$

For $\bar{y}_{t-l}$ and $\bar{x}_{t-l}$ are the cross-sectional averages and $p\bar{x} = \left[T^{\frac{1}{3}}\right]$ is the maximum lag of regressors, while $p\bar{y}$ is a random lag of a regressed variable. α_i is the fixed and unobserved country effect.

3.6.2. Panel cross-sectional augmented autoregressive distributed lags (CS-ARDL)

Chudik et al. (2016)[89] built a CS-ARDL estimator, which directly estimates long- and short-run regression coefficients between explanatory variables and variables of interest.

$$y_{it} = \alpha_i + \sum_{l}^{py}\delta_{il}y_{it-1} + \sum_{l=0}^{px}\beta_{il}x_{it-l} + \sum_{l=0}^{PT}\sigma_{il}\bar{z}_{it-l} + u_{it} \tag{11}$$

where $i = 1, 2, \ldots, N$, and $\bar{z}_t = N^{-1}\sum_{i=1}^{N} z_{it} = (\bar{y}_t, \bar{x}_t)'$, α_i and u_{it} are fixed effect and residual, respectively. The model coefficients are computed in the following expressions:

$$\hat{\theta}_{cs-ARDL} = \frac{\sum_{l=0}^{px}\hat{\beta}_{il}}{1-\sum_{l=1}^{py}\hat{\delta}_{il}} \tag{12}$$

3.6.3. Common correlated effect pooled (CCE-P)

The panel common correlated effect pooled estimator built by Pesaran, (2006) and its extension from Chudik and Pesaran, (2015) was employed. CCE-P estimates the consistent results by approximation of the common factors with cross-sectional averages of regressors, which is the unique feature that differentiates CCE-P from previous versions (undertakes the cross-sectional effect). It can be expressed as follows:

[6] *Westerlund panel cointegration computed as:* $\Delta z_{it} = \alpha_i d_i + \vartheta_i\left(z_{i(t-1)} + \pi_i y_{i(t-1)}\right) + \sum_{j=1}^{m}\varphi_{ij}\Delta z_{i(t-1)} + \sum_{j=0}^{m}\varphi_{ij}\Delta y_{i(t-1)} + \omega_{it}$, For ϑ_i is the adjustment term, d_i is a vector of deterministic components, including constant and linear time trends. $z_{it} = (x_{it}, y_{it})$ is the k + 1 dimensioned vector of integrated variables.

$$y_{it} = \alpha_i + \sum_{l=0}^{py} \beta_{il} y_{it-l} + \sum_{l=0}^{px} \delta_{il} x_{it-l} + \sum_{l=0}^{Z} \mu_{il} \bar{z}_{it-l} + \varepsilon_{it} \tag{13}$$

For $\bar{z}_t = (\bar{y}_t, \bar{x}_t)'$, $\bar{y}_t = n^{-1} \sum_i^N y_t$ and $\bar{x}_t = n^{-1} \sum_i^N x_t$, for (px, py, z) are the lags, $\bar{z}_t$ is the mixture of the cross-sectional averages, and known as the detected common impacts used coefficients available in Ref. [90]. α_i is unobserved effect, β_{il} is the impact from regressed variable at lags, δ_{il} is the regressors effect, μ_{il} is the impact of grouped cross-sectional average at lag (l), and ε_{it} residual. Therefore, Jan Ditzen.xtdcce2, (2018) recently argued that during the estimation, CS-DL and CS-ARDL are sensible for the multi-collinearity and drop them out, which assists it to produce better results than other panel cross-sectional estimators, but the difference between these two recent estimators is that CS-ARDL estimates long- and short-run effects, while CS-DL estimates mean effect between variables

3.7. Testing causalities

Dumitrescu and Hurlin, (2012)[92] proposed a causality for testing the direction of identified causation between variables. This test is suitable for the large dataset and produces reliable and robust results in the presence of cross-sectional dependence among the variables, as argued by Fahimi et al. [93]. The causal direction is noted in three hypotheses: (1) Feedback or bi-directional causal, (2) conservative/growth or unidirectional causal, which moves from one variable to the other; and (3) neutral hypothesis. Therefore, the mathematical representation of this test is:

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K} \delta_i^k y_{i,t-k} + \sum_{k=1}^{k} \beta_i^k x_{i,t-k} + \varepsilon_{it} \tag{14}$$

For y *and* x are variables to be checked, α is the static impact, δ and β are the autoregressive constraint and reversion coefficient, respectively. k indicates evidence of the optimal lag and is equal for all cross-sectional components. The reversion factor and links with the Wald statistics of Granger non-causality averaged across the cross-sectional components are the basis of the null hypothesis of the causality test. Wald statistic is given from the following expression:

$$W_{i,T} = \hat{\theta}_i' R' \left[\hat{\theta}_i^2 R \left(Z_i' Z_i \right)^{-1} R' \right]^{-1} R \hat{\theta}_i \tag{15}$$

Detail about the parameters of Eq. (15) is available in Ref. [92].

4. Findings and discussion

4.1. Peaks in drought and wind findings

The random peak analyzer approach proposed by Bardeen et al. (1986)[94] has been used to identify the most significant peaks in drought, which correspond to fluctuations in wind energy generation across the sampled countries. Fig. 4A and Fig. 4B show peaks of drought and wind energy, respectively, in a certain period across the sampled countries, whereas severe droughts period was noted in several countries (Fig. 4A for high peaks), which are inconsistence with wind energy generated (Fig. 4B for insignificant peaks), which indicates that the high production of wind energy started in 2010 and continues to increase. This implies that the presence of severe drought insignificantly affects wind energy generation in selected countries.

4.2. Cross-sectional dependence findings

Findings from tests for cross-sectional dependence [82,83] presented in Table 2 reveal that no cross-sectional independence null hypothesis is rejected at a 1% significance level. Results from the cross-sectional dependence exponent test [53], show that cross-sectional dependence is semi-weak (α<0.5) in CO_2, semi-strong ($0.5 \leq \alpha < 1$) in wind energy, industrial development, and economic growth, see last column of Table 1. Therefore, the results implying the presence of cross-sectional dependence across variables.

4.3. Panel unit root findings

CIPS panel unit root test [85] results presented in Table 3 revealed that the null hypothesis of the panel unit root is rejected at levels with constant-trend for CO_2. This hypothesis has been rejected at 1st difference with a constant for wind energy, industrial development, and economic growth. These findings imply that all variables cointegrated in 1st order. Therefore, Westerlund and Edgerton, (2007) cointegration tests are appropriate to detect the presence of the long-run relationship among variables.

4.4. Cointegration findings

Westerlund and Edgerton, (2007) cointegration findings presented in Table 4, reveal that the no cointegration hypothesis in the unit of the panel and all units of the panel have been rejected, implying that there exists cointegration in the panel. Hence, these findings approve of the long-term relationships within all variables. This suggests the occurrence of long-run causal relationships between wind energy use, indus-

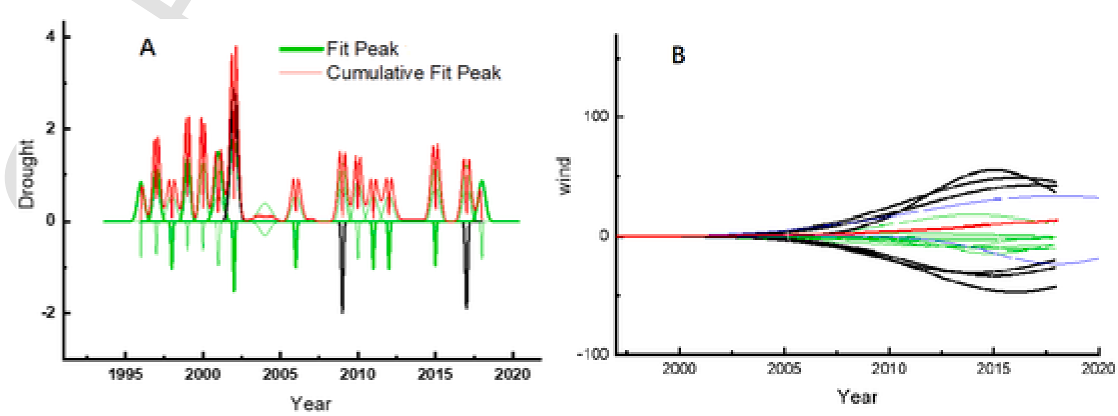

Fig. 4. The most significant peaks of drought (A) and wind energy (B) across the sampled countries, (green and black colors indicate the most significant peaks, red color indicates the cumulative peaks in drought, while peaks in wind energy are insignificant). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 2
Cross-sectional dependence results.

Variables	BPLM	PLM	PCD	α (alpha)
$\ln CO_2$	8614.561*	192.473*	6.391*	0.469
lnWE	14583.600*	339.868*	119.984*	0.769
lnID	5192.975*	107.982*	34.876*	0.698
lnEG	13345.780*	309.302*	108.613*	0.829

Notes: Alpha is a cross-sectional dependence exponent estimate that tests the level of identified cross-sectional dependence in the variable. With this test, if $0.5 \leq$ alpha < 1 implies semi-strong cross-sectional dependence. These estimates are estimated under the xtcd2 package [95]. BPLM: Breusch Pagan Lagrange Multiplier, PLM: Pesaran Lagrange Multiplier, PCD: Pesaran CD.

Table 3
CIPS unit root results.

Variables	Levels with constant-trends	1st difference-constant
$\ln CO_2$	−3.024[a]	
lnWE	−1.427	−2.850[a]
lnID	−2.094	−3.909[a]
lnEG	−1.772	−2.965[a]

[a] Indicates significance at 1%.

Table 4
Cointegration results.

Statistic	Value	Z-value	P-value
$G\tau$	−4.699*	−15.111	0.000
$G\alpha$	−5.519***	6.215	0.083
$P\tau$	−76.062*	−57.516	0.000
$P\alpha$	−25.173*	−13.401	0.000

*and *** imply a significant at 1% and 10%, correspondingly.

trial development, economic growth, and emitted CO_2 in 41 top countries in wind energy production from 1997 to 2018.

4.5. *Estimator findings*

Findings related to long-term relations between wind energy consumption, industrial and economic development, and CO_2 estimated from CS-DL, CS-ARDL, and CCE-P are available in Table 5. Outputs from three recent models reveal that wind energy use contributes to reducing CO_2, and the negative effect is statistically significant (−0.355 and −0.349 at 5% significant levels from CS-DL and CS-ARDL, respectively). The industrial and economic development promote the increment of CO_2 in the long term, with statistical significance (0.072, 0.069, and 0.085 at 1% from CS-DL, CS-ARDL, and CCE-P, respectively for industrial growth, and 0.001,0.001, and 0.002 at 1% from CS-DL, CS-ARDL, and CCE-P for growth). Consuming wind energy, on the other hand, statistically and insignificantly supports the increase in economic growth, while industrial development statistically significantly promotes the increment trends in economic growth in the long term. Based on the root mean square errors (RMSE) of estimators, results from CS-DL are stronger than results estimated from CS-ARDL and CCE-P, due to the RMSE of CS-DL being smaller than those of CS-ARDL and CCE-P, hence, the study conclusive results rely on CS-DL estimator. This coincides with the suggestion from Jan Ditzen [91], who said that findings from CS-DL are better than results obtained from previous cross-sectional estimators.

Table 5
Results from estimators.

Dependent: $\ln CO_2$ emissions			
Regressors	CS-DL	CS-ARDL	CCE-P
lnWE	−0.355**	−0.349**	−0.103
lnID	0.072*	0.069*	0.085*
lnEG	0.001**	0.001**	0.002*
Dependent: lnEG			
lnWE	0.002	0.002	−0.107
lnID	0.237*	0.252*	0.003
Dependent: lnID			
lnWE	−0.047	−0.082**	−0.016

Notes: RMSE for CS-DL, CS-ARDL, and CCEMG are 0.25, 0.25, and 0.26, respectively, *and ** show significance at 1% and 5%, respectively.

More specifically, the findings show that consuming wind energy has a significant negative effect on emitted CO_2, whereas a 5% surge in wind energy use leads to a 0.355% reduction in emitted CO_2 across 41 top countries, which are high consumers of wind energy. These results coincide with those estimated by Kuşkaya and Bilgili, (2020), where using wind energy has been seen to promote greenhouse gas and emitted CO_2 reduction in the USA. Industrial growth was noted to significantly stimulate CO_2 increment in the selected countries, whereas a 1% surge in industrial development tends to a 0.072% of emitted CO_2 increase. These outputs are parallel to those observed by Muhammad et al. (2022); Shahbaz et al. (2014), whereas industrial development severely degrades environmental sustainability in developing and developed countries. Similarly, an increment in the economy has a significant positive impact on emitted CO_2, a 5% increment in economic growth tends to a 0.001% increase in CO_2. This effect is very small compared to those obtained in existing studies, due to the selected countries being in advance to use renewable energy and implementing green growth policies [23,24,41]. Our results, on the other hand, revealed that a 1% increment in industrial development tends to a 0.237% rise in the growth of an economy across the top countries that highly consume wind energy. These findings are similar to those observed by Duarte et al. (2022), who indicated that wind energy significantly promotes socio-economic development in developed countries. Furthermore, our findings show that wind energy consumption negatively affects industrial development. This study has faced some limitations, such as considering the set of 41 countries as global, while it is supposed to be regions, due to a lack of enough data across many countries, and some variables have been limited to 2018, which enforced the entire study to consider the end of 2018. Wind energy exploration is still a challenge in low-income countries, which decline the efficacy of related policies.

4.6. *Causality results*

Findings of causality relationships between selected variables tested by Dumitrescu and Hurlin, (2012) causality test are available in Table 6 and Fig. 5 in form of hypothesized (feedback, conservative/growth or unidirectional, and neutral) across the panel of 41 World's top countries, which consume high wind energy. From the table, a feedback hypothesis was observed between growth and emitted CO_2, which implies that growth in the economy can cause a rise in emitted CO_2 increment and vice-versa, see Row 1 (R1). These findings are similar to those obtained by Ajmi et al. (2015), who noticed directional causation between economic growth to emitted CO_2 in G7 countries.

Similarly, industrial development can cause CO_2, due to the feedback causation illustrated between those variables, see R2. These findings are similar to the results established by Shahbaz et al. (2014) in

Table 6
Causality relationships among variables.

causation	W-statistic	causation	W-statistic	hypothesis
$GDP \rightarrow CO_2$	5.592*	$CO_2 \rightarrow GDP$	3.509*	Feedback
$ID \rightarrow CO_2$	4.623*	$CO_2 \rightarrow ID$	3.539*	Feedback
$WE \rightarrow CO_2$	4.298*	$CO_2 \rightarrow WE$	4.691*	Feedback
ID→GDP	4.560*	GDP→ID	6.224*	Feedback
ID→WE	4.061*	WE→ID	4.918*	Feedback
WE→GDP	3.276**	GDP→WE	6.936*	Feedback

*and ** indicate significance at 1% and 5%.

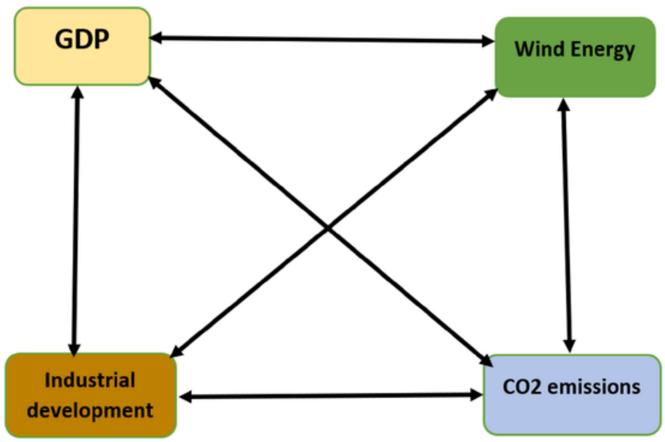

Fig. 5. Summary of causality results.

Bangladesh. This hypothesis was observed between wind energy use and emitted CO_2, which implies that wind energy reacts to CO_2 increment, see R3. A causality link was tested between covariates, whereas industrial development has been seen to cause economic growth, and simultaneously, economic growth causes industrial development, see R4 for the noted feedback hypothesis. A feedback causal link was also observed between industrial development and wind energy consumption, see R5. Similarly, in R6, a feedback association was illustrated between wind energy consumption and economic growth.

5. Conclusion and policy implications

Preceding literature has reasonably studied the influence of economic growth and renewable energy on the emitted CO_2 globally, which led to effective policy implications, such as green growth policy, reducing carbon emissions closer to net-zero agenda, and green energy use. Little attention was paid to examining the role of specific renewable energy types, including wind energy to reduce CO_2. Existing studies showed how industrial development contributes to economic growth, nevertheless, few studies attempted to detect the influence of industrial development on CO_2. Responding to these deficiencies, the main goal of this study is to detect the influence of wind energy consumption, industrial development, and economic growth on CO_2 across the panel of 41 World's top countries that highly consume wind energy. The most recent econometric estimators and updated codes have been employed to detect the relationships among variables. We furthermore, applied the Dumitrescu Hurlin causality test to detect the causal relationships between variables. The dataset from the panel of 41 countries produces and consumes higher wind energy globally.

The main findings of this article have started by investigating the drought phenomenon, results reveal that severe peaks of drought are not coinciding with peaks in wind energy. Evaluating variables, using cross-sectional dependence, exponent of cross-sectional dependence, CIPS unit root, and Westurland cointegration tests were then conducted. Results from these tests show the presence of semi-weak cross-sectional dependence in CO_2, and semi-strong cross-sectional dependence in industrial development, economic growth, and wind energy. The unit root was rejected in level for CO_2, while it has rejected in the first difference for other variables, and the presence of long-run relationships among variables was confirmed from cointegration results. The CS-DL results are more robust than other estimators and reveal that wind energy usage significantly supports reducing CO_2, while industrial and economic growth have a significant positive influence on CO_2 in the long term. Wind energy utilization has an insignificant positive long-run contribution to economic growth, while industrial development significantly and positively impacts economic growth in the long term. Furthermore, wind energy consumption negatively and insignificantly affects industrial development. We also found a directional causal link between selected variables, whereas feedback causation was noted between CO_2 and wind energy, industrial and economic growth. This causal relation was observed between industrial development, economic growth, and wind energy. Again, a two-way directional causal effect was noted between wind energy usage and economic growth.

Based on the findings and limitations, therefore, our policy implications are addressed to global and country-specific policymakers. Based on our findings, we first, suggest all countries invest in wind energy exploration to facilitate energy poverty reduction and promote CO_2 reduction policies via wind energy action across regions. Again, investment in wind energy will facilitate a green economy within countries and regions. Secondly, industrial and economic sectors should adhere to the green growth policy and green energy use to intensively reduce all CO_2 determinants. Again, the industrial sector can be designed such that it will consume renewable energy in place of traditional energy, for reducing the positive effect of industrial development on CO_2 across regions. Thirdly, reasonable attention should be paid to primitive growth determinants and supporting green growth across the globe and country-specific. Putting these suggested policies and others from previous studies into action will benefit CO_2 reduction and green industrial and economic growth across countries and regions. The next study will focus on how wind energy applications can reduce energy poverty while contributing to an economy by ensuring climate action in country-specific or the set of low- and lower-middle-income countries.

Appendix A. List of countries

Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Chile, China, Denmark, Egypt, Finland, France, Germany, Greece, Hungary, India, Iran, Ireland, Italy, Japan, Mexico, Morocco, Netherlands	New Zealand, Norway, Pakistan, Philippines, Poland, Portugal, Romania, Russia, South Africa, South Korea, Spain, Sweden, Thailand, Tunisia, Turkey, United Kingdom, United States, Uruguay

Credit of authors statement

JEAN PIERRE NAMAHORO, substantial contribution to conception and design, substantial contribution to analysis-interpretation of data, drafting the article and methodology, critically revising the article for important intellectual content, final approval of the version to be published, QIAOSHENG WU, substantial contribution to acquisition of data, critically revising the article for important intellectual content, final approval of the version to be published, Fundings, SU HUI, critically revising the article for important intellectual content, final approval of the version to be published.

Uncited references

[7]; [25]; [42]; [43]; [52]; [54]; [55]; [65]; [86]; [87]; [88]; [89]; [94]; []; [].

Declaration of competing interest

The authors declare that there is no conflict of interest and approve the submission to your reverence journal.

Data availability

The data that has been used is confidential.

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