Nuclear Engineering and Technology 54 (2022) 3682-3694



Contents lists available at ScienceDirect

# Nuclear Engineering and Technology

journal homepage: www.elsevier.com/locate/net

**Original Article** 

# Revolution of nuclear energy efficiency, economic complexity, air transportation and industrial improvement on environmental footprint cost: A novel dynamic simulation approach



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#### ARTICLE INFO

Article history: Received 17 February 2022 Received in revised form 13 May 2022 Accepted 21 May 2022 Available online 28 May 2022

Keywords: Economic complexity Industrial improvement Air transportation Energy innovation Environmental footprint

#### ABSTRACT

The expansion of a country's ecological footprint generates resources for economic development. China's import bill and carbon footprint can be reduced by investing in green transportation and energy technologies. A sustainable environment depends on the cessation of climate change; the current study investigates nuclear energy efficiency, economic complexity, air transportation, and industrial improvement for reducing environmental footprint. Using data spanning the years 1983–2016, the dynamic autoregressive distributed lag simulation method has demonstrated the short- and long-term variability in the impact of regressors on the ecological footprint. The study findings revealed that economic complexity in China had been found to have a statistically significant impact on the country's ecological footprint. Moreover, the industrial improvement process is helpful for the ecological footprint in China. In the short term, air travel has a negative impact on the ecological footprint, but this effect diminishes over time. Additionally, energy innovation is negative and substantial both in the short and long run, thus demonstrating its positive role in reducing the ecological footprint. Policy implications can be extracted from a wide range of issues, including economic complexity, industrial improvement, air transportation, energy innovation, and ecological impact to achieve sustainable goals.

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## 1. Introduction

The effects of global warming and climate change are affecting people worldwide. We need global cooperation and synchronized responses to attain low-emission economies. Climate change negatively impacts society and the economy, the ecosystem, and the environment. Ecological footprints (EF) and a continual increase in resource usage are the primary causes of environmental degradation [1,2]. Climate change poses a threat to all life on Earth, as CO<sub>2</sub> levels in the atmosphere have increased from 19,809 to 33,431 million tonnes in the last decade [3]. China accounts for one-third of CO<sub>2</sub> emissions and the world's GDP [4]. As the world's second-largest energy consumer [5] and a major source of CO<sub>2</sub> emissions [6], China may reach its peak emissions by 2030 [3]. Ecological

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degradation is a multifaceted problem that cannot be reduced to a single environmental metric. A country's economic growth is supported by a specific economic structure, which requires a unique energy consumption arrangement depending on the particular requirements of various economic sectors. In a complex economy, relevant knowledge is managed across broad networks of individuals to produce a wide variety of knowledge-intensive products [7].

The ideas of relatedness and economic complexity must be understood to grasp economic complexity fully. Hidalgo, Klinger, Barabasi and Hausmann [8] developed and enlarged the idea of economic complexity and employed machine learning to show and forecast GHG emissions, income growth, and regional disparity. While relatedness helps explain and anticipate the common regional characteristics of a particular activity and variations in specialized knowledge [9,10]. The sophistication of a state's growth can be attributed to its economic complexity, founded on knowledge and skill. When economic complexity, property rights, institutional and infrastructure quality, skills, regulations, and the rule

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https://doi.org/10.1016/j.net.2022.05.022

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of law are considered, it gives a clear picture of how the economy and its underlying structures are changing. Since the Industrial Revolution began in 1760, modern technology has profoundly impacted many businesses and sectors.

In recent years, countries' economic systems have played an increasingly vital role in reshaping their production sectors [11]. As a result, they have undergone a substantial structural shift from an agrarian economy to a more diverse economy that includes a wide range of industries and services [12,13]. The pace at which more complicated industries are changed is enhanced by an upswing, which supports economic growth. However, rising fossil fuel consumption and CO<sub>2</sub> emissions have a significant destructive environmental impact [14–17]. The growing usage of nonrenewable energy sources has been directed to hazardous CO<sub>2</sub> emissions, which have been blamed for climate change, global warming, and other contemporary challenges [18,19]. With this asymmetric growth in climate change and global warming, policymakers and researchers are becoming more concerned about carbon-free and sustainable environments. Therefore, to keep global warming below 1.5 °C, the Paris Climate Change Agreement is crucial in the fight against climate change and global warming [20–22]. The Paris Agreement's climate mitigation targets call for a major restructuring of the global production and manufacturing sectors to avert the worst impacts of climate change [23]. Despite this fundamental transformation, most countries worldwide would have to put in much work to satisfy their carbon neutrality obligations [24,25]. CO<sub>2</sub> emissions from countries like China, which rely heavily on exports, are high. Conventional fossil fuels make up 80% of the energy needed to expand an exporting country's industries and create new firms [26,27]. This piques the interest of decision-makers to keep CO2 emissions in control.

Economic nuance has been examined extensively in the quest for carbon neutrality. For example, consider the findings of Boleti, Garas, Kyriakou and Lapatinas [11], which discovered a substantial positive economic complexity and emissions correlation. Increases in the economic complexity index have made meeting the carbon neutrality objective increasingly challenging [28–33]. For both high and low levels of economic complexity, the economies of the European Union analyzed data from 1995 to 2016 using entirely modified ordinary and dynamic least square approaches, and the findings revealed that carbon neutrality goals have been hampered by economic complexity targets, which show a larger pollution risk in places with lesser economic complexity than in regions with more economic complexity. Contrariwise, economic complexity lowers greenhouse gas emissions [23]. Using a panel dataset spanning 1976 to 2012, the study found that a one-unit increase in the economic complexity index reduces CO<sub>2</sub> emissions by 23%. The reason for this abysmal relationship is due to the production technologies (manufacturing processes). This proves that economic complexity aids in enhancing environmental quality and ultimately achieving carbon neutrality goals. Similar research in France [34] on the interrelationship among economic complexity, energy usage, and CO<sub>2</sub> emissions from 1964 to 2014. The study confirmed the importance of the environmental Kuznets curve (EKC) hypothesis utilizing unit root tests of second-generation and dynamic ordinary least square techniques.

Economic growth through industrialization has led to environmental degradation around the world. The environmental impact of industrial activities is a severe issue in developed countries. However, analogous consequences in developing economies are still poorly understood despite restrictions and new technologies, industry, and rising demand pressure natural resources. Simultaneously, additional challenges that are becoming more prevalent due to industrialization include increased emissions of greenhouse gases, air and water pollution, desertification, and chemical pollution [35]. According to the theory of comparative advantage, regions containing heavy industrial agglomeration specialized in processing crude oil, coal, and metal or manufacturing automobiles, machinery, or equipment [36,37]. The per-unit output cost has significantly decreased in such places due to the apparent scale effect or agglomeration externalities. In addition, places with an intense service industry concentration focus on information and services, such as stock trading, market research, and financial consulting. To our understanding, tertiary industry, particularly the financial enterprise, produces less pollution than heavy industries. Gielen, Newman and Patel [38] advocated using commercially available sophisticated technology to save energy and minimize CO<sub>2</sub> emissions in the industry. Grossman [39] asserts that agglomeration's composition and technical consequences in the service industry. In a nutshell, there are no short-term measures that can reduce emissions quickly and effectively. Even though coal consumption emits more CO<sub>2</sub> emissions paralleling other energy sources, it is likely the most significant energy source for the expansion, and any fall in coal would have a serious impact on China's economy.

Industrial coal usage in China is predicted to rise by 67% and 94%, respectively, between 2008 and 2035. Zhou, Liang and Xing [40] used an improved weighted SBM model to evaluate the environmental efficiency of Chinese industrial sectors. Wu, Zhu, Chu and Liang [41] examined the influence of unwanted intermediate products on industrial development. Industrial eco-efficiency and environmental efficiency are the most commonly used terms to describe the green development of industry in these studies. Grossman and Krueger [42] provide a more comprehensive theoretical explanation of environmental degradation. The EKC describes the connection between economic expansion and environmental degradation. It contends that perhaps the environment degrades as the economy is flourishing at low levels of economic growth (income).

Transportation is perhaps the most challenging issue to regulate carbon dioxide emissions globally due to its rapid development in  $CO_2$  emissions and energy use [43]. Researchers have shown that transportation growth boosts  $CO_2$  emissions [44], while some researchers, on the other hand, have looked into how transportation development affects the environment. A study by Wanke, Chen, Zheng and Antunes [45] found that transportation efficiency is an important component in designing organizational procedures which influence climate change. Given the current rapid growth in the transportation sector, many policymakers and scholars have looked into the degree to which economic development and  $CO_2$  emission levels are linked [46–48]. According to Godil, Sharif, Agha and Jermsittiparsert [49], reducing reliance on traditional energy sources and encouraging the use of more energy-efficient equipment could significantly lessen transportation's negative environmental impact.

The negative environmental consequences of international tourism have been emphasized in empirical studies investigating the impact of international air travel and carbon dioxide emissions. Research shows that international tourism has a detrimental impact on CO<sub>2</sub> emissions. In addition, international trade and the use of renewable energy have been shown to affect the environment positively. Despite the environmental issues posed by international tourism, various studies have recommended using more clean and efficient energy sources to reduce carbon emissions connected with air transportation. As a result, increasing renewable energy sources is critical to lowering carbon emissions [50]. Similarly, Balsalobre-Lorente, Driha, Leitao and Murshed [50] found that more energyefficient transportation systems or technologies improved environmental quality. This is why energy innovation is critical to minimizing environmental impacts connected with transportation, particularly air travel.

Scientists are worried about the consequences of global warming on the climate and the need to shift from dirty to renewable energy sources [51,52]. It has been postulated that nuclear power could be used to reduce emissions [53]. On the other hand, renewable energy is more profitable and has much room for growth. The growth of renewables stimulates economic growth, confirms the security of the energy supply, and reduces hunger. It is possible to minimize carbon emissions by moving to renewables, which promote cleaner production [51]. Nuclear energy has the fewest environmental impacts of any renewable energy source than coal, gas, and oil. Nuclear energy has been a viable option for reducing GHG emissions over the past few decades [53]. Nuclear energy helps protect the environment while also reducing the country's reliance on foreign resources. Consequently, nuclear energy supplies are essential to addressing energy security issues and environmental deterioration [54] while also being beneficial in reducing pollution [55]. Nuclear energy may contribute to pollution because of the emission of radioactive compounds and the treatment and disposal of nuclear waste [56].

Nuclear energy's environmental impact has been debated in the scientific literature. In some cases, researchers have concluded that nuclear power is good for the planet. According to Baek and Pride [57], nuclear energy positively impacts pollution in all six nuclearproducing countries. In Japan, Ishida [58] promoted the positive significance of nuclear energy in reducing CO<sub>2</sub> emissions. In research for China, Dong, Sun, Jiang and Zeng [59] looked at the impact of nuclear energy on environmental contamination throughout the period from 1993 to 2016. Marques, Fuinhas and Nunes [60] used monthly data from 2010 to 2014 in France to examine the correlations between nuclear energy generation, economic output, and CO<sub>2</sub> emissions. Furthermore, Iwata, Okada and Samreth [61] studied 11 OECD nations on the connection between nuclear power and electricity generation between 1960 and 2003. It has been found that nuclear energy reduces CO<sub>2</sub> emissions in Japan, Korea, Spain, and Finland. A Study in China by Xie, Yu, Wang and Liu [62] concluded that nuclear energy is a superior alternative to fossil fuels than renewable energy since nuclear energy has a higher detrimental influence on Emissions of CO<sub>2</sub>. A panel of twelve major nuclear-generating countries found no evidence to support the EKC hypothesis [51].

Study variables, based on location, can have a positive or negative impact on ecological footprints, depending on methodological features of the study and the country of study. Furthermore, researchers in the literature have not concentrated on China, which produces the most CO<sub>2</sub> and has a substantial global output. China, on the other hand, is one of the world's major patent-producing countries [63]. This study adds to the existing literature by revealing new insights and using unique approaches to comprehend better the causal relationship between economic complexity, industrial improvement, air transportation, and energy innovation on the ecological footprint. Jordan and Philips [64] created a new estimating strategy based on the dynamic simulation of the ARDL approach. This novel method overcomes the difficulty in interpreting estimations caused by the existing ARDL method [64]. This study also used the recent cointegration relationship under the criteria of Kripfganz and Schneider [65], following the p-value approximation through the ARDL bound approach.

The remainder of the study is organized as follows: after an introduction and overview of related literature in Section 1, we detail our paper's materials and methods in Section 2. Afterward, in Section 3, we show the empirical findings from the robustness test before discussing them in Section 4. Conclusions and policy implications are provided in Section 5.

# 2. Materials and method

### 2.1. Data and sources

The focal objective of the study is to investigate the impact of

economic complexity, industrial improvement, air transportation, and energy innovation on ecological footprints in China. We analyze yearly data from 1983 to 2016. Based on human pressure and demand on nature, Ecological footprints (EF) are divided into 6 different areas: grazing, fishing, land for crops, infrastructure and buildings, anthropogenic CO<sub>2</sub>, and forest products. Ecological footprints offer a vast assortment of environmental data, which can be used to envisage the limited consumption of natural resources and their sustainability in the universe [66–68]. According to Geng, Zhang, Chen, Xue, Fujita and Dong [69], EF analysis is a comprehensive and holistic environmental approach between methods and determinants of sustainability analysis, demonstrated as a valuable and most precise policy tool. Furthermore, EF provides handy acumens about environmental pressure and quality. The annual data regarding EF was obtained from the Global footprint network (data.footprintnetwork.org). EF enumerates the effect of consumption and production deeds on the environment, computing sea and land areas based on residents of particular places and their lifestyles. This study used the log form of EF measured in per person global hectare (gha).

Hidalgo, Klinger, Barabasi and Hausmann [8] developed and introduced the economic complexity index (ECI). ECI is a measure of skill accumulation and structural change. The ECI, which evaluates the level of knowledge and skills needed to produce items for export, is a key factor in economic growth [12]. However, a country's environmental performance is heavily influenced by the type of its products [70]. The transition from a low-production agrarian economy to high-performing industrial sectors provides even more sophisticated outputs [11]. Although the transformation raises the energy needs, it also contributes to increased CO<sub>2</sub> emissions and environmental devastation. The ECI annual data was collected from (https://oec.world/en/profile/country/China/) a large-scale visualization site, the observatory of economic complexity 2020. The data transform into natural logarithmic form, which changes the data frequency from high to low that fetch reliable findings [68].

Industrial improvement (II) means introducing modern technologies in production for both new and existing products. According to Aluko and Obalade [71], industrialization is used as a metric for technology. Industrialization is measured as manufacturing value-added as a percentage of GDP [71,72]. However, Dong, Xue, Xiao and Liu [73] calculated the industrialization rate as "Gross Regional Industrial Product/Gross Regional Product." Thus, we calculate II as "Gross Regional Industrial Product/Gross Regional Product" from the China Statistical Yearbook [73]. The study also transforms the data into a natural logarithmic form.

Air transportation contributes to greenhouse gas emissions (GHG) such as NOx, CO2. The GHG emissions by air transportation are not limited to CO<sub>2</sub>. Following Hassan, Zhu, Lee, Ahmad and Sadiq [74], the data regarding air transportation was collected from the Yearbook of China Transportation and Communications (2019), which is measured by operation mileage per capita. Households and businesses alike rely heavily on energy for their daily needs and the manufacturing of commodities. Using nonrenewable energy sources could harm the environment and increase CO<sub>2</sub> emissions, as per a theoretical standpoint [63].

Nevertheless, on the other side, clean and pollution-free renewable sources of energy been recognized as an effective solution to energy insecurity and the effects of global warming [75]. The renewable sources of energy (such as renewable electricity) can make production, manufacturing activities, and residential consumptions more proficient and environmental friendly. In addition, the EKC theory predicts that countries with higher incomes prefer to migrate from traditional to renewable sources of energy that reduce  $CO_2$  emissions using upgraded production proficiency [12]. Energy innovation measure by proxy innovative technology data borrowed from the World Bank database [74] including residents and non-residents patent applications, World Development Indicator, World Bank 2019.

## 2.2. Model construction

Emergent apprehensions about climate change and environmental degradation make it vital to guarantee environmental protection. Economic complexity, industrialization, air transportation, and energy innovation can increase or decrease the side effects on ecological footprints. Therefore, this study follows Du, Li and Yan [76] and Danish and Ulucak [63] to construct the reduced form of the econometric model in Eq (1) to investigate the impact of economic complexity index, industrial improvement, air transportation, and energy innovation on ecological footprints in China.

$$\begin{aligned} &Ln(EF_t) = \alpha 0 + \beta_1 Ln(ECI_t) + \beta_2 Ln(INDIP_t) + \beta_3 Ln(AIRT_t) + \beta_4 \\ &Ln(ENING_t) + \mu_t \end{aligned} \tag{1}$$

Where, Ln (EFt) is the natural logarithm of ecological footprints, ECI is economic complexity index, INDIP represents an industrial improvement, AIRT shows air transportation, and ENING represents energy innovation during time t (1,2,3, ....,34; 1983–2016), the coefficients ( $\beta_{1,2,3,4}$ ) for the study variables will be estimated by Eq. (1). Finally,  $\mu$  represents the error term of the model. It is worth saying that this study tested the EKC hypothesis by following Hassan, Danish, Khan, Xia and Fatima [77] and Danish and Ulucak [63], by the trail of [78], which is grounded on long and short-run comparison of coefficients on income variables.

#### 2.3. Econometric methods

Jordan and Philips [64] developed a new estimation technique based on dynamic simulation of the ARDL approach following [78]. This dynamic ARDL approach pacts estimations interpretation problems of study variables for short- and long-run coefficients [64]. The dynamic ARDL simulations were easy to find practical results [63]. The ARDL can automatically plot, estimate, and simulate the actual negative and positive shocks independent and regressors. It is necessary to hold one integration order and integrate it with the study variables to use the dynamic ARDL simulation model. Both (+1 and-1) shocks in independent factors could be automatically checked and estimated by the dynamic ARDL simulation model, whereas the other parameters remain unchanged. The dynamic ARDL simulation models could be employed if the study variables are cointegrated. The dependent variable must be stationary at the first difference before applying dynamic ARDL simulation. This study accomplishes the estimated technique structure for the dynamic ARDL simulation model. Multivariate normal distributions were used to simulate 5000 parameter vectors in a dynamic ARDL model.

$$\begin{split} \Delta(\mathbf{y})_t &= \mathbf{a}_0 + \lambda_0 \mathbf{y}_{t-1} + \beta_1 (\mathbf{x}_1)_{t-1} + \ldots + \theta_k (\mathbf{x}_k)_{t-1} + \sum_{i=1}^p \lambda_i \Delta(\mathbf{y})_{t-1} \\ &+ \sum_{j=0}^{q_1} \beta_{1j} \Delta(\mathbf{x}_1)_{t-j} + \sum_{j=0}^{q_k} \theta_{kj} \Delta(\mathbf{x}_1)_{t-j} + \varepsilon_t \end{split}$$

$$(2)$$

where  $(\Delta y)$  shows response variable change and constant term represented by  $\alpha_0$ , while one lagged value for variables represented by t-1. However, q and p stand for one lagged value for regressors and dependent variables. Meanwhile,  $\Delta$  represents to difference operator, and the stochastic error term of examination denoted by  $\epsilon$ . However, intercepted values are shown by  $\beta$ . The ARDL bound approach is used for cointegration [79] using proposed critical values of [65], backup by response surface regressions approximately p-values. Eq. (3) estimated the error correction form of Eq. (1)

$$\begin{split} \Delta \ln(\text{EF})_t &= \alpha_0 + \beta_1 \ln(\text{EF})_{t-1} + \beta_2 \ln(\text{ECI})_t + \theta_1 \ln(\Delta \text{ECI})_{t-1} + \beta_3 \\ \ln(\text{INDIP})_t + \theta_2 \ln(\Delta \text{INDIP})_{t-1} + \beta_4 \ln(\text{AIRT})_t + \theta_3 \ln(\Delta \text{AIRT})_{t-1} + \beta_5 \\ \ln(\text{ENING})_t + \theta_4 \ln(\Delta \text{ENING})_{t-1} + \mu_t \end{split}$$
(3)

Where  $\Delta$  shows operator difference and estimations constant term indicated by  $\alpha 0$ , furthermore,  $\theta 1$  to  $\theta 4$  are short-run coefficients, and  $\beta 1$  to  $\beta 4$  are long-run coefficients. In this study, the stochastic error term of the regression denoted as  $\mu$  and t represent the study's time (i.e., 1983 to 2016).

## 3. Results

### 3.1. Descriptive statistics

Table 1 displays the descriptive statistics of the study's parameters in logarithmic form. Logarithmic conversion forms were utilized to make the information more understandable and establish more stable variation. Log variance can also be used to boost the model's specification because it decodes the rate of change through the coefficient of the log. The study variables show the normal distribution in their log form based on statistics of Skewness, Kurtosis, and Jarque-Bera [74]. Furthermore, descriptive statistics in Table 1 show that the data is free of problems and only contains variables with normally distributed variables. An overview of statistics for all chosen proxies, EF, ECI, INDIP, AIRT, and ENING is provided in Fig. 1 using a boxplot graph.

## 3.2. Unit root test results

The stationary level of independent variables (i.e., 1 (0) or 1 (1) must not be greater than one, and as for dependent variables, it should be 1 (1) in the application of ARDL. Therefore, the study applied the Phillips-Perron (PP) and Augmented Dickey and Fuller (ADF) tests to check variables stationary level. The findings of unit root tests are stated in Table 2 revealed that stationary levels do not exceed the threshold for independent variables and for dependent variable is 1 (1).

#### 3.3. Cointegration test results

In fulfillment of the preliminary measures, the long-run relationship among study variables (including ecological footprints, economic complexity index, industrial improvement, air transportation, and energy innovation) verified in next step. This study follows Sarkodie and Adams [56] to validate variables cointegration, the bound-testing method [79] joined with [65] procedure pvalue approximation together with critical values. This method

Table 1	
Descriptive	statistics.

	LOGEF	LOGECI	LOGAIRT	LOGENINN	LOGINDIP
Mean	2.247673	0.471390	3.171849	1.702343	1.649791
Median	1.870927	0.318119	3.166709	1.620497	1.656974
Maximum	3.654105	1.171070	3.243318	2.103635	1.677218
Minimum	1.354037	0.089156	3.124178	1.282542	1.597483
Std. Dev.	0.818569	0.316923	0.030922	0.266474	0.020646
Skewness	0.617464	0.918243	0.758405	0.187255	-0.722780
Kurtosis	1.837693	2.563524	2.891573	1.653942	2.670952
Jarque-Bera	4.074341	5.047852	3.275994	2.765516	3.113715

provides T-statistic and F-statistic greater and for all statistical significance statistics values are higher than upper bound besides p-value with K = 3 as parameters in the fitted model. According to Kripfganz and Schneider [65], the critical selection of values depends on its uniqueness to get reliable and robust results in a finite sample. Table 3 shows the results for bound testing. The T and F-statistic are supported by p-value and greater than the upper bound value. Therefore, the dynamic ARDL approach can be used to estimate long, and short-term parameters as the outcomes of the cointegration test confirm the relationship among the variables.

## 3.4. Dynamic ARDL simulation results

Table 4 shows the estimation findings, showing that the economic complexity index has a positive coefficient in both long and short-run China. In China, economic complexity has a positive impact on the ecological footprints. Since ECI's coefficient is greater over time, the long-term impact of economic complexity is more pronounced as compared to that of ECI's coefficient in the short run. Meanwhile, the industrial improvement is statistically significant with a negative sign in both the long and short-run as theoretically expected.

In contrast, air transportation has a positively significant relationship with an ecological footprint in both the short and long run. However, this positively significant association diminishes over time, implying that the short-run effect of air transportation is stronger than the long-run effect. Although energy innovation has considerable negative signs for both short and long-term impacts, this significantly negative connection with ecological footprints rises long-term. It signifies that energy innovations positively impact the environment, which becomes more evident with time.

The coefficients (error correction term) show the speed of adjustment and have size and sigs as expected; all the coefficients are statistically significant. Besides, the validity and reliability of the model are checked with several diagnostic tools such as the LM test, Durbin Watson (DW), LM ARCH test, and RESET test. The LM ARCH is used for heteroscedasticity, whereas the LM test is used for autocorrelations. The reliability of the model is checked by RESET. The bottom of Table 4 presents the results for these diagnostic tests. The results reveal that there is no heteroscedasticity and autocorrelation in the model. However, the results for dynamic ARDL are statistically significant and useable for policy implication.

The dynamic ARDL has one characteristic that plots the dependent variables changes because of independent variables (Shown in Fig). These changes are shown in Figs. 2–9 in the appendix for China. Figs. 2 and 3 show that predicted negative and positive changes in the economic complexity index which is affect ecological footprints in China. Moreover, the anticipated positive shocks in air transportation affect the ecological footprints (see Fig. 4). However, both negative and positive industrial improvements in China don not affect the ecological footprints, as plotted in Figs. 6 and 7. Finally, predicated an adverse change in energy innovation reduces the ecological footprints, and a positive change can increase the ecological footprints in China (see Figs. 8 and 9).

#### 4. Discussion

The study's primary objective is to explore the impact of Economic complexity, Industrial improvement, air transportation, and energy innovation on ecological footprints in China. The ECI is concerned about broadening the range of sophisticated products available to customers and encourages them to push beyond national borders while adhering to environmental regulations. There is a strong correlation between ECI and ecological footprint, which shows that ECI is an essential metric for evaluating resource consumption and developing environmental policies. The results shown in Table 4 stated the positive and statistically significant effect of ECI on ecological footprints. Specifically, one unit increase in ECI simultaneously increases ecological footprint by 0.0687 and 0.1093 in the short and long run, respectively. Indeed, a positively significant relationship between ECI and EF is explained as the increase in economic activities imposes an environmental burden. This study's findings align with preceding literature as Liu and Kim [80] used trade openness and export diversification aspects of ECI and revealed a positive relationship with EF.

Similarly, Pata [12] found an EKC hypothesis between ECI and environmental pollution in the United States of America study. Early-stage developing countries engage in less complex primarysector products and activities, contributing less harmful EF. However, as countries progress through the stages of industrialization, energy-intensive industries such as refining, textiles, and chemical industries emerge, posing a greater threat to EF. As a result, the encirclement of high-knowledge countries adopts cleaner production technologies and energy innovation, which contribute to the repair of the ECI. China's industrialization has resulted in increased water, land, noise, and air pollution [32,81]. Due to the extraction of fossil fuels for industrial growth, the process of industrialization causes environmental damage. Industrialization also leads to secondary industries, such as heavy industries, which utilize high energy and root pollution. The improvements in the industrial sector, such as the use of advanced technology and green energy, can be helpful in an increase in ecological footprint [30,32].

The results of this study reveal a negative and statistically significant relationship between industrial improvement and ecological footprints in both the long and short run. The results show that industrial improvement positively affects the ecological footprint and helps to reduce environmental degradation over time. This relationship is vital in the short-run (with coefficient –1.2239), and it gradually declines in the long run (with coefficient –0.2350). The elasticity parameter demonstrates that one percent improvement in the industry increases in ecological footprint in the short-run for 1.2239 times, and this increase condenses to 0.2350 times in the long run.

The negative and positive shock of air transport has found a significant positive relationship with ecological footprints with a coefficient of 1.3132 in the short-run and 0.7992 in the long run. Air transportation adversely affects the ecological footprint in the short run, but this adverse effect gradually weakens in the long run. China is a fast emerging country with economic development and a

### Table 2

Unit root test results.

Variables	ADF Test		PP test		
	At level	First difference	At level	First difference	
Log EF Log ECI Log INDIP Log AIRT Log ENINN	-0.553615 [0.8673] -0.270191 [0.9190] -1.689140 [0.4270] -1.209937 [0.6583] -0.804004 [0.8044]	-2.139431* [0.0014] -3.689405* [0.0092] -3.409321** [0.0180] -6.415100* [0.0000] -4.932403* [0.000]	0.518302 [0.9848] -0.281192 [0.8290] -1.053513 [ 0.7220] -1.28073 [0.8446] -0.484964 [0.8819]	-1.986029* [0.0012] -3.569428** [0.0123] -3.653730*** [0.080] -4.465435* [0.000] -2.093577* [0.000]	

Note: \*\*\*,\*\*, & \* represents 10%, 5% & 1% level of significance respectively.

LnEF = LnECI, LnINDIP, LnAIRT, LnENING

Model

#### Cointegration test.

ation test.										
	statistics	10%		5%		1%		P values		
		I (0)	I (1)	I (0)	I(1)	I (0)	I (1)	I (0)	I (1)	

5.381

-5.287

## Table 4

Simulation ARDL results

Simulation ARDL results.				
Regressors	Coefficient	P value		
Log EF	.4,856,694	0.045		
ΔLog ECI	.1,093,558	0.001		
Log ECI	.0687,489	0.082		
ΔLogINDIP	2,350,319	0.021		
LogINDIP	-1.223868	0.068		
$\Delta Log AIRT$	.7,991,857	0.077		
Log AIRT	1.313178	0.000		
ΔLogENINN	-3.72429	0.040		
Log ENINN	-1.046392	0.011		
Constant	2.882076	0.002		
R <sup>2</sup>	0.86			
sim	5000			
F-value	18.302	0.000		
Diagnostic Testsow				
DW	2.358			
$X^2 LM$	0.061441 [0.9406]			
X <sup>2</sup> ARCH	1.551225 [0.2226]			
$X^2$ Reset	0.446137 [0.6595]			

F-Value 3.5418

T-Value 3.992

3 185

-2.242

considerable population, air transportation has the advantage of time efficiency, but EF and excessive energy use adversely affect the atmospheric quality (ecological footprints). Air transportation is related to the shortest travel distance, but lack of capacity is disadvantageous to higher EF. Hence, CO<sub>2</sub> emission (per capital) steadily upsurge and affect ecological footprints as air transportation per capita rises. However, China is making unwavering efforts to condense aviation emissions by investing in the fast railway system in the country. The current study's findings are consistent with previous literature regarding established logistics and transportation debates on transport footprints [33,45,74].

However, the results in Table 4 show that the coefficient of energy innovation is negative and significant in both the short and long run, implying that energy innovation plays a positive role in lowering ecological consequences. In China, a significant boost in energy innovation might help the country break free from its reliance on fossil fuels while reducing environmental deterioration. Although the short-run relationship between energy innovation and ecological footprint is statistically significant, the significance level increases in the long run. In another way, an increase in energy innovation, in the long run, supports lessening the ecological footprint. This study shows that energy innovation can help China combat climate change challenges and reduce environmental deterioration. The study confirms that energy innovation has a stumpy impact on the ecological footprint in the short run, but with the rise in innovation, the impact upturns in the long run. Energy innovation elevates ecological footprint by reducing CO2 emissions, waste, and fossil fuel consumption that cause problems in land use [30,82].

### 5. Conclusion and policy implications

This study examines the relationship of economic complexity index, industrial improvement, air transportation, and energy innovation with ecological footprints in the context of China. The study used a newly developed dynamic ARDL approach for data between 1983 and 2016. We have applied the ADF test along with the PP unit root for study variables. Afterward, the cointegration Nuclear Engineering and Technology 54 (2022) 3682-3694

test inspected the presence of short and long run asymmetric. Furthermore, dynamic ARDL short-run (negative and positive shocks) and long-run (negative and positive shocks) were established. This study provides solid insights into the role of ECI, industrial improvement, air transportation, and energy innovation in China. The study's empirical findings are as follows: First, the study results reveal the positive and significant role of the economic complexity index in China both for the short and long run. Second, the industrial improvements can help improve China's ecological footprint in both the long and short run. Third, the study reveals that air transportation is the major source of environmental degradation that affects the ecological footprint in the short and long run. Finally, this study also encounters that energy innovation is the best opportunity to improve the ecological footprint in China, which can help reduce the damages of ECI and air transportation.

Thus, this study suggests that ECI, industrial improvement, air transportation, energy innovation, and ecological footprint are closely associated in China. Therefore, the Chinese policymakers should reduce CO<sub>2</sub> emissions and fisheries ground, cropland, and forest land. Although the impact of ECI and air transportation on ecological footprint is downward trending, which shows China's direction towards sustainability, still positive association demands more environmental protection efforts. Policymakers should encourage investment in green transportation and energy innovation to protect the environment, decreasing China's import bill and carbon footprint. Moreover, development in ecological footprint provides resources for a country's economic growth. China is a fast-emerging country with economic development and a considerable population, air transportation has the advantage of time efficiency, but CO<sub>2</sub> emission and excessive energy use adversely affect the atmospheric quality [83,84].

Therefore, public transportation can help achieve the sustainable environmental goal in China. With innovative transportation infrastructure and new technologies, China can gradually reduce CO2 emissions from the transportation sector. We conclude recommendation based on the study's empirical findings; first, the ECI can be used as an effective apparatus for monitoring and assessing policies and ensuring and promoting sustainable production that leads to achieving CO<sub>2</sub> neutrality in China. Second, companies and policymakers should concentrate on energy innovation, enhance export yields with added complexity, and encourage environmentally-friendly investments. Additionally, generating electricity from renewable sources such as wind, solar, and nuclear-based projects could be a pathway to achieving CO<sub>2</sub> neutrality targets. Third, clean energy sources can reduce the burden of air transportation and play an affirmative role in tumbling ozone depletion and air pollution.

A number of other factors that could influence nuclear energy support in China are also needed for further investigation. Future studies can ascertain whether the established findings are applicable to countries with similar proxies, like the OECD, the EU, the BRICS, and African countries such as Nigeria, where environmental degradation is still not a priority. Due to data constraints, the modeling was unable to analyze the potential benefits of decarbonisation, which warrant further research. In addition, within the scope of the present research, the model can be tested in various countries to apprehend a broader contextual view.

# Funding

This research is funded by the National Natural Science Foundation of China (71972153).

## **Declaration of competing interest**

The authors declare that they have no known competing

financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix



Fig. 1. Shows overview of the descriptive statistics of selected proxies EF, ECI, INDIP, AIRT, and ENIN.



Fig. 2. Negative changes of economic complexity over time in China.



Fig. 3. Positive changes of economic complexity over time in China.



Fig. 4. Positive changes of air transportation over time in China.



Fig. 5. Negative changes of air transportation over time in China.



Fig. 6. Negative changes of industrial improvement over time in China.



Fig. 7. Positive changes of industrial improvement over time in China.



Fig. 8. Positive changes of energy innovation over time in China.



Fig. 9. Negative changes of energy innovation over time in China.

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