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Developing environmental policy framework for sustainable development in Next-11 countries: the impacts of information and communication technology and urbanization on the ecological footprint

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Abstract

This study is structured on the Environmental Kuznets Curve (EKC) framework to explore the impacts of economic growth, energy consumption, information, and communication technology (ICT), and urbanization on the ecological footprint for the Next-11 (N-11) countries. To accomplish the objective, the Driscoll—Kraay standard error and Feasible General Least Squares (FGLS) methods were applied to investigate the long-run relationship between the highlighted variables. In addition, the Dumitrescu and Hurlin panel causality test was employed for exploring the causality path of the variables under consideration. These methods used in this study circumvent issues of cross-sectional dependence. To accommodate the panel data analysis in this study, the annual frequency data from 1992 to 2015 was used. Empirical results lend an invalid of the EKC behaviour in the N-11 countries. Hence a positive relationship is observed between energy consumption, ICT with the ecological footprint while a negative relation between urbanization and the ecological footprint was found. On the direction of causality, a unidirectional causality is observed running from economic growth, energy consumption, ICT, and urbanization to the ecological footprint. Additionally, feedback causality is observed between (1) urbanization and economic growth and (2) urbanization and ICT. These results have implications on environmental sustainability which are elucidated in the concluding remark.

Keywords Information and communication technology · Sustainable development · Urbanization · Ecological footprint · Driscoll–Kraay standard error technique · Next-11 countries

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1 Introduction

For more than three centuries, the world has shifted to more industrialization, modernization (Rehman & Rashid, 2017), and digitalization (Brennen & Kreiss, 2016). Along with that direction, the rapid growth in the economy, population, energy consumption, and technology utilization increase the imbalance of environment capacity. This leads to the degradation of the environment and pollution emissions especially in emerging countries (Lu et al., 2021). With the current challenges of the economy, social, and environmental issues, the global agenda is to combat poverty and global warming, achieving the Sustainable Development Goals (SDGs). This is a prominent development path in the twenty-first century.

Urbanization and Information and communication technology (ICT) utilization are the key activities in the modern world. Urban's areas, population, and growth are increasing worldwide, and urbanization is considered as one of the development indicators consistent with the country's development (Bairoch, 1988; Nguyen & Nguyen, 2018). To live in the urban society, modern facilities and appliances need to be improved and constructed, i.e. roads, railways, energy systems, ICT, etc. A huge investment in the different projects for supporting the people's lives would lead to an increase in the domestic economy, thus somewhat further destroying the environment. Furthermore, more than half of the world population has lived in urban areas recently (World Bank, 2019), those populations extensively utilize energy, ICT, food, etc. Likewise, ICT is also viewed as an appliance for the development process in the globalization era (Mansell & Wehn, 1998; Sharma et al., 2020). Moreover, the ICT can be viewed diversity impact on environmental degradation (Houghton, 2010). In one aspect, a positive impact between ICT and the environment nexus can be found due to the efficient use of ICT to deliver goods and services. Thus, technological advancement has led to improving a living standard more wide range of choices including sustainable development (Mansell & Wehn, 1998). The second aspect, a negative impact can be explained as the massive energy consumption through the production process, distribution, and consumption of those ICT appliances (Houghton, 2010). According to these, the misleading decision of ICT, urbanization, and energy utilization plans would adversely influence the environment.

In recent years, the total world GDP was 81.306 trillion US dollars, and the total population was 7.509 billion people in 2017 (World Bank, 2019). Both data were forecasted to be double size by 2050 (PwC, 2017). Furthermore, the world's overall final energy consumption in 2017 was at 9,753,259.0 kilotons of oil equivalent (ktoe), the US Energy Information Administration (EIA) projected to increase nearly 50% by 2050 (IEA, 2020). For the modernization aspect, the trend of urban population is inherent increasing for many decades. The percentage of urban population was at 54.82% of the total world population in 2017 (World Bank, 2019), the number will grow to 68.4% by 2050 (United Nations, 2018). With the growth of the above series, the utilization of ICT also consistently increases worldwide. Some insight of it, the mobile cellular was 7.751 billion subscriptions in 2017, this was growth sharply from 23,482 subscriptions in 1980, and 11.21 million subscriptions in 1990 (World Bank, 2019). Along with the fruitful trend of these growths, environmental degradation seems to reverse. As some indicator, the carbon emission (CO_2) was 9,420.52 ktoe in 1960, and it was at 35,998.93 ktoe in 2016 for the world in total. The amount in the year 2016 increased more than 282.10% above the year 1960 (World Bank, 2019). Furthermore, the world is posed as an ecological deficit phenomenon since 1970 until today. The ecological footprint of the world was at 20,926,093,397.79 global hectares (gha) in 2017, it was about the double size of its biocapacity. Moreover, it was increased about 198% above 1960 (Global Footprint Network, 2019).

Over the last two decades, continuous anthropogenic human activities, especially from developing/or emerging economies like the Next-11 (N-11, hereafter) economies, are believed to be the root cause of increased environmental degradation, i.e. greenhouse emissions, the ecological footprint. Thus, economies like emerging/transition economies are perpetually in the need of sustainable economic growth without compromise on environmental quality. The role of technology diffusion through the channel of globalization is pertinent to the debate for ICT-energy-growth-environmental nexus. This study concentrates on the N-11 economies, which are known to be potential next global economies. Statistics from the World Bank (2019) assert that these countries account for an estimated eight per cent of global GDP which attests to the potential of their growth potentials. These N-11 countries have together about 20% of the world population. Their urban populations kept increasing for more than 5 decades, and their urban population proportions are far above the world average, especially in the Republic of Korea, Mexico, Turkey, Islamic Republic of Iran, and Indonesia, respectively (World Bank, 2019). Furthermore, fact from the US Energy Information Administration documents that approximately ten per cent of global pollutant emission (CO_2) is from the N-11 bloc (EIA, 2015).

The present study extends and compliments the frontiers of knowledge in three ways. First, the choice of the study variables are following the United Nations Sustainable advancement Goals (UN-SDGs-7, 8, 9, 11, 12, and 13), this goal addresses pertinent issues to the attainment of the "UN-vision 2030" that boarders around clean and responsible energy consumption, access to energy, investment in infrastructure and innovation, sustainable economic growth, and mitigation of climate change issues. Furthermore, the present study draws motivation from the Environmental Kuznets Curve (EKC) phenomenon where human anthropogenic activities over time compromise environmental quality until a turning point. The N-11 economies are still at the scale stage that focuses on GDP growth relative to the quality of the environment. This phenomenon is addressed in the carbon-income environment for the countries under consideration. These traits distinct our study from the bulk of documentation in the extant literature.

Second, the distinction of the current study is in terms of the scope by exploring the urbanization-ICT-growth-energy-environment nexus for the N-11 countries, which has, witness little or no documentation in the literature. The N-11 economies are interesting blocs with huge energy poverty and dynamics worth of scientific investigation. There are several frameworks for exploring the connection between GDP growth and environmental pollution. Our study augments the carbon-income function by leveraging on the Environmental Kuznets Curve (EKC) setting with additional demographic indicators of urbanization and macroeconomic indicators like energy consumption, ICT to avoid model miss-specification. We also used a broader measure for emission known as ecological footprint, which is more comprehensive relative to the widely used carbon dioxide emissions (CO_2). The indicator of ecological footprint is more inclusive because it accounts for both nature's demand and supply. Despite this, it compares human consumption with the biocapacity in many components including built-up land, carbon emission, cropland, fishing grounds, forest products, and grazing land (Global Footprint Network, 2019; Katircioglu et al., 2018). Statically, total N-11 accounted for more than 12 per cent of the global ecological footprint, and their ecological footprints tend to increase. In addition, all 11 counties are facing an ecological deficit, and Indonesia, Mexico, and the Korea Republic are the top three ecological deficit countries among this bloc (Global Footprint Network, 2019).

Third, this study contributes by methodological advancement by the adoption of robust and state-of-the-art econometrics procedures that accounts for cross-sectional dependency and heterogeneity, i.e. second-generation panel methods. To substantiate the validity of regression/coefficients of estimators, we rely on the Regression with Driscoll—Kraay standard errors and the Feasible General Least Squares (FGLS) approach. To affirm the cointegration relationship among outlined variable, the Westerlund cointegration test, which report four test statistics, is applied. While the analysis for the direction of causality is achieved by Dumitrescu and Hurlin panel causality test.

The next section of this investigation follows with the literature review in Sect. 2 while in the third section data and methodological sequences. The results and discussion are presented in the fourth section and the closing comments and policy recommendations are rendered in Sect. 5.

2 Literature review

This section of this study presents the stylized review of related literature on the theme under consideration. This will be carefully considered in sub-sections that are rendered.

2.1 The nexus between economic growth and the ecological footprint

In particular, at the beginning of country development, the growth of the economy is one of the causes of environmental deterioration (Shafik, 1994; Stern, 2004; Stern et al., 1996). The current world trend is to minimize environmental impacts for achieving sustainable development. Many scholars disclosed the growth-induced environmental degradation hypothesis, especially after the explosion of the industrial revolution. One of the core approaches, Simon Kuznets proposed the environmental Kuznets Curve (EKC) approach in 1955 (Kuznets, 1955). At the present, the EKC approach for studying the association between economic growth and environmental deterioration has been widely researched, especially in carbon emission issues (Danish et al., 2019; Kongbuamai et al., 2020a, 2020b). The EKC approach indicates that the country will experience environmental deterioration as its economic growth and will change its environment after reaching some point in its economic progress (Kuznets, 1955).

For the impact of economic growth on the ecological footprint, many studies have shown economic growth that benefits the environment as the result of an inverted U-shaped EKC relationship. These have been confirmed in several countries and regions. Recently, Kongbuamai et al., (2020a, 2020b) confirmed the inverted U-shaped EKC relationship in ASEAN countries. Their study was based on the data between 1995–2016 with the analysis method of the Driscoll–Kraay panel regression model (Kongbuamai et al., 2020a, 2020b). Further study conducted in 14 European (EU) countries, Altıntaş and Kassouri (2020) found the inverted U-shaped EKC relationship. Their study confirmed the results by using the fixed effect (FE) methods, and the data from 1990–2014 (Altıntaş & Kassouri, 2020). In the same year, Wang et al. (2020) also confirmed the inverted U-shaped EKC relationship in the case of G7 countries. This study employed dynamic seemingly unrelated regression (DSUR) using the data covering from 1990 to 2018 (Wang et al., 2020). In a similar direction, Ahmed and Wang (2019) (2019 also established the result of the inverted U-shaped EKC relationship in India. They did that using the Autoregressive Distributed Lag (ARDL) for 1971–2014 (Ahmed & Wang, 2019). Lastly, Sharif et al. (2020)

confirmed the inverted U-shaped EKC relationship using the Quantile ARDL in Turkey. The data of 1965Q1 to 2017Q4 were used in their study (Sharif et al., 2020).

Conversely, economic growth has been described as accelerated environmental deterioration as invalid of the environmental Kuznets curve approach in many studies by using the ecological footprint as the indicator of environmental degradation. Some updated results, Aşıcı and Acar (2018) revealed the invalid of the EKC approach in 87 countries. Their result was confirmed by using the methods of FE and Random Effect (RE) (Aşıcı & Acar, 2018). Also, Dogan et al. (2020) cordially confirmed the invalid of the EKC approach in BRICST countries. Their finding was evidenced by using the method of Augmented Mean Group (AMG), Dynamic Ordinary Least Squares (DOLS), and Fully Modified Ordinary Least Squares (FMOLS) (Dogan et al., 2020). Lastly, Yilanci and Pata (2020) demonstrated the invalid of the EKC approach in the case of China, the Bootstrap Fourier ARDL (FARDL) was used in this study (Yilanci & Pata, 2020). Table 1 presents a summary of related studies on the theme; it summarized the existing EKC outcomes.

2.2 The nexus between energy consumption and the ecological footprint

After revealing the core evidence of the economic growth-environment nexus, energy consumption is also one of the main concerns for environmental degradation and development in the twenty-first century. As of the current situation, the world demand for energy will increase alongside the rise of population and economic activities, this will lead to the depletion of the environment (Adeleye et al., 2020; Omer, 2008; Owusu & Asumadu-Sarkodie, 2016). Computability, the confirmation of the positive relationship between the energy utilization (non-clean energy) and the environmental quality was inquired in several regions and countries. In the recent literature, Alola et al. (2019) employed the Panel Pool Mean Group Autoregressive distributive lag (PMG- ARDL), they confirmed the positive sign in the energy and environment nexus in EU countries (Alola et al., 2019). Later, Kongbuamai et al., (2020a, 2020b) employed the ARDL bounding approach, the positive sign in the energy and environment nexus was also confirmed in Thailand (Kongbuamai et al., 2020a, 2020b).

Also, Ahmed et al. (2020) demonstrated the positive impact of energy consumption on the ecological footprint in G7 countries by CUP-FM and CUP-BC methods (Ahmed et al., 2020). Furthermore, Destek and Sinha (2020) also exhibited a similar result of a positive relationship of energy and environment nexus in the Organization for Economic Co-operation and Development (OECD) countries. They employed the DOLS and FMOLS methods (Destek & Sinha, 2020). Lastly, Kongbuamai et al. (2021) confirmed the positive impact of renewable energy consumption and non-renewable energy consumption on the ecological footprint. The method of DSUR was used in their research (Kongbuamai et al., 2021).

On the contrary, the diminishing of environmental degradation was evidenced following an increase in energy consumption, especially the evidence of environmentally friendly energy sources (renewable energy). In some studies, Danish, Ulucak, et al. (2019) found the negative impact of renewable energy on the ecological footprint in BRICS countries by DOLS and FMOLS methods (Danish, Ulucak, et al., 2019). In the same direction, Balsalobre-Lorente et al. (2019) demonstrated the negative relationship between renewable energy and the ecological footprint nexus in MINT countries. Their study employed the methods of DOLS and FMOLS (Balsalobre-Lorente et al., 2019). Furthermore, the negative relationship was also confirmed between renewable energy and the ecological footprint in OECD by Destek and Sinha (2020). The methods of DOLS and FMOLS were employed in

Table 1 Summary of related studies on the EKC framework on the ecological footprint

Authors	Regions	Period	Methodology	EKC approach (inverted U-shape)
Al-Mulali et al., (2015a, 2015b)	93 countries	1980–2008	FE, GMM	Valid in the upper-middle and high-income countries
Aşıcı and Acar (2016)	116 countries	2004–2008	FE	Valid
Mrabet and Alsamara (2016)	Qatar	1980–2011	ARDL	Valid
Ozturk et al. (2016)	144 countries	1988–2008	GMM	Valid in high- and upper middle-income countries
Charfeddine and Mrabet (2017)	15 MENA countries	1975–2007	DOLS, FMOLS, VECM	Valid
Ulucak and Bilgili (2018)	45 countries	1961–2013	CUP-FM, CUP-BC	Valid
Sarkodie and Strezov (2018)	Australia, China, Ghana, and the US	1971–2013	Utest algorithm and Dumitrescu Hurlin panel causality tests	Valid in Australia and China
Desteket al. (2018)	EU countries	1980–2013	DOLS, FMOLS	Valid in France and Portugal
Bello et al. (2018)	Malaysia	1971–1990 1991–2014	ARDL, VECM	Valid from 1991 to 2014
Katircioglu et al. (2018)	Top 10 tourist countries	1995–2014	RE	Valid
Hassan et al. (2019)	Pakistan	1970–2014	ARDL, VECM	Valid
Destek and Sarkodie (2019)	11 newly industrialized countries	1977–2013	AMG, heterogeneous panel causality	Valid in Mexico, Philippines, Singapore, and South Africa
Danish, Ulucak, et al. (2019)	BRICS countries	1992–2016	DOLS, FMOLS	Valid in individual counties of BRICS
Balsalobre-Lorente et al. (2019)	MINT countries	1990–2013	DOLS, FMOLS	Valid
Ahmed and Wang (2019)(2019	India	1971–2014	ARDL, VECM	Valid
Gormus and Aydin (2020)	10 innovative economies	1990–2015	MG, AMG	Valid in Israel
Kongbuamai et al., (2020a, 2020b)	ASEAN countries	1995–2016	Driscoll–Kraay panel regression model, Dumitrescu and Hurlin panel causality	Valid
Sharif et al. (2020)	Turkey	1965Q1–2017Q4	QARDL	Valid
Aziz et al. (2020)	Pakistan	1990–2018	QARDL	Valid
Altıntaş and Kassouri (2020)	14 EU countries	1990–2014	FE, Dumitrescu and Hurlin panel causality	Valid

Table 1 (continued)

Authors	Regions	Period	Methodology	EKC approach (inverted U-shape)
Wang et al. (2020)	G7 countries	1980–2016	DSUR, Dumitrescu and Hurlin causality	Valid
Bagliani et al. (2008)	141 countries	2001	OLS, WLS	Invalid
Caviglia-Harris et al. (2009)	146 Countries	1961–2000	OLS, 2SLS	Invalid
Wang et al. (2013)	150 countries	2005	OLS, the spatial econometric models	Invalid
Hervieux and Darné (2013)	15 countries	1961–2007	OLS, ECM	Invalid
Mrabet et al. (2017)	Qatar	1980–2011	ARDL	Invalid
Charfeddine (2017)	Qatar	1970–2015	Markov Switching Equilibrium Correction Model	Invalid
Aşıcı and Acar (2018)	87 countries	2004–2010	FE, RE	Invalid
Sarkodie (2018)	17 African countries	1971–2013	FE, RE	Invalid
Dogan et al. (2020)	BRICST countries	1980–2014	AMG, DOLS, FMOLS	Invalid
Yilanci and Pata (2020)	China	1965–2016	Bootstrap FARDL	Invalid

FE Fixed Effect; *RE* Random Effect; *GMM* Generalized method of moments; *ARDL* Autoregressive Distributed Lag; *DOLS* Dynamic Ordinary Least Squares; *FMOLS* Fully Modified Ordinary Least Squares; *CUP-FM* continuously updated fully modified; *CUP-BC* continuously updated bias-corrected; *MG* mean group; *AMG* augmented mean group; *QARDL* Quantile ARDL; *DSUR* dynamic seemingly unrelated regression; *OLS* Ordinary Least Squares; *WLS* Weighted Least Squares; *2SLS* two-stage least squares; *ECM* error-correlation models; *FARDL* Fourier ARDL their study (Destek & Sinha, 2020). Lastly, renewable energy was also confirmed to lessen the ecological footprint in EU countries using the FE method (Altıntaş & Kassouri, 2020).

2.3 The nexus between urbanization and the ecological footprint

The challenge of the world in the twenty-first century is tended to live urbanization and avail the ICT appliances. Due to that direction, urbanization is a major challenge of social transformations in the current century (Bai et al., 2017). Linking between urbanization and the environment is multifaceted and varies identified (Bai et al., 2017). One of the core findings is that urbanization is found to accelerate the ecological footprint in different countries' studies. Firstly, Al-Mulali et al., (2015a, 2015b) revealed the positive sign between urbanization and the ecological footprint in the case of the 93 Countries. There was also confirmation of a positive relationship between urbanization and the ecological footprint in Qatar by Charfeddine (2017), this study employed the Markov Switching Equilibrium Correction Model. Later, Danish and Wang (2019b) confirmed a positive relationship between urbanization and the ecological footprint in the N-11 countries. The Common Correlated Effects Mean Group (MG – CCE) estimator was applied in their study (Danish & Wang, 2019b). Moreover, Wang and Dong (2019) also concluded the positive impact of urbanization on the ecological footprint in the 14 SSA countries. The Augmented Mean Group (AMG) estimator was used (Wang & Dong, 2019).

On the other hand, urbanization is found to have a negative relationship with the ecological footprint in the upper-income and high-income nations by Ozturk et al. (2016). They employed the generalized method of moments (GMM) in the study (Ozturk et al., 2016). Next, Charfeddine and Mrabet (2017) employed the DOLS and FMOLS methods, they also found urbanization has a negative relationship associated with the ecological footprint in 15 MENA countries (Charfeddine & Mrabet, 2017). Furthermore, Katircioglu et al. (2018) employed the RE to conduct a study of the top 10 tourist destination countries. They confirmed the negative sign of urbanization and the ecological footprint nexus (Katircioglu et al., 2018). Also, the evidence of the negative relationship between urbanization and the ecological footprint was confirmed in BRICS countries. They used DOLS and FMOLS (Danish, Ulucak, et al., 2019). However, urbanization was found to be insignificant with the ecological footprint in Pakistan by Danish et al. (2019). Their study employed the ARDL, DOLS, and FMOLS methods (Danish, Hassan, et al., 2019).

2.4 The nexus between ICT and the ecological footprint

Although the link of technology on economic growth (Romer, 1994) and human health (Masys, 2002), the ICT also has the linkage on the environment positively and negatively (Jaffe et al., 2002). Thus, the ICT indeed leads to sustainable development likewise (Hilty & Hercheui, 2010). Based on the literature review of the effect of ICT on environmental deterioration, the study of ICT and the ecological footprint nexus is scant, this gap of literature review needs to be investigated.

Due to the impact of ICT on the carbon emissions (CO_2), there are several studies on the significance of the ICT on CO_2 nexus (Al-Mulali et al., 2015a, 2015b; Amri et al., 2019; Añón Higón, et al., 2017; Asongu et al., 2017; Danish et al., 2018; Haseeb et al., 2019; Khan et al., 2020; Ozcan & Apergis, 2018; Salahuddin et al., 2016; Zhang & Liu, 2015). Firstly, Salahuddin et al. (2016) found a positive impact of ICT (the use of the internet) on the emissions of carbon (CO_2) in OECD countries over 1991–2012 by using the Pedroni panel co-integration and pooled mean group estimators (Salahuddin et al., 2016). Next, Asongu et al. (2017) employed the GMM technique to analyse the impact of information and communication technology (ICT) on environmental degradation (CO_2) in 44 SSA countries over the data of 2000–2012. The ICT (internet and mobile phone penetration) found a significant positive effect on CO_2 emissions (using the interactive regressions), whereas, the ICT had an insignificant effect on CO_2 (using the non-interactive regressions) (Asongu et al., 2017). Futhermore, Danish, Khan, et al. (2018) investigated the nexus between information and communication technology (ICT) and emissions of carbon in the N-11 countries by employing MG and AMG estimators from 1990 to 2015. They found the positive impact of ICT on CO_2 in these countries (Danish, Khan, et al., 2018).

On another note, Al-Mulali et al., (2015a, 2015b) explored the nexus between web retailing and CO_2 emissions in 77 countries for the data over 2000–2013. The GMM and two-stage least square methods were employed and it discovered that internet retailing diminishes CO_2 emissions in advanced countries, while, an inconsiderable effect of internet retailing on CO_2 emissions was found in developing countries (Al-Mulali et al., 2015a, 2015b). Later, Zhang and Liu (2015) examined the relationships between ICT and CO_2 nexus in China at regional and national levels over the period of 2000–2010 by using the STIRPAT model. The ICT was discovered to reduce the CO_2 as a higher impact in the central region in comparison with the eastern part, while the unimportant effect was found in the western region (Zhang & Liu, 2015). Similarly, Añón Higón et al. (2017) investigated 142 economies (116 are developing and 26 are developed countries) from 1995 to 2010.

ICT is found to help in declining of CO_2 emissions after the achievement of the threshold level of ICT development (Añón Higón et al., 2017). Furthermore, Ozcan and Apergis (2018) investigated the impact of ICT on CO_2 emissions in 20 emerging economies by using AMG and FMOLS from 1990 to 2015. The ICT (internet users) was found to lessen the level of air pollution (CO_2) (Ozcan & Apergis, 2018). Nevertheless, Haseeb et al. (2019) employed the dynamic seemingly unrelated regression (DSUR) in BRICS countries during 1994–2014. This study found that ICT (internet usage and mobile cellular subscriptions) has an adverse effect on CO_2 significantly (Haseeb et al., 2019). Moreover, Khan et al. (2020) applied the pooled OLS, FE, and GMM estimator techniques with panel-corrected standard errors (PCSE) in 91 countries over the period 1990 to 2017. They found that ICT reduces CO_2 emissions (Khan et al., 2020). Nevertheless, Bhujabal et al. (2021) pointed out the negative relationship of ICT-CO_2 nexus in major Asia Pacific countries by using the Pooled Mean Group (PMG) for the data from the year 1990 to 2018 (Bhujabal et al., 2021).

However, there are some findings of insignificant of the ICT and environmental degradation nexus. For instance, Amri et al. (2019) examined the impact of ICT on CO_2 emission in Tunisia over the period of 1975–2014 by using the ARDL approach. The study probed an insignificant relationship between ICT and environmental quality (CO_2) (Amri et al., 2019).

The extant literature has documentation on the EKC phenomenon. However, there is a paucity of studies that addressed the EKC phenomenon via the channel of urban population growth (urbanization) and access to ICT for the case of emerging blocs like N-11 economies. The need to explore the pivotal role of energy consumption, urbanization, and ICT in an ecological-income framework. From the above literature, we discovered a gap that should be investigated the effect of ICT and urbanization on the ecological footprint in the N-11 countries. Also, there are rare studies available that examined this issue. More importantly, this study aimed at addressing this dilemma to look into account cross-sectional dependence issue which has sought to fulfil the research gap. Against this background and the extant literature, we seek to advance the extant literature in the following front;

i. This current study augments the conventional EKC framework with energy consumption, access to ICT and urbanization on ecological balance. The motivation for the choice of the variables model stems from the United Nations Sustainable Development Goals (SDGs) crusade to be achieved by 2030 which is crucial for the Next 11 economies as our case study.
ii. Next, our study investigates the highlighted variables their influence on either favourable or otherwise on environmental sustainability for the Next 11 economies
iii. This study advances the extant literature by adopting second-generational econometrics techniques such as Westerlund cointegration, Feasible General Least Squares (FGLS) approach and Driscoll—Kraay standard error technique. Driscoll–Kraay standard errors and the Feasible General Least Squares (FGLS) approach in the methodology section. We choose this method because it helps circumvent the problem of cross-sectional dependence and heterogeneity, which has been confirmed in the model.

3 Data and econometrics methods

The series of econometric methods and data are exhibited in the next section.

3.1 Data sources and model construction

The panel data of the N-11 countries, including Egypt Arab Republic, Bangladesh, Indonesia, Mexico, Korea Republic, Iran Islamic Republic, Philippines, Nigeria, Pakistan, Turkey, and Vietnam have been used in this investigation. All the data covers the span period of 1992–2015. This study employed the ecological footprint (EF) as an explained variable. While for the explanatory variables, it included the gross domestic product (GDP), energy consumption (ENU), information and communication technology (ICT), and urbanization (URB). The trends of each variable are illustrated in the appendix. EF was measured as the total ecological footprint captured in the global hectare (gha) per capita. Economic growth (GDP) was used as a unit of per capital (constant \$2010 US dollars); ENU was measured as kg of oil equivalent per capita. Mobile cellular subscriptions were represented the information and communication technology (ICT). It was measured as (per 100 people). URB depicts the urban population as % of the total population. The EF was collected from the Global footprint network (2019), whereas the data of GDP, ENU, ICT, and URB were gathered from the World Bank (2019)-the world development indicators. The summary of the descriptive statistics is presented in Table 2.

Due to the lack of EKC investigation in the N-11 countries, this study constructed the model based on the EKC approach. The econometric model is formulated as in Eq. (1) to research the connection between the ecological footprint and its determinants namely economic growth, energy consumption, ICT, and urbanization. This study current study draws motivation based on the EKC hypothesis to construct the model after empirical studies from Sarkodie and Strezov (2018)

$$\mathrm{EF} = f(\mathrm{GDP}, \mathrm{GDP}^2, \mathrm{ENU}, \mathrm{ICT}, \mathrm{URB}), \tag{1}$$

Table 2 Descriptive statistics of variables

	lnEF	lnGDP	lnGDP^2	lnENU	lnICT	lnURB
Mean	0.499	7.911	63.713	6.698	1.600	3.831
Median	0.369	7.704	59.353	6.612	3.038	3.814
Maximum	1.783	10.121	102.443	8.596	5.081	4.405
Minimum	−0.779	6.031	36.374	4.780	−8.370	3.025
Std. Dev	0.623	1.059	17.072	0.864	3.233	0.393
Skewness	0.199	0.247	0.434	0.109	−0.930	−0.140
Kurtosis	2.302	2.020	2.129	2.827	2.780	1.934
Jarque–Bera	7.066	13.181	16.586	0.851	38.612	13.313
Probability	0.029	0.001	0.000	0.653	0.000	0.001
Observations	263	263	263	263	263	263

Source: Authors compilations

where EF is the amount of ecological footprint, GDP and GDP^2 are GDP per capita and its square, ENU is energy consumption, ICT is information and communication technology, and URB is urbanization. These variables were then translated into natural logarithm forms to capture the growth effects (Katircioglu et al., 2018) and elude the dynamic properties' problems in the data series (Paramati et al., 2017a, 2017b). Therefore, Eq. (1) in its transformed form into a natural logarithm is presented below:

$$\ln\ \mathrm{EF}_t = \beta_0 + \beta_1 \ln \mathrm{GDP}_t + \beta_2 \ln \mathrm{GDP}^2 + \beta_3 \ln \mathrm{ENU}_t + \beta_4 \ln \mathrm{ICT}_t + \beta_5 \ln \mathrm{URB}_t + \varepsilon_t, \tag{2}$$

where $\beta_i, i = 1, 2, \ldots, 5$ represented the coefficients of the long-run elasticity of ecological footprint about real GDP per capita, energy consumption, ICT, and urbanization, respectively. t represents a time frame, and ε represents the stochastic error term of the study. The fundamental strategies of econometrics are described in the below section.

3.2 Econometric methodologies

3.2.1 Cross-sectional dependence and Panel unit root test

This study is first using the distinct measurements and connection lattice to define the descriptive relation among the highlighted variables. Additionally, a cross-sectional dependence (CD) test was used to validate whether or not cross-sectional issues occurred in the data.

The CD test is formulated as following:

$$\mathrm{CD} = \sqrt{\left(\frac{2T}{N(N-1)}\right)}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\rho_{ij}\right), \tag{3}$$

where T represents the period and N denotes the number of cross-section units, while ρ_{ij} indicates the pairwise correlation of the errors between country i and country j.

The information of N-11 countries have diversification of economic structures and levels of series, to avoid unbiased results and forecasting errors; it is important to check for stationary properties, as recommended by Danish and Wang (2019a). To do this, the stationary problem was observed by second-generation estimators of the Cross-sectional Im, Pesaran, and Shin tests (CIPS) and Cross-sectional Augmented Dickey-Fuller (CADF) (Pesaran, 2007). This is because the use of first-generation was not taken into account of the cross-sectional issue. Therefore, the CADF test is constructed based on the following form:

$$\Delta y_{it} = a_i + \rho_i y_{it-1} + \rho_i \overline{y}_{it-1} + \sum_{j=0}^{k} \gamma_{ij} \Delta \overline{y}_{it-1} + \sum_{j=0}^{k} \delta_{ij} y_{it-1} + \varepsilon_{it}, \tag{4}$$

where a_i is the constant value, κ identifies lag specification, and $\overline{y}_t$ is the mean of CD value for time t.

The CIPS is formulated based on the mean values of CADF of Eq. 4, and the estimation model is demonstrated below:

$$\text{CIPS} = \left(\frac{1}{N}\right) \sum_{i=1}^{k} t_i(N, T), \tag{5}$$

3.2.2 Westerlund cointegration test

The next purpose of the econometric method is to identify possible cointegration between the variables. Miscellaneous cointegrations were proposed namely the Pedroni, Fisher-Johnson, and Kao panel cointegration tests; these tests fail to overcome the cross-sectional problem in panel data. However, the Westerlund cointegration test was used in this study to rectify the issues of cross-sectional dependence properties (Westerlund, 2007).

The Westerlund cointegration test is appropriated for panel data analysis which is centred on basis of panel statistics (Ps, Pa) and group statistics (Gs, Ga). Panel statistics pooling information from error correlation mechanisms in conjunction with cross-sectional units is used; while group statistics do not depend on information for error correction terms. Furthermore, due to the short time series fraction of each cross-section variable, the Westerlund cointegration approach provides a reliable approximation as proposed by Baloch and Meng (2019).

The Westerlund (2007) model has estimated the existence of cointegration between series $x_{i,\,t}$ and series $y_{i,\,t}$ as bellow:

$$\Delta y_{it} = \delta_i' d_t + \alpha_i \left(y_{it-1} - \beta_i' x_{i,t-1} \right) + \sum_{j=1 j=1}^{P_i} \alpha_{ij} \Delta y_{i,t-j} + \sum_{-q_i}^{P_i} \gamma_{ij} \Delta x_{i,t-j} + \varepsilon_{it}, \tag{6}$$

where d_t, P_i and q_i indicate component (0, 1) or a $(1, t)'$ vector, lag order, and lead order for i, respectively. While, $y_{it-1} - \beta_i' x_{i,t-1}$ denotes the co-integration, and α_i exhibits speed of system corrects return to long-run equilibrium.

3.2.3 The Driscoll–Kraay standard error technique

Driscoll and Kraay first introduced the Driscoll–Kraay standard error technique in 1998, as a non-parametric approach to examine the connection between the board arrangement (Driscoll & Kraay, 1998). The standard error technique of Driscoll–Kraay offers a continuous and precise result that accounts for the problem of cross-sectional dependence

(Sarkodie & Strezov, 2019; Wang, 2019). Additionally, the Driscoll and Kraay technique is superior because of its adaptability, and enormous time component as reported by Baloch and Meng (2019) and Baloch et al. (2019). The Driscoll–Kraay standard error technique has concurred several benefits as; (i) it counters missing values and implement in both unbalanced and balanced panel data, and (ii) it further resolves the issue of cross-sectional dependence, heteroscedasticity, and spatial problems in the analysis of the panel data (Baloch & Meng, 2019; Baloch et al., 2019; Sarkodie & Strezov, 2019). Consequently, the Driscoll–Kraay standard error technique was used in this study to investigate the relationship between the ecological footprint and the highlight variables reported in the N-11 countries data for the period 1992 to 2015. By doing so, the average values for independent variables and residuals were obtained in the prior stage. In addition, these values were further used in the weighted heteroskedasticity and autocorrelation consistent (HAC) estimator for computing and generating standard errors of additional consistency to cross-sectional dependence (Heberle & Sattarhoff, 2017). The Driscoll–Kraay standard errors model is expressed below:

$$y_{i,t} = x'_{i,t}\beta + \varepsilon_{i,t}. \tag{7}$$

3.2.4 Feasible General Least Squares (FGLS) approach

After the long-run analysis by the Driscoll–Kraay standard error approach, the estimation of panel-corrected standard errors (PCSE) has further been applied to robust the long-run relationship of the analysed variables. The PCSE provides a consistent long-run coefficient, thus mitigating the problem of a cross-sectional issue (Hoechle, 2007; Parks, 1967; Reed & Ye, 2011). According to our data in the analysis, the number of periods (T = 24 Years) is greater than the number of cross-sections (N = 11 Countries). The FGLS is appropriated for the long-run analysis as suggested as the number of periods (T) ≥ the number of cross-sections (N) (Reed & Ye, 2011). The empirical formula for FGLS can be estimated as follows:

$$\hat{\beta}_{\text{FGLS}} = \left(X'\hat{\Omega}^{-1}X\right)^{-1}X'\hat{\Omega}^{-1}y, \tag{8}$$

where $\hat{\Omega}$ denotes an innovations covariance.

Along with Eq. (8), the matrix of covariance can be computed as below:

$$\hat{\sum}_{\text{FGLS}} = \hat{\sigma}^2_{\text{FGLS}}\left(X'\hat{\Omega}^{-1}X\right)^{-1}, \tag{9}$$

where $\hat{\sigma}^2_{\text{FGLS}} = y'\left[\hat{\sigma}^{-1} - \hat{\sigma}^{-1}X\left(X'\hat{\Omega}^{-1}X\right)^{-1}X'\hat{\sigma}^{-1}\right]y/(T-p)$,

3.2.5 Dumitrescu and Hurlin panel causality test

The path of the relationship, i.e. causal link between the analysed variables should be investigated because policymakers can enforce suitable policies regarding the causal relationship. Dumitrescu and Hurlin (2012) proposed the Dumitrescu and Hurlin panel causality test as a revised and improved version of the Granger causality test to assess the path of the causal relationship. This causality test is based on two different statistics; the Z-bar statistics (standard normal distribution) and Wbar statistics (to take average statistics of the test). To achieve study objectives, the Dumitrescu and Hurlin panel causality was used in this study because it overcomes the cross-sectional dependence and heterogeneity issues which delivers more robust, rigorous, and accurate results in establishing this causal relationship (Danish et al., 2018; Danish & Wang, 2019a; Dumitrescu & Hurlin, 2012; Haseeb et al., 2019). According to Dumitrescu and Hurlin (2012), the causal relationship between variables Y and X can be formalized in the linear model as:

$$y_{it} = \alpha_i + \sum_{k=1}^{K} \gamma_i^{(k)} Y_{i,t-k} + \sum_{k=1}^{K} \beta_i^{(k)} X_{i,t-kt} + \varepsilon_{i,t}, \tag{10}$$

where α_i defines individual constants, $\gamma_i^{(k)}$ is the lag parameter, K denotes the lag length, $\beta_i^{(k)}$ represents the slope coefficients, and $\gamma_i^{(k)}$ $\beta_i^{(k)}$ illustrates the differences between cross-section units.

4 Empirical results and interpretation

This section concentrates on the empirical results, discussions accordingly. The section set off with basic summary statistics and subsequently pair-wise correlation analysis to explore the basic relationship of the outlined variables for the N-11 countries. In Table 2, we find the most elevated instability in ICT and the least unpredictability in the ecological footprint. The quadratic form of economic growth (GDP) is possessing the highest average, maximum, and minimum values. It is followed by energy consumption from fossil fuel sources and urbanization. All series exhibits light tail as reported by the Kurtosis with a total sample size of 263 for 11 countries.

The correlation matrix is presented in Table 3, a positive correlation is seen between the growth of the economy (GDP), the use of energy (ENU), ICT, and urbanization (URB) with the ecological footprint in the N-11 countries.

The boxplots for all the involving variables namely the ecological footprint (EF), economic growth (GDP), the square of GDP (GDP^2), energy consumption (ENU), information and communication technology (ICT), and urbanization (URB) are shown in Fig. 1. It provides the data distribution of all factors for the selected panel of N-11

Table 3 Correlation analysis

Probability	lnEF	lnGDP	lnGDP^2	lnENU	lnICT	lnURB
lnEF	1.000					
	–					
lnGDP	0.962	1.000				
	(0.000)	–				
lnGDP^2	0.960	0.997	1.000			
	(0.000)	(0.000)	–			
lnENU	0.955	0.928	0.922	1.000		
	(0.000)	(0.000)	(0.000)	–		
lnICT	0.435	0.457	0.446	0.396	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	–	
lnURB	0.913	0.962	0.952	0.894	0.466	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	–

Source: Authors compilations

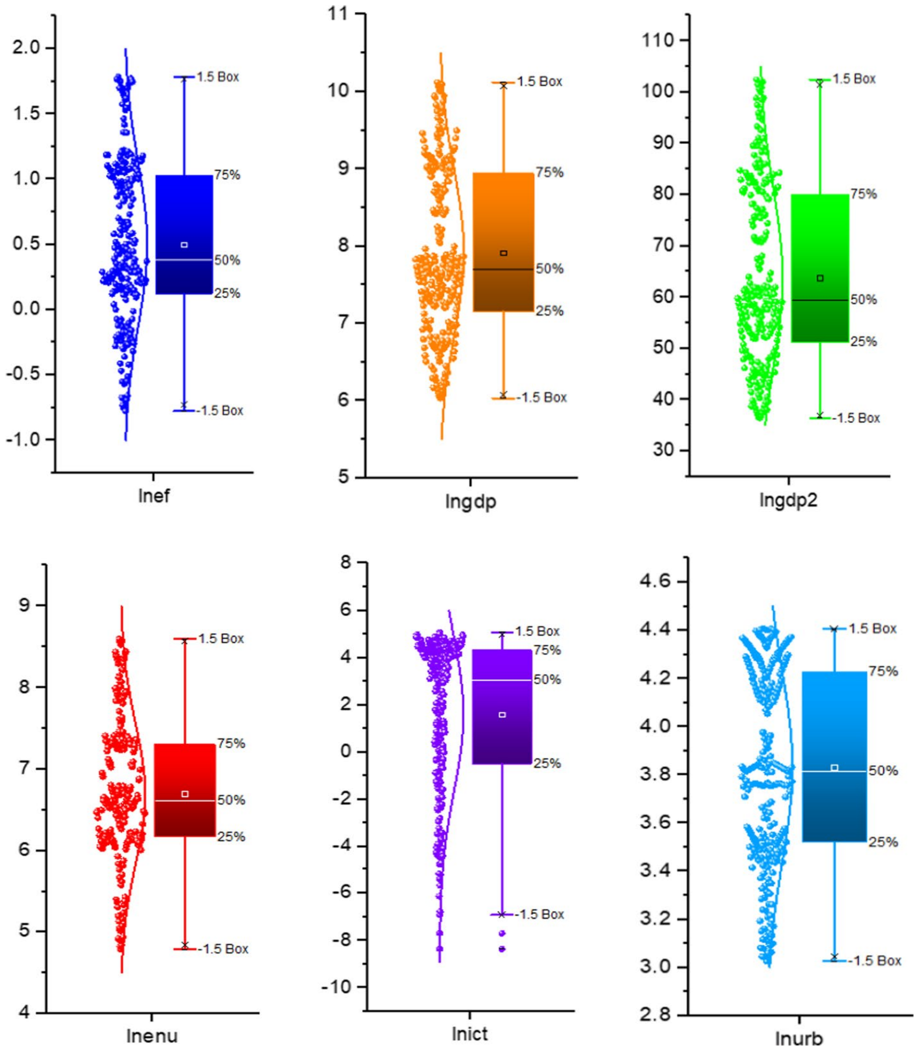

Fig. 1 Whiskers plot (boxplot) of the variables under consideration

countries from 1992 to 2015. The scatter plot boxes show that each plots' percentile is 25/50/75, whisker caps represent the 1/99 percentiles. The dots indicate the maximum (top) and minimum (down) values, while their mean values are signified by the square.

Subsequently, we proceed to investigate the appropriate modelling techniques for either first- or second-generation panel techniques. Thus, we conduct the cross-sectional (CD) test, and the results are illustrated in Table 4. Based on a *p*-value of less than 0.01, the null hypothesis is significant evidence to reject according to the CD test, Breusch-Pagan LM, and Pesaran scaled LM. Consequently, the results prove that the cross-sectional dependence has existed for EF, GDP, GDP^2, ENU, ICT, and URB. This outcome necessitates the need to proceed with second generational panel econometrics to avoid the pitfall of a spurious regression and by extension misleading inferences.

Table 4 Panel unit root test

Variables	CD test		Breusch-Pagan LM		Pesaran scaled LM	
	Statistic	p-value	Statistic	p-value	Statistic	p-value
lnEF	14.877[a]	0.000	478.369[a]	0.000	40.366[a]	0.000
lnGDP	33.702[a]	0.000	1139.944[a]	0.000	103.445[a]	0.000
lnGDP^2	33.709[a]	0.000	1140.507[a]	0.000	103.499[a]	0.000
lnENU	21.622[a]	0.000	837.588[a]	0.000	74.616[a]	0.000
lnICT	33.534[a]	0.000	1134.366[a]	0.000	102.913[a]	0.000
lnURB	19.207[a]	0.000	963.933[a]	0.000	86.663[a]	0.000

[a,b,c]are statistically significant at 1%, 5%, and 10% levels, respectively

Next is to investigate of stationarity properties of the outlined variables. On the premise of the CD test results, we proceed with the unit root test that accounts for cross-sectional. The outcomes of unit root tests are summarized in Table 5. The results of the CIPS and CADF panel unit root reveal that the rejection of the null hypothesis (no stationarity) is not confirmed at the level. Whereas the null hypothesis (no stationarity) is confirmed to reject at the first difference I(1), therefore it is integrated at I(1).

To explore the long-run equilibrium traits of the outlined variable we rely on the Westerlund cointegration test. As per the analysis of the Westerlund cointegration test, the rejection of the null hypothesis (no cointegration) is confirmed due to the p-value. Thereupon, Table 6 exhibits the cointegration from the Westerlund cointegration test. Thus, the existence of cointegration is confirmed, it reveals concrete proof of the long-run relationship between underlying variables.

Table 5 Panel unit root tests

Variable	CIPS test statistic		CADF test statistic	
	Level	First difference	Level	First difference
lnEF	−1.146	−4.320[a]	−1.970	−3.011[a]
lnGDP	−1.327	−3.174[a]	−1.985	−3.508[a]
lnGDP^2	−1.203	−3.129[a]	−1.952	−3.505[c]
lnENU	−1.112	−4.104[a]	−2.445	−4.489[a]
lnICT	−1.411	−3.483[a]	−2.272	−3.498[a]
lnURB	−0.884	−1.673[b]	−3.756[a]	−1.660

[a,b,c]are statistically significant at 1%, 5%, and 10%, respectively

Table 6 Cointegration results (Westerlund cointegration)

Statistic	Value	z-value	p-value	Robust p-value
Gt	−4.494[a]	−5.331	0.000	0.000
Ga	−4.756	5.221	1.000	0.960
Pt	−11.283[c]	−2.052	0.020	0.050
Pa	−5.750	3.651	1.000	0.740

[a,c]are statistically significant at 1% and 10%, respectively

The analysis of the Driscoll–Kraay regression model is illustrated in Table 7. The results indicate that the coefficient of economic growth (GDP) is statistically significant positive with the ecological footprint (0.448, P< 0.01). Oppositely, the square of economic growth (GDP^2) is insignificant and negative with the environmental pollution of the ecological footprint (-0.001, $p > 0.1$), suggesting a surge in economic growth, leading to a depletion of the ecological footprint (EF) in the N-11 countries, and the economic growth is not reached the certain level of environmental improvement according to the EKC approach. Based on the result, it confirms that EKC behaviour is invalid between economic growth and ecological footprint in the N-11 countries. This indicates the emphasis on the growth of the economy relative to deplete of the environment where priority is placed on economic growth. Thus, suggesting the N-11 countries is at a scale stage of their growth trajectory. Specifically, the ascent in GDP leads to an increase in the degree of the ecological footprint (EF) in the N-11 countries. That is due to the N-11 countries are the emerging countries aiming for high economic growth every year. Manufacturing and industrial sectors are the main drives of their economy, thus their practices in these sectors rely on low efficient technology as saving initial cost at the beginning stage of development. This could increase the amount of pollution emission, for example in air pollution from the industrial zone in Bangladesh, Indonesia, and Vietnam. Furthermore, the resources/agriculture products were heavily drawn for the production of goods and services, which leads to an increase in economic growth as well as an increase in land-use conflicts between forest and commercial agriculture areas. Therefore, biological capacity and environmental quality were degraded in these countries. The result of invalid of EKC is in the same direction with the study in 150 countries (Wang et al., 2013); 15 countries (Hervieux & Darné, 2013); 87 countries (Aşıcı & Acar, 2018); BRICST countries (Dogan et al., 2020); and China (Yilanci & Pata, 2020).

However, this result is in contrast with an inverted U-shaped EKC behaviour between GDP and the ecological footprint in 116 countries (Aşıcı & Acar, 2016); Pakistan (Aziz et al., 2020; Hassan et al., 2019); MINT countries (Balsalobre-Lorente et al., 2019); ASEAN countries (Kongbuamai et al., 2020a, 2020b); Turkey (Sharif et al., 2020); EU countries (Altıntaş & Kassouri, 2020); and G7 countries (Wang et al., 2020).

Besides, energy consumption (ENU) has been exhibited as a positive relationship with the ecological footprint (0.3266, $p < 0.000$). As the consumption of energy increases by 1%, it enhances the ecological footprint increases by 0.326% in the N-11 countries. This implies that the N-11 counties invigorate their ecological footprint

Table 7 Regression with Driscoll–Kraay standard errors

Variables	Coefficient	Standard errors	t-stat	p-value
lnGDP	0.448[a]	0.111	4.04	0.001
$\ln GDP^2$	−0.001	0.005	−0.23	0.816
lnENU	0.326[a]	0.015	20.58	0.000
lnICT	0.002[c]	0.001	1.97	0.061
lnURB	−0.316[a]	0.105	−3.01	0.006
Constant	−3.947[a]	0.227	−17.35	0.000
F statistics	14,378.17			
p value	0.000			
R^2	0.957			
Observation	264			
Number of groups	11			

[a,c]are statistically significant at 1% and 10%, respectively

through the consumption of energy unavoidably. This is because the N-11 countries rely heavily on conventional energy, i.e. fossil fuel, coal, natural gas, etc. Furthermore, there is some huge fossil fuel production in members of N-11, i.e. Mexico and Indonesia, etc. Also, there is a huge population in Indonesia, Pakistan, Mexico, Nigeria, Bangladesh, etc. They could consume a high amount of energy accordingly. Furthermore, the low efficient production and massive consumption could contribute to the big-scale negative effect of the energy sector on the ecological footprint. Moreover, some countries also faced an energy shortage. For example, Pakistan is one of the world's energy shortage countries, the low technology of agriculture biomass/other energies are widely used. This practice of technology could harm the air quality, thus harming people's health. This positive relationship is in the same finding as to the analysis by Al-Mulali et al., (2015a, 2015b) in 93 countries; Destek and Sarkodie (2019) in 11 newly industrialized countries; Zafar et al. (2019) and Ahmed and Wang (2019) (2019 in the US; Alola et al. (2019) in EU countries; Saud et al. (2019) in one-belt-one-road initiative countries; Kongbuamai et al., (2020a, 2020b) in ASEAN countries; Ahmed et al. (2020) in G7 countries; and Destek and Sinha (2020) in the OECD countries.

Additionally, ICT also reveals a statistically positive relationship with EF. As ICT increases by 1%, it enhances the ecological footprint increased by 0.002% in the N-11 countries. Thus, suggesting that ICT innovation is dirty driven in the N-11 countries. This is because ICT appliances require a lot of energy in these N-11 countries. As of today, almost 10% of all energy used and 4% of carbon emissions in the environment are estimated as coming from ICT only (Baracchi, 2016). Furthermore, the construction and development of ICT required various resources and physical geography for example the land for antenna setting, distributor, satellite dish, etc. In addition, the importing of used ICT/ electronics devices from developed countries also main cause the environmental quality in the N-11 countries for example huge amounts of used ICT imported to Nigeria. This result is in the same finding of the positive relationship between ICT and CO_2 in OECD countries (Salahuddin et al., 2016); 44 SSA countries (Asongu et al., 2017); and the N-11 countries (Danish, Khan, et al., 2018). On the other hand, ICT was also found to reduce the CO_2 in 77 countries (Al-Mulali et al., 2015a, 2015b); the central region and eastern part of China (Zhang & Liu, 2015); 142 economies (Añón Higón et al., 2017); 20 emerging economies (Ozcan & Apergis, 2018); BRICS countries (Haseeb et al., 2019); and 91 countries (Khan et al., 2020).

The interaction that exists between urbanization and EF shows a statistical negative. As a 1% increase in urbanization leads the ecological footprint decreased by 0.316% in the N-11 countries. This indicates that the urban population in N-11 countries is more conscious of environmental sustainability. Due to the huge amount of population and growth rate in N-11 countries, many countries sustainably revise their urban planning. For example, South Korea urges sustainable urban planning by integrating energy, transportation, environmental, and technology aspects. This initiative purpose is to help to increase the efficiency of resource/energy utilization which mitigate the negative effect on the environment. Furthermore, the appropriate number of populations in the city/ area could also help to obtain the economics of scale which are a benefit for both goods and services providers and users. This result is the same finding in the upper-middle- and high-income countries (Ozturk et al., 2016); 15 MENA countries (Charfeddine & Mrabet, 2017); top 10 tourist destination countries (Katircioglu et al., 2018); Malaysia (Bello et al., 2018); Pakistan (Hassan et al., 2019); and BRICS countries (Danish, Ulucak, et al., 2019). Whereas, it is the opposite with the analysis in the 93 Countries

(Al-Mulali et al., 2015a, 2015b); Qatar (Charfeddine, 2017); the N-11 countries (Danish & Wang, 2019b); and 14 SSA countries (Wang & Dong, 2019).

To confirm the robust result of the long-run relationship, the FGLS analysis is computed and illustrated the results in Table 8. Firstly, the result of the FGLS analysis is following the long-run results of the Driscoll–Kraay standard errors. The FGLS estimation suggests that a 1% increase in economic growth enhances ecological footprint by 0.453% in N-11 countries. Moreover, it is the largest coefficient among underlying variables. In addition, the relationship between the ecological footprint and GDP^2 is found insignificant. In conclusion, the result of FGLS confirms the invalid of ECK in these11 countries which is similar to the result of Driscoll–Kraay standard errors. For energy consumption, the FGLS estimation also reveals that a 1% increase in energy consumption increases the ecological footprint by 0.326% in this case. Furthermore, ICT increases the ecological footprint in N-11 countries. The analysis of FGLS has confirmed a 1% increase in ICT increases the ecological footprint by 0.002%. On contrary, the negative relationship between urbanization and the ecological footprint is also confirmed which is following the result of Driscoll–Kraay standard errors in the case of N-11. The FGLS analysis has confirmed that a 1% increase in urbanization reduces the ecological footprint by 0.308% in those countries.

For the path of causality analysis, the result of the Dumitrescu and Hurlin panel causality test is presented in Table 9. We observe a feedback causality between urbanization and economic growth. This is in line with the analysis in MENA countries (Charfeddine & Mrabet, 2017), BRICS nations (Haseeb et al., 2019), and G7 countries (Ahmed et al., 2020). Also, bidirectional causality between urbanization and ICT is confirmed in this study. This causal linkage between urbanization and ICT is scant.

Furthermore, it shows that a one-way Granger-causation (unidirectional) runs from the growth of the economy, the consumption of energy, urbanization, and ICT to the ecological footprint. This suggests that the growth of the economy, the use of energy, urbanization, and ICT drive environmental sustainability one way. Progressively, the one-way causal relationship also exists from the economic growth, urbanization, and ICT to energy consumption in the N-11 countries. Those causality relationships illustrate conclusively in Fig. 2.

Table 8 Results of FGLS estimation

Variable	FGLS			
	Coefficient	Standard errors	*z*-test	*p*-value
lnGDP	0.453[a]	0.028	15.96	0.000
$\ln GDP^2$	−0.001	0.002	−1.00	0.319
lnENU	0.326[a]	0.005	61.89	0.000
lnICT	0.002[a]	0.001	3.92	0.000
lnURB	−0.308[a]	0.019	−16.37	0.000
The Wald Chi^2	100,424.47			
p-value	0.000			
Observation	264			
Number of groups	11			

[a]denote statistical significance at the 1%

Table 9 Causality analysis

Null hypothesis:	*W*-Stat	Zbar-Stat	Prob
lnGDP → lnEF	6.18350[a]	5.01177	0.0000
lnEF → lnGDP	3.34640	1.38157	0.1671
lnENU → lnEF	3.20875[a]	4.06292	0.0000
lnEF → lnENU	2.99396	0.93061	0.3521
lnICT → lnEF	4.61773[a]	3.00829	0.0026
lnEF → lnICT	2.87213	0.77472	0.4385
lnURB → lnEF	6.07103[a]	4.86786	0.0000
lnEF → lnURB	2.56808	0.38567	0.6997
lnENU → lnGDP	2.87696	0.78090	0.4349
lnGDP → lnENU	4.66126[a]	3.06399	0.0022
lnICT → lnGDP	3.48049	1.55314	0.1204
lnGDP → lnICT	2.94343	0.86595	0.3865
lnURB → lnGDP	10.4655[a]	10.4908	0.0000
lnGDP → lnURB	6.52226[a]	5.44522	0.0000
lnICT → lnENU	5.33629[a]	3.92773	0.0000
lnENU → lnICT	1.78739	−0.61325	0.5397
lnURB → lnENU	8.26301[a]	7.67259	0.0000
lnENU → lnURB	1.82772	−0.56165	0.5744
lnURB → lnICT	6.72006[a]	5.69832	0.0000
lnICT → lnURB	5.13466[a]	3.66973	0.0002

[a]is statistically significant at 1%

Source: Authors compilations

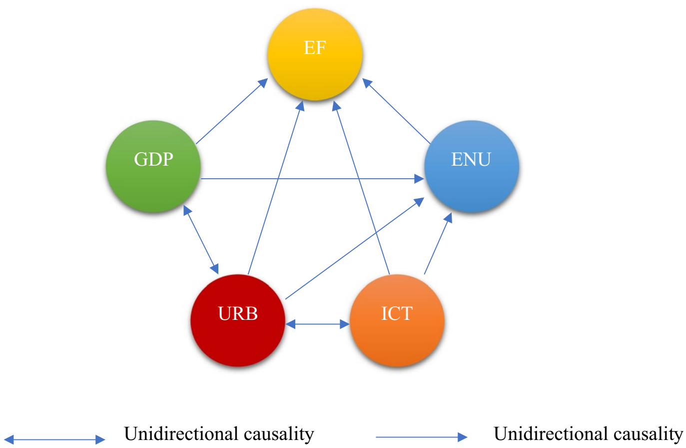

Fig. 2 The causality relationship among the underlying variables

5 Concluding remarks and policy directions

This study analysed the influence of urbanization, ICT, GDP growth, and energy consumption on the environmental quality as measured by (ecological footprint) for the case of N-11 economies. The panel data for the N-11 countries were used from 1992 to 2015 to explore the hypothesized relationship while accounting for regular stun impact (cross-sectional dependence). To this end, a series of panel econometrics techniques were used to achieve rigorous empirical analysis, the result indicates the invalidation of EKC behaviour (inverted U-shape) in the N-11 countries. This implies the blocs of 11 countries are dirty economic driven relative to the quality of the environment. The plausible explanation for this is the fact that most N-11 countries are emerging economies at the early stage of technology improvement and development. Also, the land uses in these countries are mainly occupied by the primary agriculture sector which has a conflict with the biocapacity reserve. Furthermore, we found that urbanization has an adverse disturbance on ecological footprint, while the use of energy and ICT reveal a positive impact (the same direction) on the ecological footprint of the N-11 countries. On the direction of causality among the highlighted variables, the causality analysis shows a feedback causality relationship between economic advancement (GDP) and urbanization as well as between ICT and urbanization. Moreover, a one-way causality nexus exists which runs from economic growth, ICT, urbanization, and energy consumption to the ecological footprint.

This study adds empirical findings to extant literature with policy suggestions. First, the N-11 economies do not meet the turning moment of the EKC hypothesis. Therefore, the N-11 countries' advancement plan should integrate the framework of the green economy/green growth in compliance with the UN-SDGs goals (UN, 2015) to preserve sustainable economic growth and environmental sustainability targets. Second, the N-11 economies demand a high energy consumption to maintain their growth-goal economy. Policymakers should pay heed to the advancement of sustainable technologies by transitioning from conventional energy sources to clean and environmentally friendly energy sources as suggested by Owusu and Asumadu-Sarkodie (2016). In addition, environmental taxes or subsidies can be imposed in the energy sector to decrease their impact on the environment as advocated by Zhang and Yousaf (2019). This would help to meet the UN-SDGs goals (UN, 2015) by the energy aspect. Third, ICT instruments can contribute immensely as an integral part in strengthening policies on environmental sustainability (Jaffe et al., 2002). The government should emphasize the use/development of advanced and clean ICT technology (i.e. internet usage, mobile subscribers) to facilitate the efficiency of resource use and energy-saving as suggested in one of the SDGs (UN, 2015). More important, the government should reduce the number of imported-used ICT and electronics e-waste to the region. On top of that, advanced and clean ICT technology can help to increase the countries' productivity, it will lead the N-11 countries to obtain the growth of their economic activities as the suggestion by the endogenous growth model of Romer (1994). Thus, it will also help to reduce the adverse impact on the environment.

Finally, policymakers should continually lay a plan of sustainable urban planning in the N-11 countries. This plan could further help to increase efficiency and saving of all types of resources in preparing for the large growth of the population in achieving the 2030 SDGs (UN, 2015). To achieve this, environmental awareness, renewable energy, sustainable transportation, and clean technology/ICT utilization can be suggested to include in their sustainable urban planning. In the end, this will improve environmental quality in N-11 countries which further reduces the rate of environmental depletion.

This study concentrates on the interrelationship that exists among ICT, urbanization, the growth of the economy, the consumption of energy, and environmental degradation (the ecological footprint) for N-11 economies which is less documented in extant literature with available data. This econometric approach can be further explored by extending to more countries and a long period. Additional research in time series analysis can also be considered to deepen knowledge of the ecological footprint and ICT nexus. Future research will also add new variables that link environmental deterioration and ICT nexus like $PM_{2.5}$, other emission indications, human resources, etc. Finally, nonlinear regression approaches may also use for the analyses in further study.

Appendix

See Figs. 3, 4, 5, 6 and 7.

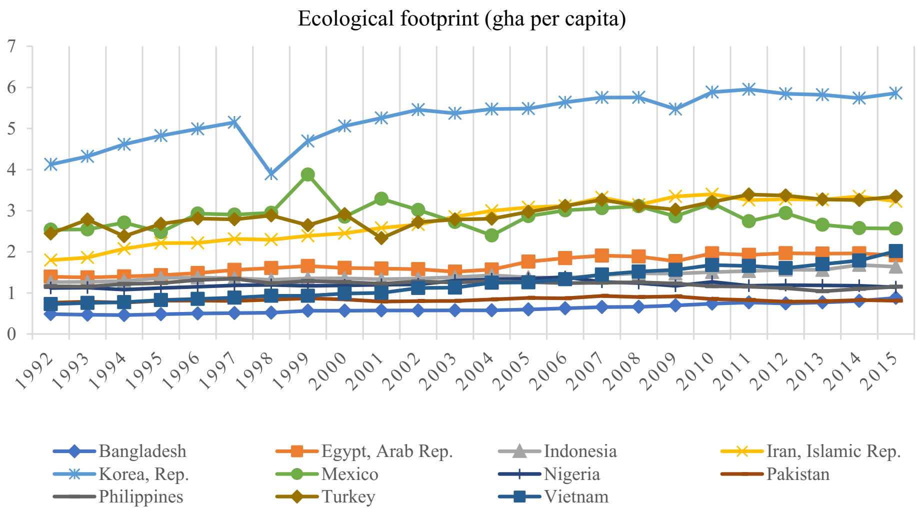

Fig. 3 The trend of the ecological footprint in the N-11 countries. Source: Global Footprint Network (Global Footprint Network, 2019)

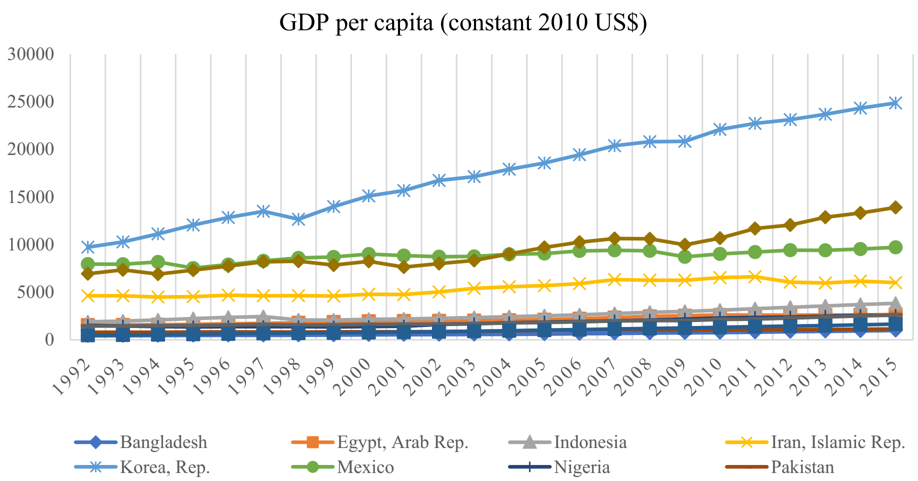

Fig. 4 The trend of the economic growth in the N-11 countries. Source: The World Bank (World Bank, 2019)

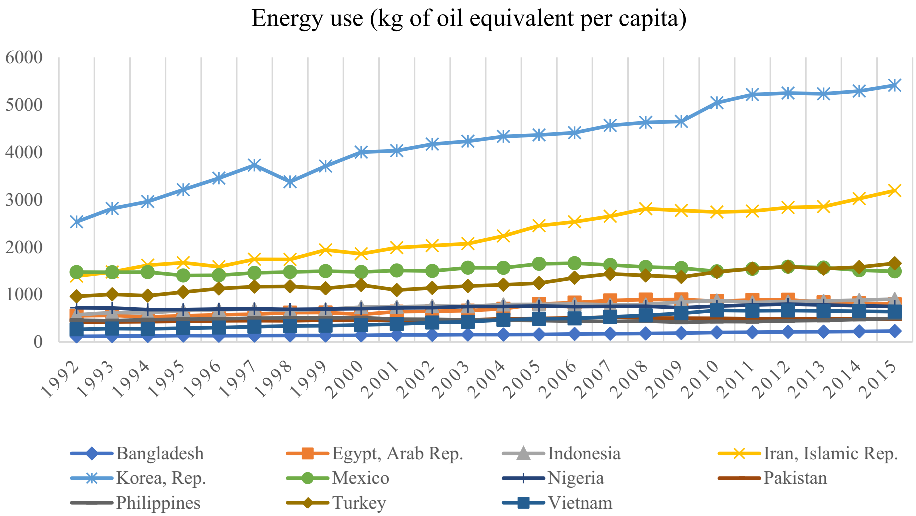

Fig. 5 The trend of the energy consumption in the N-11 countries. Source: The World Bank (World Bank, 2019)

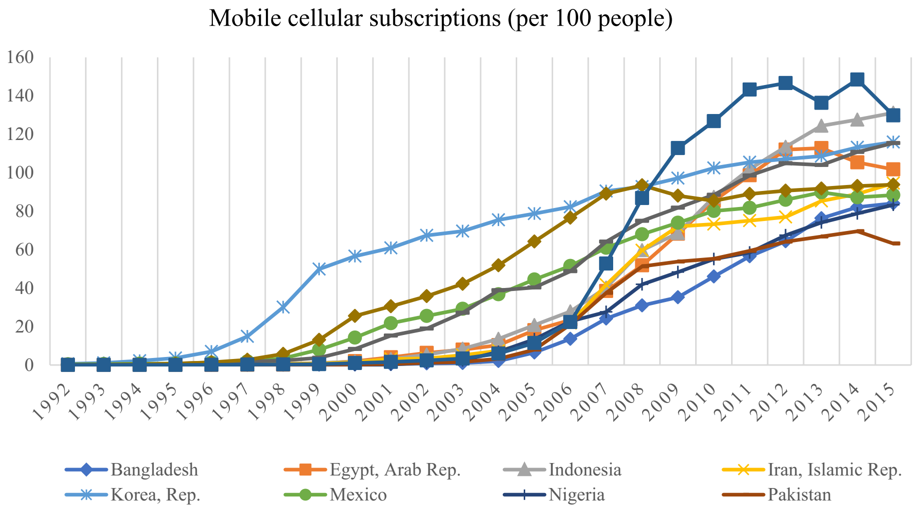

Fig. 6 The trend of the information and communication technology in the N-11 countries. Source: The World Bank (World Bank, 2019)

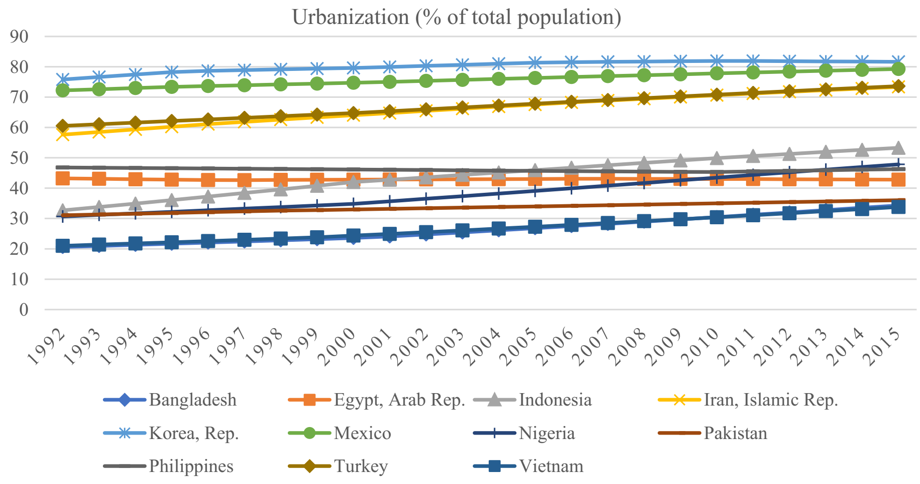

Fig. 7 The trend of the urbanization in the N-11 countries. Source: The World Bank (World Bank, 2019)

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