Georgian Environmental Kuznets Curve:
An Appropriate Estimation.

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ABSTRACT

Empirical EKC literature has conceptual flaws that arise due to the inclusion of polynomials and cointegrating relationships of powers of integrated processes. Additionally, previous studies focused on a narrow nexus between environmental degradation and economic growth that yield only a partial EKC. Considering hereinabove mentioned points the aim of this study is to assess the EKC hypothesis in the case of Georgia using a composite measure of environmental degradation and employing the appropriate estimation of the cointegrating polynomial relationship developed by Wagner (2015). The proposed estimation model is an extension of a fully modified estimator of Phillips and Hansen (1990). Additionally, the model specification and cointegrating relationship have been tested using a special KPSS-type test derived by Wagner (2015). The main findings suggest that an inverted U-shaped relationship exists when changes in biocapacity deficit/reserve, Kyoto basket of greenhouse gas emissions, and carbon dioxide emissions are incorporated into the analysis. However, Environmental Degradation Index does not support the existence of EKC.

Keywords: Environmental Kuznets Curve, integrated processes, Planetary Boundary, Environmental Degradation Index

"Is this how our story is due to end? A tale of the smartest species doomed by that all too human characteristic of failing to see the bigger picture in pursuit of short-term goals?"

- Sir David Attenborough

1. INTRODUCTION

1.1 Acknowledgement of environmental problem

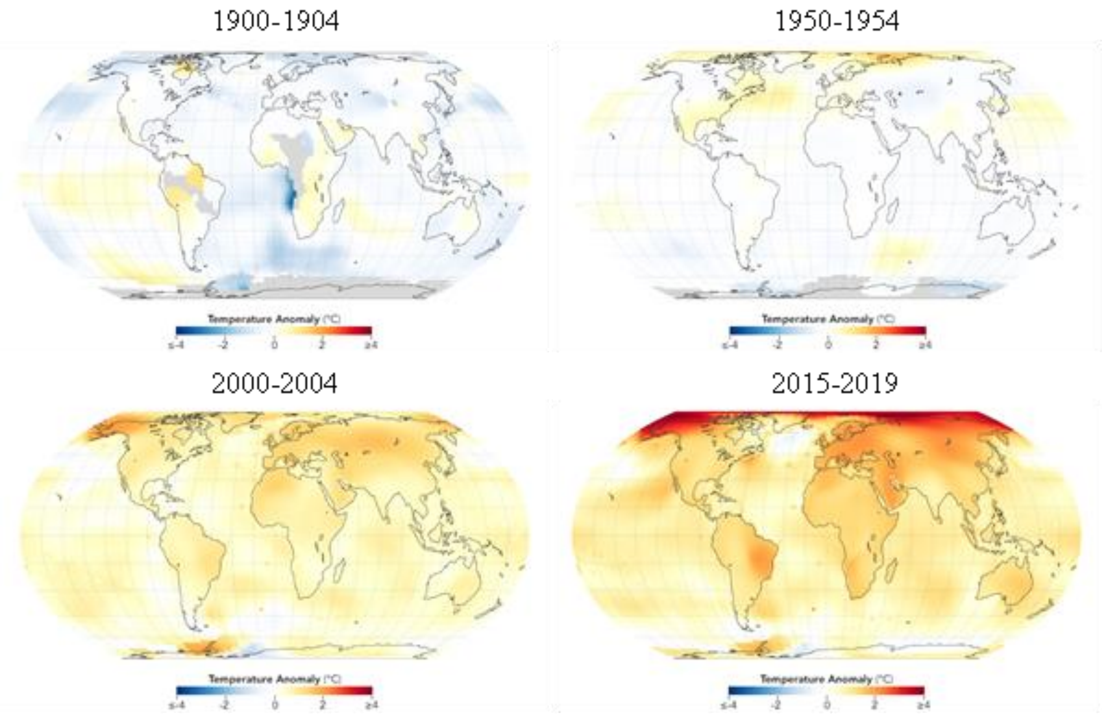
The exponential growth of environmentally destructive human activities over the last century has reached such levels that become hard to be neglected and raised serious concerns regarding the stability and the balance of Earth Systems. The term *Anthropocene Epoch,* an unofficial unit of geologic time, describes the most recent interim in Earth's history when it is being forced into planetary *terra incognita* by profound anthropogenic causes (Steffen et al., 2007). The "Great Acceleration" graphs[1] that illustrate Earth Systems trends over the 260 years show that most of the indicators have grown exponentially, while only two, atmospheric methane concentration and stratospheric ozone loss, exhibited some stabilization pattern over the past decades (Steffen et al., 2015). According to Global Footprint Network[2], Ecological Footprint from human activities exceeded Earth's total Biocapacity by approximately 9.1 billion gha[3] in 2018. In other words, to maintain the current level of consumption of goods and services and simultaneously for all the generated waste to be absorbed by nature we need the regenerative capacity of 1.56 Earth (World Wide Fund for Nature, 2020). In that respect, climate change and the concentration of greenhouse gases in the atmosphere is the most important chain of the Earth Systems, as its negative consequences are more pervasive. The latest Intergovernmental Panel on Climate Change (2021) report stated that climate changes have been observed in every region of the world (see Figure 1). The report used the words "irreversibility" and "irreversible" 28 and 74 times respectively, referring to the more visible aftermath of climate change. The fact that it took only 3.5 years for A68A[4] (the largest iceberg that broke from Antarctica in 2017) to melt is just one of the recent examples of how climate change is a serious issue (Braakmann-Folgmann et al., 2022).

Starting from the second half of the last century, humanity started acknowledging environmental and climate change risks and their catastrophic consequences gravely. 1979 was the first time when countries gathered under the same roof to discuss climate change issues at The First World Climate Conference in Geneva. This conference has been followed by a series of meetings and roundtables where several important action plans and treaties have been signed. 1997 Kyoto Protocol which is an extension of the 1992 United Nations

[1] The "Great Acceleration" graphs were last updated to 2010 and they comprise 12 Earth System indicators from atmospheric carbon dioxide concentration to terrestrial biosphere degradation.
[2] See: www.data.footprintnetwork.org
[3] Global hectares
[4] The iceberg was on average 230 meters thick and covered an area of nearly 6,000 square kilometres.

Framework Convention on Climate Change was based on the scientific consensus that CO_2 emissions stemming from human activities are driving global warming and immediate action must be taken to reduce greenhouse gas emissions. Then, the 21st century started with the adoption of the United Nations Millennium Declaration, followed by the establishment of the Millennium Development Goals (MDG) for 2015. Although very important achievements have been made on many of the MDGs in the world, advancement has been uneven across regions and countries, leaving telling gaps. Hence, to close all these gaps and achieve a sustainable future for all, in 2015 UN General Assembly set up Social Development Goals by 2030. A turning point for global climate action was the 2015 Paris Agreement where nearly all nations gathered at the United Nations Framework Convention on Climate Change's (UNFCCC) 21st Conference of the Parties came to complete unanimity to combat climate change by setting a comprehensive goal for the century of limiting global temperature increase to 2° C. Followingly, it has been estimated that 6.35 trillion EUR is required yearly to meet Paris Agreement globally (OECD, 2017), which puts high pressure on economic growth in the context of sustainability.

Figure 1. Air temperature anomaly on Earth



Source: *www.earthobservatory.nasa.gov/world-of-change/global-temperatures*

Note: NASA's Goddard Institute for Space Studies (GISS) scientists have reported at least 1.1° C increase in the average global temperature on Earth since 1880. 2021 was the sixth warmest year on record.

1.2 Environmental Kuznets Curve

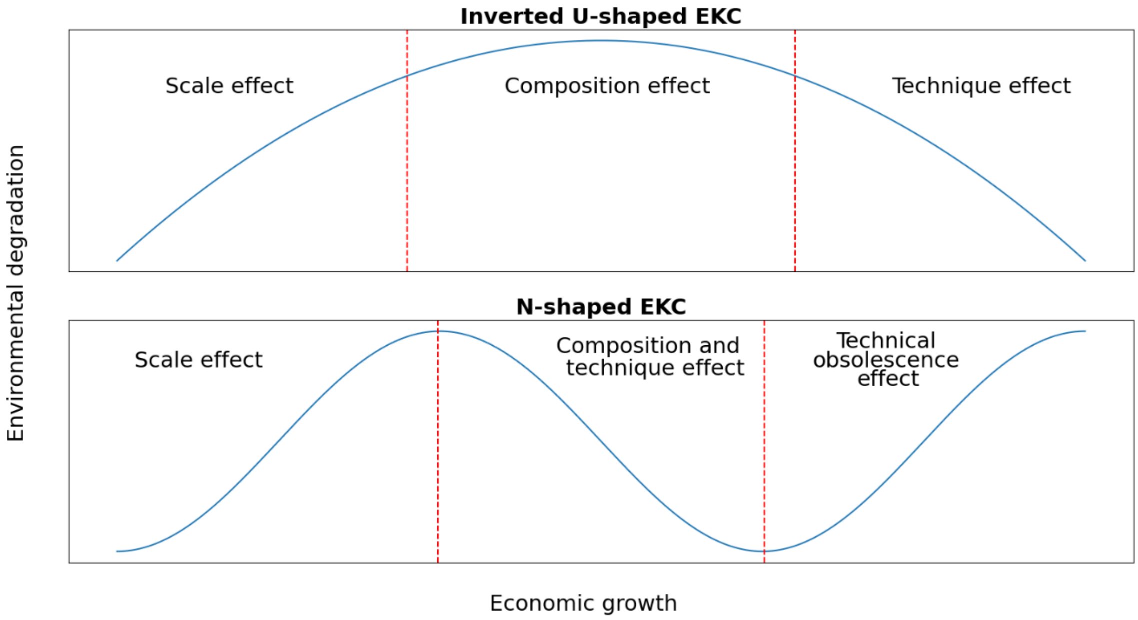
As environmental awareness rose the nexus between economic growth and environmental degradation has become a hot topic since the late 1980s. The major studies on this topic can be traced back to Grossman and Krueger (1991) who realized that their findings resemble those of Simon Kuznets (1955), which they named after an Environmental Kuznets Curve (EKC) hypothesis. Since then, the vast literature in energy and environmental economics has evolved around it. Bashir et al. (2021) have identified 1775 studies (in nine languages) centred around EKC between 1999 and 2020 that are published in 20 major scientific journals.

The main idea of the EKC hypothesis is that there is some type of a relationship between economic growth and environmental degradation which is positive at first but turns slowly into a negative one. Modern literature mainly specifies such a relationship as quadratic or cubic leading to an inverted U-shaped or N-shaped curve respectively. Although some researchers including Narayan and Narayan (2010) used linear specification of the EKC hypothesis, they have been criticised that the reduction of the value of elasticity of measure of pollution with respect to economic growth indicator does not provide any information that the EKC curve is downward, upward or constant sloping. It only represents how this relationship changes with time (Brown and McDonough, 2016).

There are several effects (see Figure 2) that could explain the curvature of the EKC: scale, composition, and technical (Grossman and Krueger, 1991). Also, there is a technical obsolescence effect that is valid for N-shaped EKC (Lorente and Álvarez-Herranz, 2016).

- *Scale effect*: the transitional period from pre-industrial to industrial economy causes intensified use of natural and energy resources. This gradually leads to the regeneration rate of natural resources falling behind their depletion rate. Amplification of non-recyclable waste by spurring industrialization results in increased pollution. Consequently, the scale effect contributes to environmental degradation (Torras and Boyce, 1998; Prieur, 2009).
- *Composition effect*: further economic growth makes knowledge and technology-intensive economy surpass agrarian centred one. Through this structural transformation a more developed, efficient, and environmentally friendly economy emerges. As a result, the developed economy starts exploiting more efficient energy sources and procedures, which lessens the demand for non-renewable resources and reduces pollution (Hettige et al., 2000).

Figure 2. EKC curvature formation



Source: author's own drawing

Note: N-shaped EKC is validated by calculating local maxima and minima (inflection points) of the first derivative of cubic equation. Inflection points must be real numbers:

$Y_{maxima} > Y_{minima}$: N-shaped EKC

$Y_{maxima} < Y_{minima}$: inverted N-shaped EKC

- *Technique effect*: allocation of more resources to R&D, replacement of outmoded and contaminating production technologies with cleaner alternatives enhances environmental quality level (Copeland and Taylor, 2004). Moreover, the increase in environmental awareness initiates stricter environmental laws and regulations. Porter and Van Der Linde (1995) asserted that stringent environmental regulation can stimulate innovation and induce efficiency while reducing environmental degradation (also known as Porter Hypothesis).
- *Technical obsolescence effect*: among all stated effects technical effect is the most important one as it is the reason for the amelioration of environmental degradation (Andreoni and Levinson, 2001). However, technical obsolescence ensues once the scale effect transcends the technical effect leading to rises in the environmental deterioration. Eventually, growing yields from the technical innovations do not persist in the long term and they begin catalysing the economy to rebound to a state of growing ecologic destruction (Lorente and Álvarez-Herranz, 2016). Therefore, the technical obsolescence effect gives a rise to the N-shaped EKC.

1.3 Planetary Boundaries

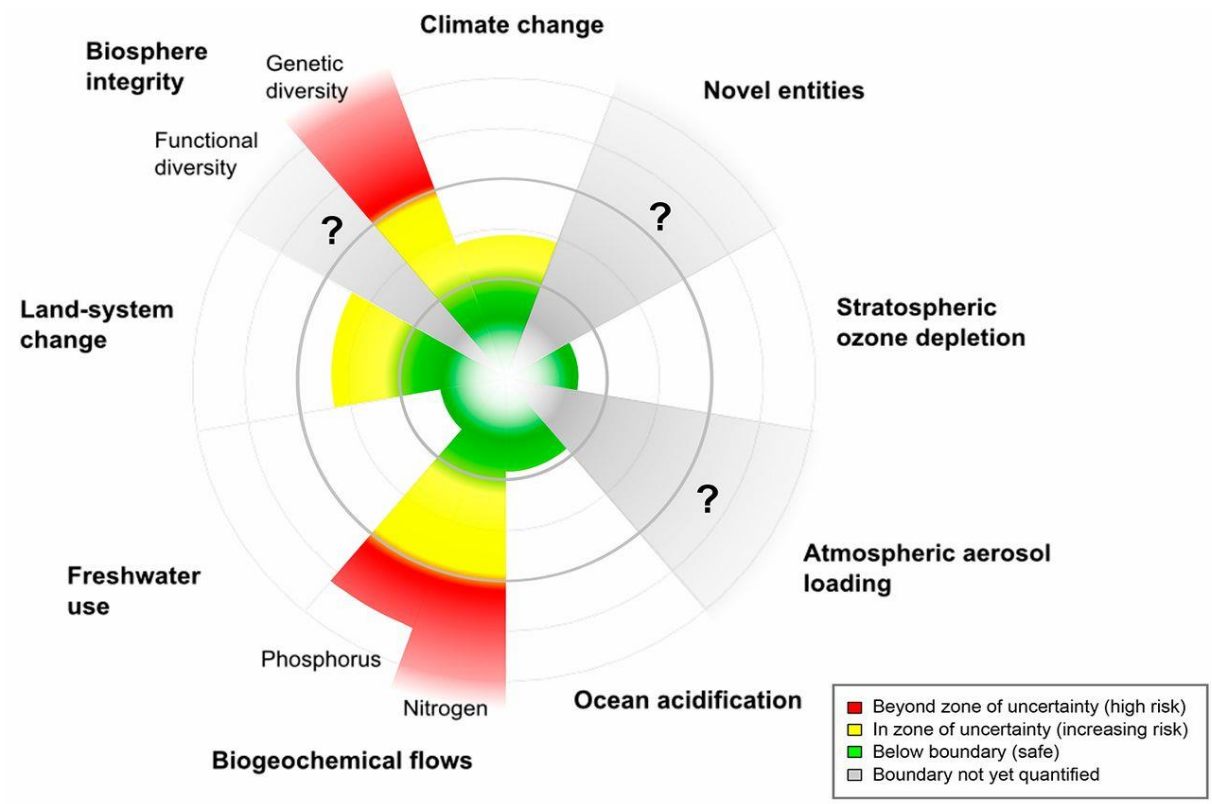
Even though the majority of EKC studies use air pollutants as a proxy for environmental degradation, other pollutants (or causes) should not be overlooked as well. In that respect, the use of Planetary Boundaries (PB) presents a more integrated perspective to EKC. PB framework has been developed by 29 leading Earth System experts to conceptualize and define certain global environmental limits within which the humanity is expected to operate safely. Nine key boundaries and thresholds with their respective approximations of how close humanity is to the maximum capacity of Earth Systems have been identified. Of those proposed nine, seven were quantified (see Figure 3) according to current scientific understanding (Rockström et al., 2009):

- PB-1: Climate change
- PB-2: Ocean acidification
- PB-3: Stratospheric ozone depletion
- PB-4: Biogeochemical nitrogen and phosphorus cycle changes
- PB-5: Global freshwater use
- PB-6: Land-system changes
- PB-7: Rate at which biological diversity is lost
- PB-8: *Chemical pollution (not quantified)*
- PB-9: *Atmospheric aerosol loadings (not quantified)*

Following this study, Steffen et al. (2015) conducted an updated and extended analysis of the PB framework and concluded that humanity has already exceeded the safe limits of four key boundaries: climate change, biodiversity loss, land-system changes, and biogeochemical cycle changes. Rockström et al. (2009, p. 1) stressed that going beyond each of these limits will induce a domino effect for environmental destruction: *"Transgressing one or more planetary boundaries may be deleterious or even catastrophic due to the risk of crossing thresholds that will trigger non-linear, abrupt environmental change within continental- to planetary-scale systems"*

The main difference between PB and other previously presented global sustainability indices is that it provides more viable and meaningful grounds for the assessment of studies that use sustainability and environmental measures (Whiteman et al., 2013). In this regard, PB might serve as a good proxy for a more comprehensive aggregate measure of environmental degradation to understand the relationship between economic growth and the environment.

Figure 3. Planetary Boundaries



Source: Steffen et al. (2015)

1.4 Motivation and aim of study

The motivation behind this study is stemming from critiques of the previous EKC publications and country sample selection rationale:

(i) **Vast majority of previous studies focused on a narrow relationship between environmental degradation and economic growth.** Carbon dioxide (CO_2), carbon monoxide (CO), sulphur dioxide (SO_2), nitrogen dioxide (NO_2), total suspended particulates (TSP), smoke, faecal and heavy-metal contamination in rivers, and oxygen regimes are the most studied pollutants in the voluminous EKC literature (Pincheira and Zuniga, 2021). However, associating only one pollutant with economic development does not yield a complete picture, because many causes of environmental degradation are interconnected (Jha and Murthy, 2003). Also, specific physical/chemical properties of pollutants under consideration might also have different impacts on the EKC profile. Therefore, recent works started considering composite and more sophisticated measures of environmental quality, such as ecological footprint (Caviglia-Harris et al., 2009; Aurélien, B et al., 2006), index constructed using a group of pollutants (Jha and Murthy, 2003; Liuet al., 2018), etc.

(ii) **Empirical EKC literature has conceptual flaws that arise due to the incorporation of polynomials and cointegrating relationship of powers of integrated processes.** One of the criticisms of the methodological aspect of EKC specification is related to the possible multicollinearity problems while incorporating polynomials (Al-Mulali et al., 2015; Narayan and Narayan, 2010). Apart from that Wagner (2015) argued that previous studies ignored the fact that powers of integrated processes (quadratic or cubic) are not integrated processes of any order. Instead, the quadratic (or cubic) transformation of a variable is deterministically related to the basal integrated process. Hence, the use of cointegration techniques is inadequate in this case and the results of studies that used inappropriate methodologies are potentially misleading.

(iii) **Most studies cover the same set of countries.** OECD, SSA, EU, GCC, MENA, and ASEAN countries are the most used samples for panel EKC studies, while China, USA, Turkey, Pakistan, India, UK, Spain, Brazil, and several developed countries are the most used for time series analysis (Aslan and Altinoz, 2019). To the best of my knowledge, there is only one publication that focused on EKC estimation of emerging Industry 4.0[5] economies and no study on the Republic of Georgia. However, this country represents an interesting case regarding its commitment to Paris Agreement. Georgia set a target to unconditionally reduce its greenhouse gas emissions by 35% below the business-as-usual scenario for the year 2030 (Government of Georgia, 2021). However, this target was already achieved in 1993 and according to World Bank data in 2019, Georgia's greenhouse gas emissions were about 63% below the business-as-usual scenario. The loose environmental target gave freedom to the government to exploit it, which it does by incentivizing and highly subsidizing carbon-intensive cryptocurrency mining industry in the country. Consequently, Georgia ranked third in the world for Bitcoin mining in 2018 (World Bank, 2018).

Considering hereinabove mentioned points the aim of this study is to assess the EKC hypothesis in the case of Georgia using a composite measure of environmental degradation and employing the appropriate estimation of the cointegrating polynomial relationship developed by Wagner (2015). The proposed estimation model is an extension of a fully modified estimator of Phillips and Hansen (1990). Additionally, the model specification and

[5] Refers to 4th industrial revolution: when transformative technologies (smart factories, artificial intelligence-based production lines, connected machines and intelligent robots) are changing the industry.

cointegrating relationship have been tested using a special KPSS-type test derived by Wagner (2015).

PB indicators have been utilized in a single environmental index using Principal Component Analysis. Moreover, to check the robustness of calculations biocapacity reserve/deficit[6] (BR) indicator, greenhouse gas and carbon emissions also were used as environmental quality measures in the model.

The framework of this paper is organized as follows: Section 2 gives some insight into existing EKC literature from a critical and innovative perspective, while employed methodology and utilized data are described in Section 3. Section 4 presents empirical results and Section 5 concludes.

2. LITERATURE REVIEW

In their research, Pincheira and Zuniga (2021) identified that the current research direction of the EKC literature comprises four new streams: (i) methodological critique of previous EKC studies, (ii) extension of EKC studies by incorporating new environmental indicators, (iii) identification of new factors/determinants that affect the EKC and (iv) examination of income-energy nexus in the context of EKC hypothesis. The study also showed that Grossman and Krueger (1991; 1995), Selden and Song (1994), and Shafik (1994) are the most cited papers in the EKC literature. In his bibliometric review, Anwar et al. (2022) identified evolutionary articles[7] that connect several clusters of research streams. In that sense, Cole (2004) has been identified as the most influential evolutionary study, where he found relatively small effects of the pollution haven hypothesis[8] on EKC compared to other explanatory variables. The rest of this section is mainly based on the literature review of studies that can be classified as evolutionary in criticising existing and developing new methodologies for EKC estimation, and studies that used different and more sophisticated environmental indicators.

Notably, the studies that confirm the EKC hypothesis outnumber those that do not find any evidence in favour of its validity (Aslan et al., 2019). As EKC varies with model specification, econometric techniques used, data and its quality, environmental indicators, and countries, it is accepted that there is no universal shape of EKC. All these factors raise

[6] This concept has been defined by Global Footprint Network.
[7] Innovative studies that initiate new directions or change the previous understanding of a subject.
[8] The hypothesis postulates that the inverted U-shaped relationship between economic growth and environmental pollution can be explained by the strategy of developed countries that displace dirty industries in developing countries.

many concerns regarding the validity of existent literature. For example, Sinha et al. (2019) identified that many studies (Martínez-Zarzoso and Bengochea-Morancho, 2004; Bagliani et al., 2008; Dijkgraaf and Vollebergh, 2005; Galeotti and Lanza, 2005; Mazzanti et al., 2008; Akbostancı et al., 2009; Mohapatra and Giri, 2009; Brajer et al., 2011; Uddin et al., 2016; das Neves Almeida et al., 2017; etc.) reported the establishment of N-shaped EKC, which were actually invalid. All those studies concluded their findings based on the respective signs of coefficients and failed to mathematically validate their results[9]. In the end, turnaround points of reported N-shaped curves lay on the imaginary plane. On top of that, Wagner (2008; 2015) and Wagner and Hong (2015) argue that empirical literature has been ignoring two major econometric problems that fundamentally invalidate commonly used cointegration techniques in the context of EKC: first, stochastic properties of non-linear terms of integrated processes, and second, cross-sectional dependence in panel data. The authors proposed new methodologies to overcome those problems. Also, to address the same issues Stern (2010) suggested using the between estimation technique. Moreover, the implementation of between estimator allows not only to overcome problems identified by Wagner (2008) but also addresses the concerns raised by Vollebergh et al. (2009) regarding the identification of time effects in the EKC model. Furthermore, the work of Apergis (2016) on time-specific effects showed that EKC is not time-invariant by proving the time dependency of coefficients, which puts the appropriateness of commonly used methodologies under the question. Additionally, Van Hoa and Limskul (2013) pointed out that previous literature did not account for the possibility of reverse and directional causality between economic growth and the environment. Hence, to provide robust empirical findings, they developed a new dynamic endogenous multi-equation model. Contrary to parametric approaches, there is a strand of studies that employed more flexible techniques, such as semi and nonparametric methods (Shahbaz et al., 2017; Xie et al., 2019; Xu et al., 2017; Wang, 2011; Tsurumi and Managi, 2010). Among them, the works of Millimet et al. (2003) and Ordás et al. (2011) empirically showed that semi and nonparametric methods actually performed better than parametric ones. It is also notable that several researchers started exploiting machine learning techniques, such as wavelet coherence approaches (Adebayo, 2020; Rej et al., 2022) in the EKC analysis recently.

[9] In an EKC model with a cubic specification as: $y = \alpha_0 + \alpha_1 x + \alpha_2 x^2 + \alpha_3 x^3 + \varepsilon$, the following conditions must be satisfied for N-shaped EKC to be valid:

1) $\alpha_2^2 - 3\alpha_1\alpha_3 > 0$ (Sufficient condition)
2) $\alpha_1, \alpha_3 > 0$ and $\alpha_2 < 0$

Sufficient condition guarantees that the turnaround points are on the Cartesian plane. Otherwise, N-shaped EKC can never be estimated.

To bring forth width and depth in the study, and to avoid omitted variable bias it is necessary to include more variables in the EKC model (Stern, 2004). However, the choice of variables should not be done arbitrarily, otherwise, the model might suffer from misspecification bias. Temporal and geographical contexts must be considered, and the chosen variables must comply with those contexts (Sinha et al., 2019). For example, Sinha and Bhattacharya (2016) explain the rationale for including population, petroleum consumption, and electricity consumption in their study by arguing that air pollution in Indian cities is strongly connected to the population of a particular city, which consumes electricity generated from fossil fuels. Shahbaz et al. (2018) exploited the fact that since the mid-1950s French public and private corporations poured heavy financial resources into the research and development process and imported technological innovations to make production cleaner. Consequently, the authors included FDI, energy consumption, and energy innovation as explanatory variables in their model. Karasoy (2019) explains that the use of renewable energy consumption and trade openness as explanatory variables in the EKC study for Turkey is valid because more than half of the primary energy needs in Turkey have been met by imports since 2011. Also, Turkey introduced a new policy, called “Turkey’s vision 2023”, to maximize the use of renewable energy sources to raise the share of renewables in energy mix to 30% by 2023.

It is a fact that the researchers were more prone to using single pollutants along with CO_2, such as NO_2 (Sinha and Bhattacharya, 2016; Rudra and Chattopadhyay, 2018; Gao et al., 2017), SO_2 (Chen et al., 2019; Ridzuan, 2019; Hao et al., 2018a), total suspended particulates (Marbuah and Amauakwa-Mensah, 2017; Stern and Zha, 2016;) and so on. However, several studies focused not on the factors that cause environmental damage, but rather on the result of deterioration. Zambrano-Monserrate et al. (2018) and Bhattarai and Hammig (2001) used deforestation as a proxy for environmental degradation and both studies found supporting evidence for EKC. Biodiversity loss has been a variable of interest in the studies of McPherson and Nieswiadomy (2005), and Mills and Waite (2009). Unlike the former study, the latter did not find any support for the presence of EKC. The study by Pincheira et al. (2021) is the first study that incorporated the Planetary Boundary framework into EKC analysis. The authors used PB variables and economic output in a worldwide sample and implemented a panel dynamic system generalized method of moments approach. EKC hypothesis was supported only for the climate change and ocean acidification panels.

Unlike mentioned indicators, several studies considered the existing EKC methodology inappropriate to fully illustrate the nexus between environmental pollution and economic growth. Hence, they used indicators that represent a cumulative measure of environmental degradation such as Ecological Footprint (Charfeddine and Mrabet, 2017; Destek and Sarkodie, 2017; Mrabet and Alsamara, 2017; Khan et al., 2022; Pata, 2021) or custom constructed pollution/degradation index (Pata et al., 2022; Hao et al., 2018b; Başar and Tosun, 2021). Jha and Murthy (2003) used six different environmental variables to construct an environmental degradation index using Principal Component Analysis. The authors reported the establishment of an inverted N-shaped global EKC.

Table 1 briefly outlines different measures of environmental quality that have been present in the empirical EKC literature.

Table 1. EKC studies with various environmental quality indicators

Environmental indicator	Authors	Title	Findings
SO_2, suspended particulate matter, oxygen regime, concentration of heavy metals	Grossman and Krueger (1995)	Economic growth and the environment.	Supporting EKC
Deforestation	Bhattarai and Hammig (2001)	Institutions and the Environmental Kuznets Curve for deforestation: A cross-country analysis for Latin America, Africa, and Asia.	Supporting EKC
Threatened bird and mammal species	McPherson and Nieswiadomy (2005)	Environmental Kuznets Curve: threatened species and spatial effects	Supporting EKC
Ratio of good efficiency performance and bad efficiency measure	Halkos and Tzeremes (2009)	Exploring the existence of Kuznets curve in countries' environmental efficiency using DEA window analysis	Not supporting EKC
Ecological Footprint	Charfeddine and Mrabet (2017)	The impact of economic development and social-political factors on ecological footprint: A panel data analysis for 15 MENA countries.	Supporting EKC
Land consumption	Bimonte and Stabile (2017)	Land consumption and income in Italy: a case of inverted EKC.	Not supporting EKC

The percentage of national protected areas	Bimonte (2002)	Information access, income distribution, and the Environmental Kuznets Curve.	Supporting EKC
Land footprint	Dai et al. (2022)	Whether ecological measures have influenced the environmental Kuznets curve (EKC)? An analysis using land footprint in the Weihe River Basin, China	Not supporting EKC
Fisheries production	Rashdan et al. (2021)	Investigating the N-shape EKC using capture fisheries as a biodiversity indicator: empirical evidence from selected 14 emerging countries.	Supporting EKC
Environmental Pollution Index	Başar and Tosun (2021)	Environmental Pollution Index and economic growth: evidence from OECD countries.	Supporting EKC
Bird population	Lantz and Martínez-Espiñeira (2008)	Testing the Environmental Kuznets Curve Hypothesis with Bird Populations as Habitat-Specific Environmental Indicators: Evidence from Canada.	Mixed results
Water quality	Farzin and Grogan (2013)	Socioeconomic factors and water quality in California.	Not supporting EKC

3. METHODOLOGY AND DATA

3.1 Methodology

Cointegrating polynomial relationships require a different approach for testing and estimation because nonlinear functions of integrated processes cannot be treated as integrated processes (Wagner, 2015; Wagner and Hong, 2015). Wagner (2015) proposed a new estimation and inference tool based on the extension of the FM-OLS estimator claiming that the use of inappropriate methods leads to conceptually problematic and invalid conclusions.

3.1.1 Unit-root test

No consensus exists between researchers on which test should be preferred while checking for the stationarity of series. Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) unit root tests are the most common tests that have been used in the EKC literature. However, there are some criticisms regarding the preference of one over another (Chaudhuri and Wu, 2003; Halkos and Kevork, 2005; Zivot and Wang, 2006). Besides those commonly used unit-root tests, there is a class of "efficient tests" with much better statistical properties. A Monte-Carlo experiment by Elliot et al. (1996) demonstrated that a modified version of the Dickey-Fuller (DF-GLS) test (member of the efficient test family) dominated its counterparts in terms of power and size. Most importantly, the experiment indicated that the proposed DF-GLS performed particularly well in small samples. Müller (2004) by studying the performance of commonly used unit-root tests versus efficient tests also concluded that the former have much less discriminatory power than the latter.

By considering the small sample size and trending pattern of data used and several comparative studies that conducted simulations, the DF-GLS test with constant and trend has been chosen for this study. This test uses interpolated critical values from tables presented by Elliot et al. (1996). The optimal lag order has been chosen based on Ng-Perron's (1995) sequential t-test criterion.

3.1.2 Extended Fully Modified Ordinary Least Squares (FM-OLS) estimator

This paper utilizes quadratic specification of the EKC curve without polynomial time trends, but it can also be extended to the cubic formulation as described by Wagner (2015) and Wagner and Hong (2015). Hence, the EKC curve is constructed as:

$$y_t = \alpha + \beta_1 x_t + \beta_1 x_t^2 + \gamma z_t + u_t \tag{1}$$

$$x_t = x_{t-1} + v_t \tag{2}$$

$$z_t = z_{t-1} + \rho_t \tag{3}$$

$$\varepsilon_t = \begin{bmatrix} u_t \\ v_t \\ \rho_t \end{bmatrix} \tag{4}$$

where y_t is environmental degradation measure, x_t is economic development indicator, z_t is a control variable, and $t = 1, \dots, T$. α is a constant and ε_t is a stationary ergodic martingale difference sequence with the finite covariance matrix. The long-run and one-sided long-run covariance matrices are defined as ω and δ respectively, and Bartlett kernel function with Newey and West (1994) automatic bandwidth selection techniques has been implemented in their estimation. Both matrices are partitioned as in Phillips and Hansen (1990):

$$\omega = \begin{bmatrix} \omega_{uu} & \omega_{uv} \\ \omega_{vu} & \omega_{vv} \end{bmatrix} \qquad \delta = \begin{bmatrix} \delta_{uu} & \delta_{uv} \\ \delta_{vu} & \delta_{vv} \end{bmatrix} \tag{5}$$

Estimation of FM-OLS requires series of transformations. Firstly, dependent variable must be transformed as:

$$y_t^* = y_t - v_t \widehat{\omega}_{vv}^{-1} \widehat{\omega}_{vu} \tag{6}$$

$$y^* = [\, y_1^*, \dots \dots, y_T^* \,]' \tag{7}$$

where $\widehat{\omega}_{vv}$ and $\widehat{\omega}_{vu}$ are consistent estimators of ω_{vv} and ω_{vu}. This procedure is done exactly as proposed by Phillips and Hansen (1990): considering standard assumptions on the kernel and bandwidth, long-run and one-sided long-run variances/covariances are estimated using OLS residuals of equation (1) and first differences of x_t as indicated in equation (2). However, the correction factor has been modified to fit cointegrating polynomial regression and a detailed discussion of relevant assumptions and their proofs are provided by Wagner (2015):

$$\Phi = \Delta \begin{bmatrix} 0 \\ \mathrm{T} \\ 2\sum_{t=1}^{T} x_t \\ \mathrm{T} \end{bmatrix} \tag{8}$$

where $\Delta = \hat{\delta}_{vu} - \widehat{\omega}_{uv} \widehat{\omega}_{vv}^{-1} \hat{\delta}_{vv}$. Here again consistent estimators of long-run and one-sided long-run variances/covariances are used. Finally, the FM-OLS estimator θ is computed as:

$$\hat{\theta} = (Z'Z)^{-1}(Z'y^* - \Phi) \tag{9}$$

where $\theta = [\, \alpha, \beta_1, \beta_2, \gamma \,]'$, $Z = [\, Z_1, \dots \dots, Z_T \,]'$, and $Z_t = [\, 1, x_t, x_t^2, z_t \,]'$. The asymptotic distribution of $\hat{\theta}$ is Gaussian mixture with zero-mean and its covariance matrix Σ is calculated as:

$$\hat{\Sigma} = \widehat{\Omega}(Z'Z)^{-1} \tag{10}$$

with $\widehat{\Omega}$ being a consistent estimator of $\Omega := \omega_{uu} - \omega_{uv}\omega_{vv}^{-1}\omega_{vu}$. Wagner (2015) notes that limiting distribution of FM-OLS estimator allows for derivation of standard Wald and LM test statistics which are asymptotically Chi-squared distributed under the null hypothesis.

3.1.3 KPSS-type test

Numerous cointegration tests are currently used by researchers which have several pros and cons depending on model specification, sample size, and other factors. However, neither of them can be directly applied to the extension of FM-OLS that has been derived above. For that purpose, Shin's (1994) test of cointegration has been retrofitted for cointegrating polynomial regressions as well (Wagner, 2015). This KPSS-type test is based on FM-OLS residuals. Because it is not possible to observe the true error process, the test needs to be calculated based on observable residuals of FM-OLS:

$$\hat{\epsilon}_t = y_t^* - Z_t'\hat{\theta} \tag{11}$$

Then the test statistics is calculated as:

$$CT = \frac{1}{T\hat{\Omega}} \sum_{t=1}^{T} \left(\frac{1}{\sqrt{T}} \sum_{j=1}^{t} \hat{\epsilon}_j \right)^2 \tag{12}$$

Wagner (2015) mentions that there is no limiting distribution for general cases when multiple integrated polynomial regressors are present. However, by considering certain factors such as the number of polynomials and their order, specification of the deterministic component, etc. it is possible to derive relevant critical values. For the case with only one integrated regressor with a polynomial of degree two critical values have been simulated by Wagner (2015).

One of the advantages of using this test is that it can be interpreted as a specification test to a certain extent. If u_t in equation (1) is a stationary process, then this test converges to a well-defined distribution, otherwise, it diverges. Non-stationarity in errors can be a result of omitted relevant regressors, which will cause the KPSS test to reject its null. Hence, the null hypothesis can be specified as the presence of cointegration as well as stationarity of u_t.

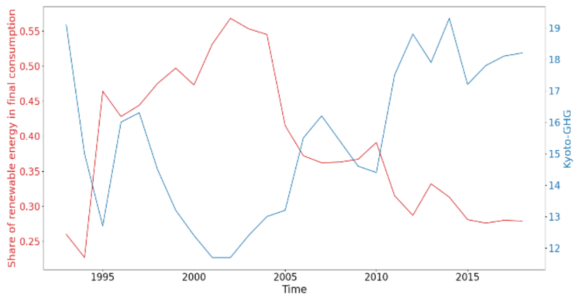
3.2 Data

The data used in this study has been collected from 10 different sources and has a yearly frequency from 1993 to 2018 (Table 1). Some of the indicators in panel A of Table 1 represent aggregated values and consist of several components. There are 6 pollutants in the Kyoto greenhouse gas basket (Kyoto-GHG), which have been weighted by their global warming potential: carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), sulphur hexafluoride (SF_6), hydrofluorocarbons and perfluorocarbons (PB-1). Seawater acidity represents an index constructed by using different measures of acidity, alkalinity, and their subcomponents in the Black Sea (PB-2). 30 institutions including universities, research centres, and observatories from 6 Black Sea basin countries gathered this data from 1899. As there were multiple observations in a single timeframe the average value has been chosen as an indicator of seawater acidity. Total ozone-depleting substances comprise 4 components in the case of Georgia: chlorofluorocarbons (CFCs), halons, hydrochlorofluorocarbons (HCFCs), and methyl bromide (PB-3). A set of three fertilizers - nitrogen (N), phosphate (P_2O_5), and potash (K_2O) (fertilizers that are used in Georgia) - are included in the total fertilizer use (PB-4). The sum of surface water (from rivers, lakes, and reservoirs) and groundwater (from aquifers) withdrawals make up total freshwater withdrawal data (PB-5). Agricultural land represents the total share of land area that is arable, under permanent crops, and permanent pastures (PB-6). Red List Index (RLI) measures the extinction risk of sets of species, which include mammals, birds, and amphibians (PB-7). The lower the value of the index the higher the risk of extinction.

Panel B of Table 2 illustrates two variables that have been used to derive Georgia's BR. Global Footprint Network[10] defines ecological footprint as "how much area of biologically productive land and water an individual, population, or activity requires to produce all the resources it consumes and to absorb the waste it generates" and biocapacity as "the capacity of ecosystems to regenerate what people demand from those surfaces".

The last panel of Table 2 outlines the variables that are used as regressors: real GDP and renewable share in the final energy consumption. Energy consumption has been established as the major factor that links economic development to the environment (Inglesi-Lotz, 2019). Several studies emerged advocating that without energy consumption economic growth cannot be achieved (Ahmed et al., 2015; Kohler, 2013; Saboori and Sulaiman, 2013; Yavuz, 2014). In spite of continuous GDP growth and increasing demand for energy resources, renewable share in the final energy consumption has been decreasing in Georgia since 2002. A clear negative relationship can be observed in Figure 4 between Kyoto-GHG and the share of renewable energy in final consumption. Considering this decrease, in 2016 the government aimed to attract new investments to increase the share of renewables in the total energy mix and during the next four years 98% of new electricity generation projects fell into the category of renewables: hydropower, wind power, and solar photovoltaic (OECD, 2021). For these reasons, renewable share in total final consumption has been accepted as a reasonable control variable for the EKC model.

Figure 4. Renewable energy-GHG relationship



[10] See: www.data.footprintnetwork.org/#/abouttheData

Table 2. Data

Variable	Unit of measure	Source
A: Planetary Boundaries		
1. Kyoto-GHG (GHG)	$MtCO_2e$[11]	Climate Watch[12]
2. Red List Index (RLI)	unit	International Union for Conservation of Nature's Red List of Threatened Species[13]
3. Total ozone depleting substances (ODP)	ODP tonnes[14]	United Nations Environment Programme – The Ozone Secretariat[15]
4. Seawater acidity (Acidity)	mg/l	SeaDataNet - Pan-European Infrastructure for Ocean & Marine Data Management[16]
5. Total fertilizer use (Fertilizer)	thousand tonnes of nutrients	International Fertilizer Association[17]
6. Fresh water withdrawal (Water)	10^9 m^3/year	Food and Agriculture Organization of the United Nations[18]
7. Agricultural land (Land)	km^2	World Bank[19]
B: Environmental quality indicators		
8. Ecological footprint	gha	Global Footprint Network[20]
9. Biocapacity	gha	Global Footprint Network
C: Other indicators		
10. GDP (GDP)	USD	World Bank
11. Renewable share in the final energy consumption (Energy)	%	International Energy Agency[21]

Note: Short names in the brackets have been introduced to make communication easier.

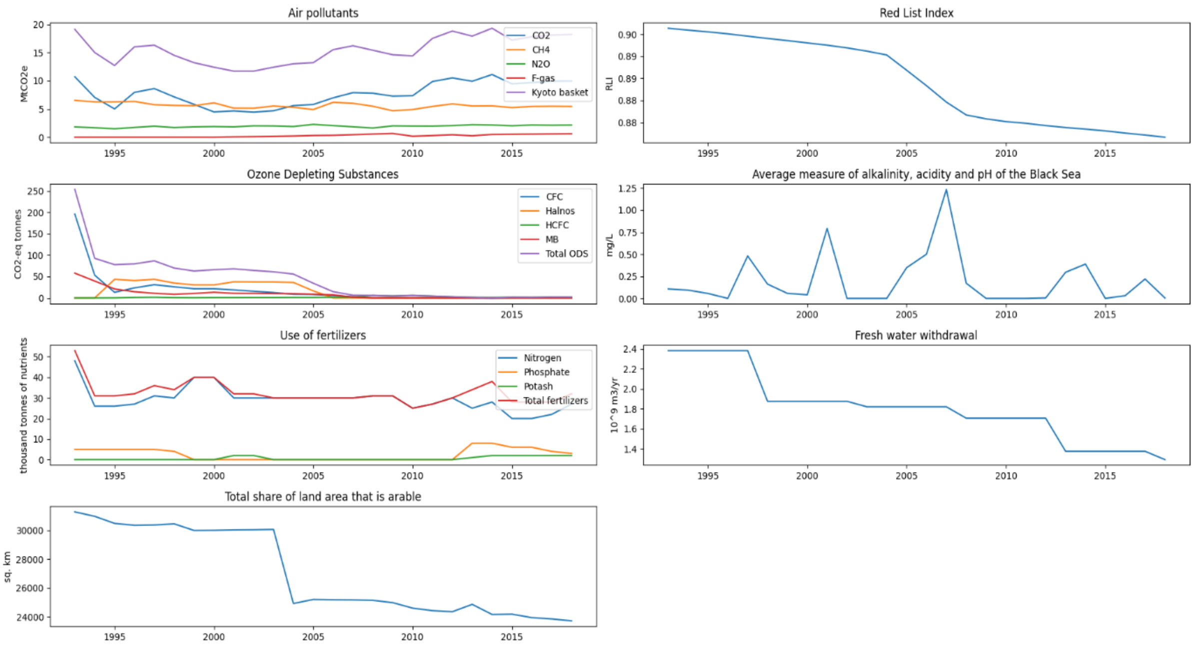
[11] Metric ton of carbon dioxide
[12] See: www.climatewatchdata.org
[13] See: www.iucnredlist.org
[14] Ozone Depleting Potential tonnes
[15] See: www.ozone.unep.org
[16] See: www.seadatanet.org
[17] See: www.ifastat.org
[18] See: www.fao.org
[19] See: www.data.worldbank.org
[20] See: www.footprintnetwork.org
[21] See: www.iea.org

3.2.1 Constructing Environmental Degradation Index (EDI)

Principal Component Analysis (PCA) has become a very handy tool for index construction in modern literature. It is an unsupervised machine learning algorithm that enables dimensionality reduction. In other words, PCA captures variation in a large set of interdependent observations and converts them into a low-dimensional vector of significant and linearly uncorrelated components using orthogonal transformation. This vector is interpreted as the common shock that is responsible for co-movements in the data (Bai and Ng, 2006). In this context, EDI can be understood as a latent or unobserved variable, which is assumed to have a linear relationship with other observable variables plus a disturbance term.

EDI is a composite index consisting of weighted PB variables that are indicated in panel A of Table 2. It is constructed in a way that the higher the index, the greater the environmental degradation. From Figure 4 it is visible that consumption of ozone-depleting substances, freshwater withdrawals, and total share of arable land has decreased significantly. Also, the average value of the Black Sea acidity indicator was lower in recent years. It is evident that only Kyoto-GHG and biodiversity loss (decreasing RLI) showed an increasing pattern, while total use of fertilizers remained almost constant. Visual inspection of Figure 5 hints that EDI is not likely to have an increasing trend.

Figure 5. Planetary Boundary indicators in Georgia



To form EDI, the methodology introduced by Nagar and Basu (2002) has been employed. As a first step, selected indicators must be transformed into a standard scale, and to fit the outlined structure all variables are considered to have a positive effect (increasing) on environmental degradation except Red List Index and agricultural land.

Positive indicator: $z_t = \frac{x_t - \min(x_t)}{\max(x_t) - \min(x_t)}$ (13a)

Negative indicator: $z_t = \frac{\max(x_t) - x_t}{\max(x_t) - \min(x_t)}$ (13b)

where, z_t is the standardized value, x_t is original observation and $t = 1, \ldots, T$.

Secondly, before PCA analysis correlation between PB indicators has been checked since the uncorrelated variables should be removed from the analysis. As is seen in Table 3, seawater acidity shows almost no correlation with other variables, hence it is excluded from PCA.

Thirdly, after implementing PCA, the components with eigenvalues higher than one have been Kaiser-Varimax rotated to maximize the sum of the variance of the squared loadings. This procedure leads to maximization of information involved among the set of indicators

(Gupta, 2008). As a result, only two components have eigenvalues over one and they together capture 88% of the variation in the data (Figure 6). The Kaiser-Meyer-Olkin (KMO) Test value (0.734) greater than 0.7 (threshold level) confirms that the sampling adequacy is at a satisfactory level (Jolliffe, 1972). Variances and scores of rotated principal components are illustrated in Table 4.

Table 3. Correlation matrix of PB indicators

Variables	GHG	RLI	ODS	Acidity	Fertilizer	Water	Land
GHG	1.00						
RLI	0.61	1.00					
ODS	-0.15	-0.79	1.00				
Acidity	**0.01**	**-0.01**	**-0.08**	**1.00**			
Fertilizer	0.13	-0.46	0.76	**0.01**	1.00		
Water	-0.35	-0.86	0.76	**0.03**	0.37	1.00	
Land	0.50	0.93	-0.79	**0.04**	-0.52	-0.81	1.00

Lastly, to establish EDI following calculations are made:

$$P_{tj} = z_{ti} S_{ij} \tag{14}$$

where, S_{ij} is a score of a principal component j for respective variable i, and P_{tj} is a principal component j. Then, proportion of total variance is accounted as a weighting factor:

$$EDI_t = \frac{\sum_{j=1}^{J} \lambda_j P_{tj}}{\sum_{j=1}^{J} \lambda_j} \quad (15)$$

where, λ_j is a variance of component j.

The final index has been depicted in Figure 7. As has been expected the EDI does not have an upward slope.

Table 4. PCA result

	Comp. 1	Comp. 2
Variance	3.938	1.383
Difference	2.555	
Proportion	0.656	0.231
Cumulative	0.656	0.887
Principal component scores		
GHG	-0.102	0.741
RLI	-0.440	0.262
ODS	0.495	0.219
Fertilizer	0.413	0.533
Water	0.421	-0.146
Land	-0.450	0.170

Figure 6. Scree plot of eigenvalues

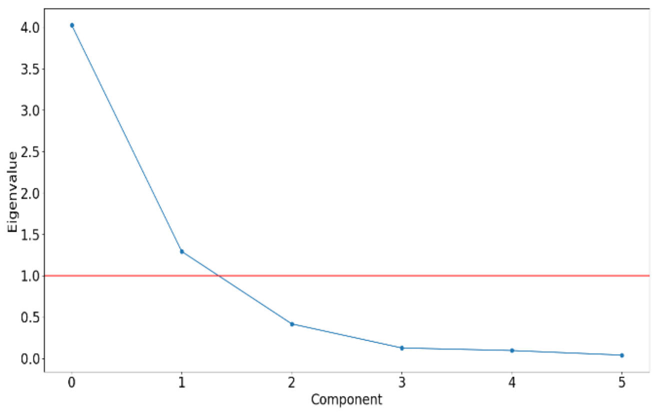
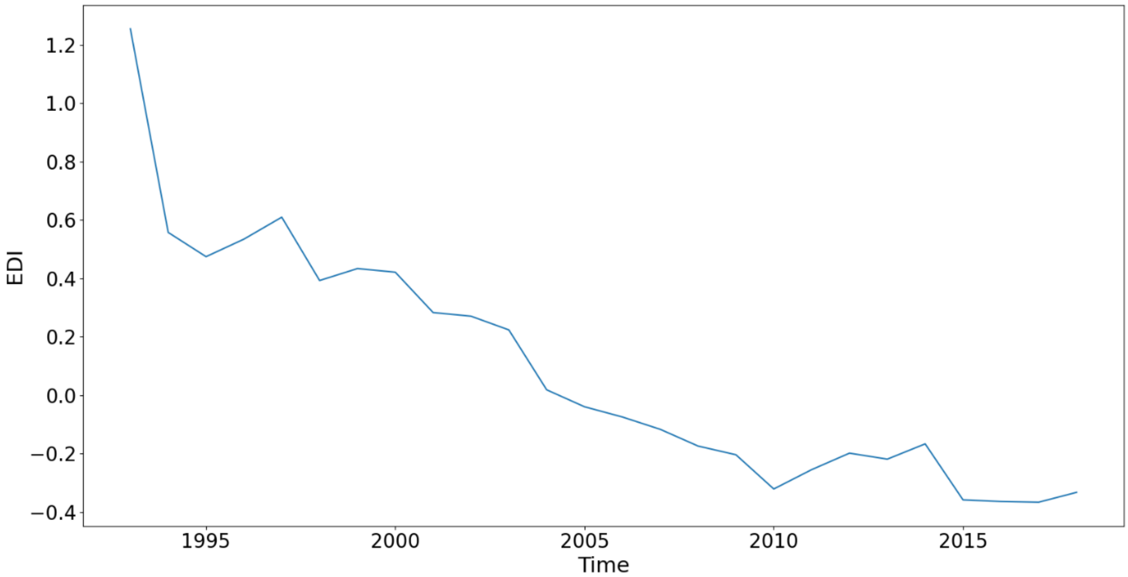


Figure 7. Environmental Degradation Index in Georgia



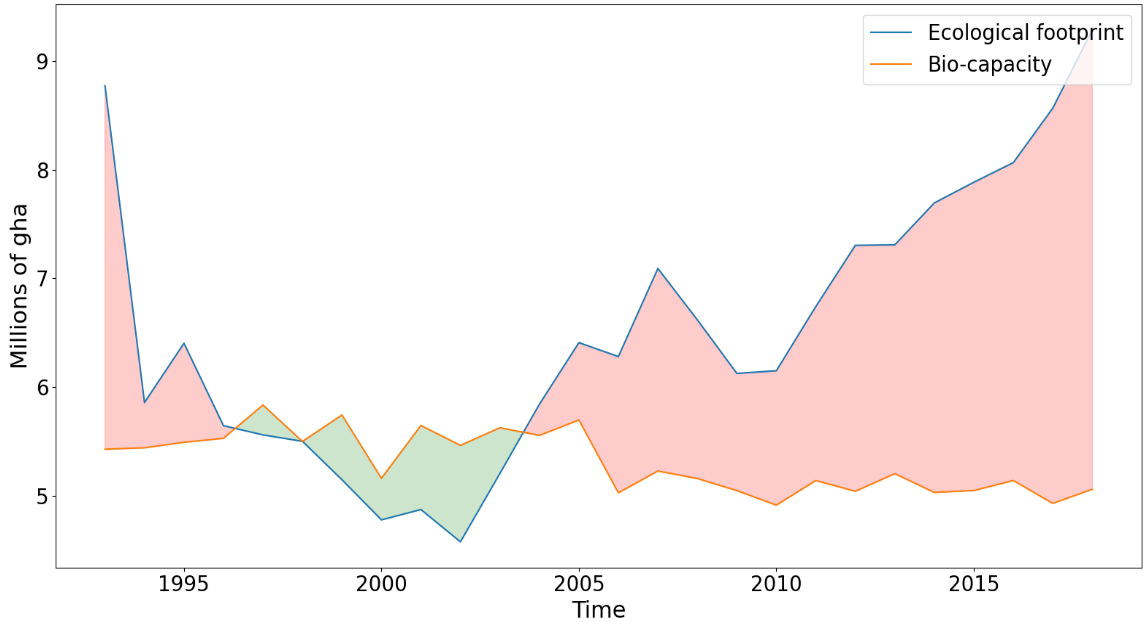
Note: EDI indicates that from 1993 to 2018 the environmental deterioration in Georgia has declined significantly. Even though greenhouse gas emission is increasing in Georgia, other factors such as notable decrease of population, quantitative decrease of carbon intensive industries, etc. slowed the degradation process.

3.2.2 Other environmental degradation measures and descriptive statistics

BR has been considered in this study as another measurement of environmental quality. BR is a difference between biocapacity and ecological footprint, and it measures how fast we consume resources and generate waste compared to how fast nature can absorb our waste and generate new resources (Figure 8). According to the Global Footprint Network data, Georgia has been experiencing a growing biocapacity deficit since 2004.

Apart from that, to make comparisons with composite and more sophisticated indicators such as EDI and BC, GHG and CO_2 have also been utilized to estimate EKC. As a result, 4 models have been established where each dependent variable indicates a different scale of environmental degradation – from general to specific.

Figure 8. Biocapacity reserve/deficit for Georgia



Source: *www.data.footprintnetwork.org/#/countryTrends?cn=73&type=BCtot,EFCtot*

Table 5 presents descriptive statistics of the variables, where GHG, CO_2, and GDP indicate the per capita level of respective observations. Additionally, GHG and CO_2 have also been rescaled to metric kilograms of carbon dioxide equivalent ($MkgCO_2e$). It is notable that per capita GHG and CO_2 emissions are about two times lower than the world average for the same time frame.

Table 5. Descriptive statistics					
	Mean	**Median**	**Std. dev.**	**Min.**	**Max.**
EDI	0.089	-0.057	0.409	-0.366	1.255
BR	-0.315	-0.303	0.379	-1.135	0.223
GHG	0.004	0.004	0.001	0.003	0.005
CO_2	0.002	0.002	0.001	0.001	0.003
GDP	2540.264	2446.557	1148.372	969.713	4539.087
Energy	0.388	0.370	0.102	0.227	0.568

4. EMPIRICAL RESULTS AND DISCUSSION

Depending on the measure of environmental degradation following four models have been estimated:

Model I : $EDI_t = \alpha + \beta_1 lnGDP_t + \beta_1 (lnGDP_t)^2 + \gamma Energy_t$

Model II: $BR_t = \alpha + \beta_1 lnGDP_t + \beta_1 (lnGDP_t)^2 + \gamma Energy_t$

Model III: $lnGHG_t = \alpha + \beta_1 lnGDP_t + \beta_1 (lnGDP_t)^2 + \gamma Energy_t$

Model IV: $lnCO_{2t} = \alpha + \beta_1 lnGDP_t + \beta_1 (lnGDP_t)^2 + \gamma Energy_t$

As is seen all the variables have been converted to the logarithmic scale except EDI and BR. Because these two composite measures of environmental quality are indices, and they only assign some numeric value or rank ($\in \mathbb{R}$) to the environmental state of Georgia at a certain year. Hence, it makes no economic sense to convert them into logarithmic scale, so Models I and II have a level-log specification. Consequently, the coefficients of the first two models are interpreted as (1/100) unit change, while the coefficients of the last two models are elasticities.

Table 6 illustrates unit-root test results of variables in level and differenced form. According to the DF-GLS test, all variables are stationary at their first difference at least at a 5% significance level.

Table 6. DF-GLS test results		
	Level	**1st difference**
EDI	-1.118	-4850***
BR	-0.605	-5.397***
lnGHG	-2.923	-4.376***
$lnCO_2$	-2.649	-4.256**
lnGDP	-3.001	-3.990**
$lnGDP^2$	-3.091	-3.946**
lnEnergy	-2.395	-6.307***

Note: Significance level: ** 5%
*** 1%

Estimation output is reported in Table 7. Firstly, KPSS-type test results should be inspected, where they suggest that the null hypothesis of cointegration cannot be rejected. The test statistics have been compared to the critical values derived by Wagner (2015). With 3 degrees of freedom the critical value at the 5% significance level is 2.421, and 1.934 at 10%. Additionally, as discussed in Section 3.1.3

the null hypothesis also indicates the stationarity of residuals, which confirms the correct specification of the model. Hence, the correct specification of the model has been supported by the test.

To establish an inverted U-shaped relationship between environmental degradation and economic development the signs of the regression coefficients β_1 and β_2 must be positive and negative respectively. In that respect, all models meet these criteria. However, neither of the coefficients of Model I is statistically significant and as a result, only Models II, III, and IV support the EKC hypothesis.

Table 7. FM-OLS estimation results

	I	II	III	IV
α	-6.010 (3.985)	-83.944*** (4.625)	-35.459*** (3.470)	-44.518*** (7.231)
β_1	2.286 (1.042)	22.546*** (1.210)	5.656*** (0.908)	7.656*** (1.892)
β_2	-0.195 (0.067)	-1.514*** (0.080)	-0.355*** (0.060)	-0.480*** (0.125)
γ	-0.097 (0.060)	-0.263* (0.070)	-0.541*** (0.053)	-0.919*** (0.110)
CT	1.336**	1.503**	1.471**	1.043**

Note: Significance level: * 10%
** 5%
*** 1%

Considering the environmental scope of EDI and the evolution of its components over time, the results were expected. Because only two out of seven planetary boundary indicators in Georgia illustrated increasing negative impact. During the Soviet period, heavy contaminating industry with little to no regard for deteriorative environmental consequences was prevalent in the country. After gaining independence, production and economic development decreased considerably due to political and economic turmoil and long-lasting civil war. These, in turn, also lowered industrial waste. However, that was only a quantitative decrease. In terms of quality, nothing changed: there were still no industrial waste treatment facilities during the 1990s and early 2000s. Hence, the shape of EDI regarding these facts is apropos. From the 1990s to the early 2000s environmental degradation decreased mainly because of quantitative changes in polluting activities. Then, towards the 2010 EDI curve became flattered as economic recovery and increase in production started increasing the pressure on the environment.

As is seen from Models II-IV, the increase of renewable energy share in final consumption has a positive environmental effect. It decreases CO_2 emissions by 0.92% and GHG by 0.54%. Considering that CO_2 share in total GHG emissions has been approximately 50% over the specified period in Georgia, the obtained results complement this fact. Additionally, as indicated by Model II Energy decreases biocapacity deficit (or increases biocapacity reserves), which can stem from three possible scenarios: either a decrease in consumption of goods and services that have environmentally damaging consequences or an increase in nature's regenerative power (possibly by increasing environmental awareness, more efficient use of resources, more efficient waste disposal and recycling technology) or a mix of both stated scenarios. Furthermore, from a BR perspective, higher GDP has a greater positive effect on the environment than Energy. Because renewable energy plays only a partial role in the overall environmental quality that BR captures. This is also visible from the fact that γ in Model II is only significant at a 10% significance level.

5. CONCLUSION

This study has been developed to apply an appropriate methodology that can deal with conceptual shortcomings in the previous empirical EKC literature rooting from the implementation of standard methods for linear cointegrating relationships to powers of integrated processes that are not integrated processes themselves. Hence, the methodology introduced by Wagner (2015) has been utilized to examine the relationship between environmental degradation and economic growth in Georgia. Estimation of equations performed by using an extension of FM-OLS model and cointegration of the variables has been tested by modified KPSS-type test.

Four environmental measures allowed to see the relationship between environmental quality and economic growth from a broad to more specific perspective. The environmental degradation index based on the PB framework and BR presented the general and more sophisticated measure, while the Kyoto basket of greenhouse gases and carbon dioxide emissions focused specifically on air pollution. Findings present mixed evidence.

Estimated results illustrate that an inverted U-shaped relationship with economic growth exists when changes in BR, GHG, and CO_2 are incorporated into the analysis. However, EDI does not support the existence of the EKC hypothesis in Georgia. Paruolo et al (2015) mention that failing to find any evidence in favour of EKC cannot prove the absence of it. Ergo, additional investigation in the future when more datapoints and extra explanatory variables are available might be undertaken. In fact, the use of only one additional explanatory variable (Energy) is the main limitation of this study. Wagner (2015) also mentions that this methodology cannot cope with the use of cross-products of explanatory variables and in this respect more general specification tests need to be developed.

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