Why the Environmental Kuznets Curve should be the Emission Kuznets Curve

Dissecting the relationship between the environment and income

Kars Boucher, 06-02-2022

Student Number: 576631

Supervisor: Dr. Jurjen Kamphorst

Second Reader: Prof. Dr. Maarten Bosker

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1. Introduction

The world has made tremendous economic progress over the last decades, but this has also put great pressure on our planetary boundaries. Our lives have improved economically, but problems like climate change, the plastic soup, and mass extinction are imminent threats. This looming danger has brought environmental concerns to center stage in the academic world. Such a focus is necessary and commendable; however, it has also caused words such as 'environment' and 'sustainability' to be reduced to overused buzzwords. This has resulted in an unfortunate loss of nuance, and even worse, significant misconceptions.

This paper discusses environmental economics' own buzzword: the Environmental Kuznets Curve (EKC). This name is borrowed from the Kuznets Curve, a bell-shaped curve representing the relationship between income inequality and economic growth, where economic inequality would rise up to a certain level of income and then fall with further increases in income. Applying this finding to the environment, initial research in the 1990s found that the relationship between air pollution and income was best represented by an inverted U-shaped curve - the EKC.

This thesis proposes that the 'Environmental' Kuznets Curve is in fact a misnomer for what should more accurately be called the 'Pollution' or 'Emission' Kuznets Curve. In the initial research that described the EKC, pollutants and greenhouse gasses formed the proxies to measure the state of the environment. These studies used one aspect of the environment – the level of local polluters like nitrogen and carbon dioxide – to derive a relationship between environmental sustainability and economic growth (Chung et al., 2004; Narayan & Narayan, 2010; Cole, 2003; Apergis & Özturk, 2014). These articles describe the EKC as "an inverted U-shaped relationship between per capita income and damage to the environment" (Balin, 2021, p.1). One paper, cited over 750 times, suggests that "there is a tendency for the environment to at first worsen at low levels of income but then improve at higher incomes." (Brock & Taylor, 2004, p.3). These authors extended findings that only considered certain environmental parameters to the environment as a whole. This overgeneralization has led to the erroneous assumption that the so-called EKC represents the relationship between income and all possible proxies for the state of the environment, when in fact, it only truly represents the relationship between economic growth and a single group of environmental indicators – emission levels.

This unfortunate assumption that economic growth does at some point begin to benefit the environment could have far-reaching consequences as it may influence policy in a direction detrimental to environmental sustainability. It gives policy makers justification to argue, "why focus on costly environmental regulations when boosting economic growth could have the same outcome?"

This paper therefore seeks to establish a model which account for multiple facets of the environment. The environment and environmental sustainability are broad concepts of which individual components might not all correlate with economic growth in similar ways. For example, aspects like water availability and biodiversity are unlikely to relate to economic growth in the same way as air pollution and environmental health issues. By dissecting the different components that constitute environmental sustainability, one can shed light on the different ways in which the various proxies correlate with economic growth.

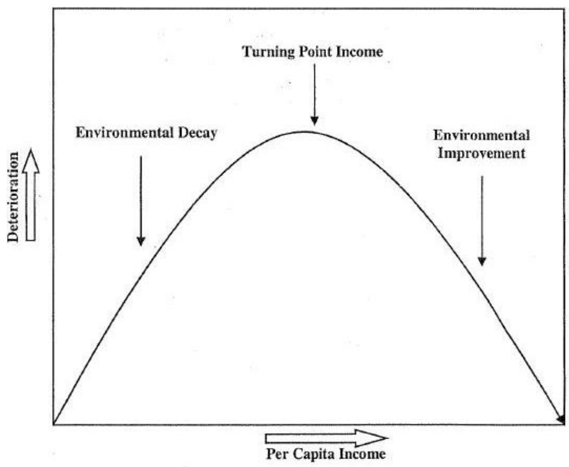
This leads to the main purpose of this thesis: to add nuance to the EKC theory and consider for which factors the EKC may hold true, and for which proxies it potentially does not. By understanding the intricacy of the concept of the environment and shining light on how the different aspects of our environment are affected by a growing economy, this paper aims to answer the following research question: "How does economic growth affect different aspects of environmental sustainability?" With a more accurate picture of how different components of environmental sustainability are affected by economic change, environmental policy can be formulated in a more effective and specifically impactful manner.

The first part of the paper discusses previous literature on the relationship between economic growth and environmental sustainability. Then, the concept of environmental sustainability is introduced along with an explanation of where prior literature misses important nuance in understanding the environments various components. The next section contains evidence – through literature and graphs – that shows that different environmental proxies differ in their relationship with economic growth. The following section explains the quantitative methods that are used to properly estimate the relationship between increases in income and the state of the environment. Finally, the results are presented and discussed, highlighting interesting findings as well as limitations.

2. Related Literature

This section covers the main academic literature on the relationship between the state of the environment and the income per capita. After discussing some of the major contributions to the field, this paper will explain where it could add to the discourse.

2.1 The Environmental Kuznets Curve in academia



Over the last decades the Environmental Kuznets Curve has become a commonly accepted term to describe the relationship between environmental degradation and income per capita. The Kuznets curve was originally meant to describe the relationship between income inequality and economic growth but was borrowed by environmental economists. The curve follows a U-shape where initially the two variables are positively correlated but become negatively correlated after a certain turning point. As Stern et al. (2004) and Ekins (1999) record in their extensive coverage of the history of the EKC, in classical economic theory, increased income per capita was associated with environmental degradation. However, in the 1990s researchers noticed the improvements in air and water quality in more developed economies compared to the 1960s (Krueger et al.,1995; Shafik, 1994; Seldonn & Shung, 1995). This gave way to the idea that there is a relationship between economic growth and the state of the environment, where initially the increased economic growth reduces the quality of the environment. Then, a turning point would be reached after which an increased income per capita would be related with a decrease in environmental degradation (Krueger et al., 1995). This point reflects "the ability to have a conscience once you can afford one" (Smith, 2014).

It was argued that humans at some point would prefer to live in a healthier, cleaner surrounding and therefore that the environment could be a luxury good. The notion that with more growth, in the end a better environment could be obtained, came as good news to governments, as it would mean that current economic growth policies would align with environmental targets. The belief in an EKC could thus have policy consequences, being a favorable example for the ones who would deem drastic climate actions not to be necessary.

2.2 Previous research: the theoretical model

In literature, the mere existence of the EKC has been disputed, but overall, some sort of non-linearity has been found in most studies (Aspergis, 2016; Youssef, et al. 2016; Grossman & Krueger, 1995). The focus of previous research has been on OECD countries due to data availability, but more recently the scope has expanded to a more diverse panels of nations (Awaworyi Churchill et al., 2018). The main regression used in research has been the following:

$$E = F\,(Y,\ Y^2,\ Z)$$

Here, E is an environmental factor, Y the income per capita, Y^2 the square of Y, and Z a set of control variables. The Environmental Kuznets Curve is caught in the Y and Y^2 terms where the linear income per capita captures the scale effect of the income per capita. As humans get wealthier, the tendency arises to consume more, leading to an overall larger pressure on the environment. Wealthier nations have in general more cars per capita, larger houses and travel more. These trends degrade some parts of the environment. On the other hand, we have the composition effect, represented by Y^2 (Awaworyi Churchill et al., 2018). Our consumer behavior alters with increases in income, we do not just want more of the same thing but might want more of other things. What the EKC suggests is that with more income, the consumption of environmentally degrading products falls relatively and that there is a certain turning point at which the composition effect outweighs the scale effect. Our preference to consume non-degrading goods exceeds the general increase in consumption. One can understand how this reasoning makes sense; reducing air pollution might cost money as filters need to be placed, but at a certain threshold one cares more about their health than the loss in wealth due to the installment of filters.

2.3 What is environmental sustainability

In the next section, the focus turns to the environment and the concept of environmental sustainability. What constitutes it and which dichotomies exist between environmental factors? These differences raise the question of whether it then makes sense to assume that the EKC holds true for the entire environment or that there exist different relationships between economic growth and each environmental factor.

Is there a division between different aspects of environmental sustainability?

Environmental sustainability means acting in a way towards the environment that ensures future generations can live in a similar if not better way than now (Evans, 2020; UN, 2020). This is a broad concept as many different factors affect our environment, like biodiversity, air quality and water availability. Humans, being part of our surroundings, interact with these factors all the time, whether we are farming, fishing, or playing football. In general, there are two sets of indicators that show the performance of a country in terms of their environmental sustainability: pollution measures and more fundamental eco(system) efficiency measures (Lee, 2005). Pollution indicators are often related to environmental health and involve measures like air quality, ozone exposure and the quality of drinking water. To measure the efficiency of an ecosystem, the degree of protected landmass, biodiversity levels and water usage are monitored.

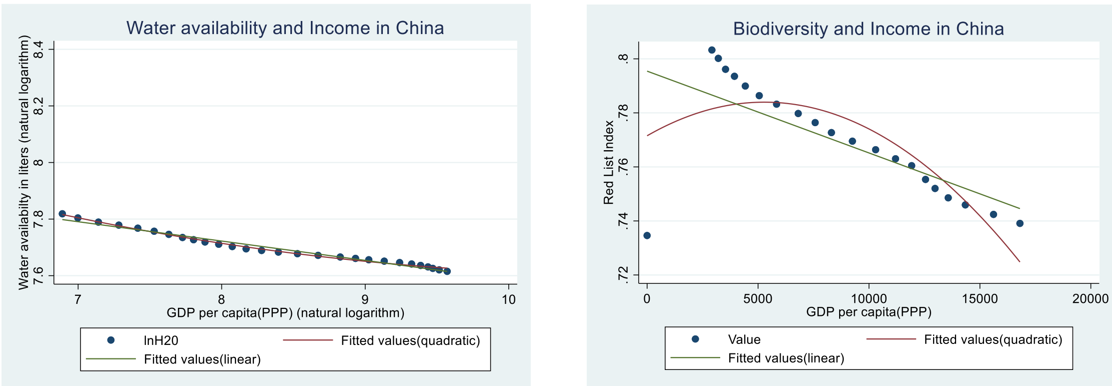
The reason for the difference

It seems that these two groups of environmental indicators are distinctly different from each other and that it is not necessarily the case that the EKC holds for both. Looking at pollution indicators, contamination of air and water bodies in economically advanced countries indeed has decreased. In Western Europe for example, acid rains and rivers covered in foam are stories of the past. However, ecosystem efficiency aspects, such as biodiversity and water availability seem to follow a different trend. Insect and bird populations are plummeting in Western Europe and the US west coast's water levels are plummeting (Chris, 2021; Guardian, 2019). Where pollution levels then have decreased with income there has been no increase in ecosystem efficiency.

Theoretically, the following argumentation explains the divergence in trends between the pollution aspects of environmental sustainability and eco-efficiency measures. At higher levels of income, humans value their health and environment more, but also spend more on luxury goods. Therefore, the willingness to pay for pollution-reducing measures increases with income but also the willingness to pay for goods that degrade the ecosystem. At higher income levels, we fly more, eat more meat, buy more clothes and live in more spacious houses (WWF, 2020). This corresponds to more pressure on local ecosystems, where nature needs to make space for infrastructure and agricultural fields, and local water aquifers are diminished for agriculture, industry and recreational purposes. If we relate this to the distinction made in this paper between pollution and ecosystem efficiency, it seems that at higher levels of income the marginal willingness to pay for reducing pollution increases, but that this is not the case for the protection of ecosystem services, like biodiversity. What strengthens this is the fact that pollution can be exported to other nations while water usage and increased infrastructure takes place within the same region. This theoretically explains the difference in found trends between the two.

To some, the discussion whether there is an inverted U-shape between economic development and (some) ecosystem efficiency factors is inherently flawed (Dietz & Adger, 2003; Czech, 2008). This argument stems from the difference in the reversibility of the two sorts of environmental sustainability. Pollution is something humans cause and therefore can stop; nature has no role in this decision making. Hypothetically, human society could stop most of its polluting and then the air and water quality would slowly return to what it was before we started polluting. For most ecosystem services however, this is not the case. Water aquifers take millions of years to refill and biodiversity losses cannot be undone by inventing new species. This means that human society does not have the ability to restore some of the ecosystem efficiency components of our environment. From this point of view, it puts into question whether it even makes sense to search for a turning point or is impossible regardless. One therefore must be careful on how to include ecosystem efficiency measures into research when looking for a turning point. For biodiversity for example, it seems more appropriate to capture the state of biodiversity by looking at the average loss in habitat per species than at the occurrence of species. Habitat loss can be reversed whilst the presence of a species cannot be reversed after extinction.

Table 1 Ecosystem efficiency indicators and their relationship with income



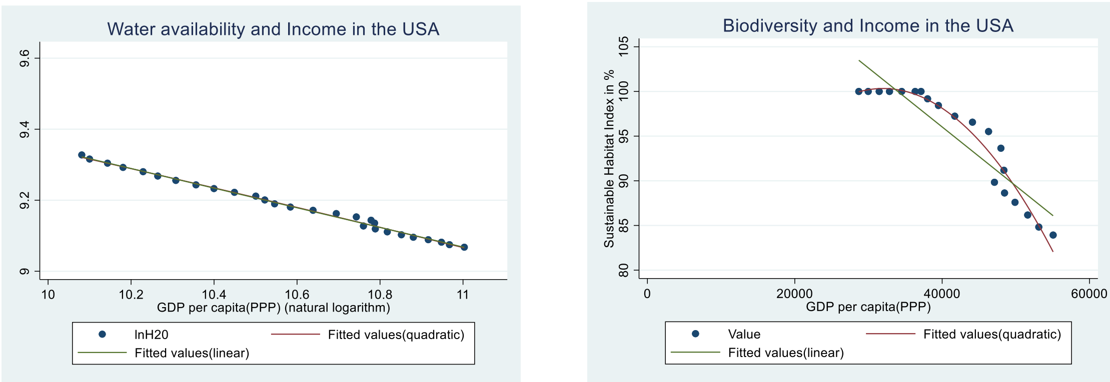
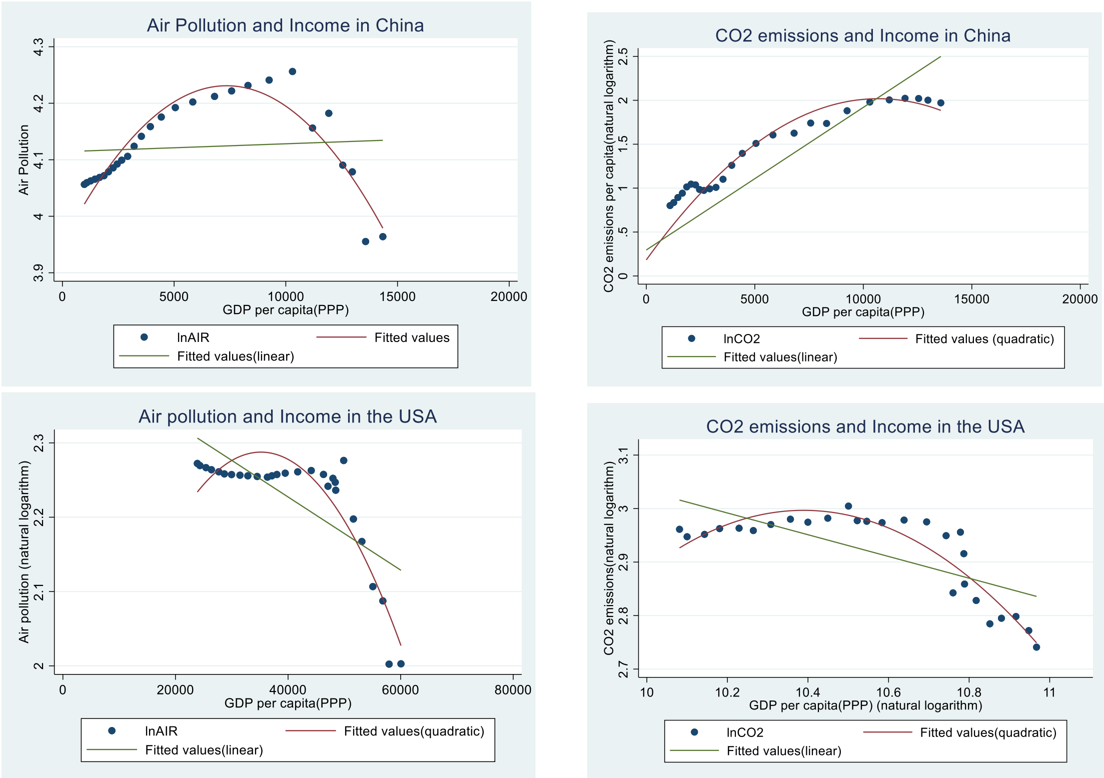


Table 2 Pollution indicators and their relationship with income



Studying the graphs above, the distinction between eco-efficiency and pollution indicators is not only justifiable theoretically but is also represented in the data. For pollution measures the quadratic fit seems more apt, while for the ecosystem efficiency measures this is not the case. Given, however, that cofounding variables could cause this apparent distinction, multivariate regressions will be necessary.

Empirical evidence for the EKC between different environmental factors

How much is this observation of diverging trends between the environmental indicators justified by academic literature? In the first research that tried to present evidence for the EKC, local pollutants were mainly used as proxies (Cole, 1997; Shafik, 1994; Stern et al. 2004). This initial focus on local pollutants made sense placing it in the context of its time. Acid rains and river pollution were making headlines, whilst global warming was still seen as a relatively harmless process. This research showed that the EKC does exist when one looks at economic growth and local pollutants as proxies for the environment and made the EKC a mainstream concept.

The focus from local to global pollutants shifted during the 90's with more evidence indicating the earth to get warmer and stressing the potential consequences this could have. In the academic literature this increased interest in finding a relationship between carbon dioxide and methane emissions and economic growth. As mentioned before some sort of non-linearity has been found when studying the emission patterns of countries over time and the EKC could still be argued to exist.

As outlined above, academic research by economists tried to find an EKC by focusing on local pollutants or CO_2. This is indicative of the fact that although both eco-efficiency and pollution measures contribute to environmental sustainability, the focus in academic literature has been predominantly on the latter. The somewhat positive message that there exists an inverted U-shape for local pollutants and for CO_2 emissions might not exist for the eco efficiency components.

Although there have not been many studies focusing on finding the EKC for eco efficiency measures, some components and their relationship to economic growth have been researched. In the case of biodiversity degradation, wealthier nations have lower levels of biodiversity with little indication of this trend changing (Leclère et al., 2020; Otero et al., 2020). An often-cited study claiming an EKC to exist for biodiversity is written by Ulucak and Bilgili (2018). However, their study ignores population density as a control variable, despite it being an important explanatory determinant in other studies (Adger & Dietz, 2003; Koo et al. 2004). Similarly, for water consumption, there seems to be no presence of an EKC (Yoo, 2007; Expósito et al., 2019). Some evidence from Iran and China, however, supports a bell-shaped pattern (Heidari et al., 2020; Zue et al., 2017). Another measure of ecosystem efficiency, albeit more disputed, is tree coverage (Chen et al., 2019). The reason that this is controversial is that the expanded tree coverage is largely the result of planted forests and plantations replacing the original ecosystem. Insofar as the original ecosystem is important for biodiversity, the resulting gain in carbon storage capacity comes at the cost of biodiversity.

Overall, for eco efficiency measures suffer from a lack in available data. Since many eco-efficiency measures have only been monitored accurately over the last 30 years, they were difficult to use for panel data analysis until recently. This meant that while some researchers did study biodiversity, they had to use inadequate proxies like tree coverage. In other cases researchers narrowed down the sample of countries, often to OECD nations (Tanoli, Yousaf et al., 2017, Cole, 2004), which constrained the external validity of research as not all nations followed or will follow a similar growth pattern.

Research thus suggests that an EKC is likely to exist for pollution measures but seems less likely for ecosystem efficiency measures. To summarize, both theoretical and empirical evidence cast doubt upon whether the EKC holds true for all aspects of environmental sustainability.

2.4 Contributions to the literature

There have been some limitations to previous studying of the EKC that are outlined in the section above. This study tries overcoming these limitations in several ways. Firstly, unlike much of previous literature, it will use a more diverse range of proxies for the environment, also including eco-efficiency measures. Secondly, the inclusion of many developing nations in the data will shine a light on the future of environmental sustainability. These countries will have the most impact on the state of nature as they are in general more endowed with natural capital, but also undergo faster economic growth. A larger dataset will therefore allow the examination of a global trend and using dummies to create regional subpanels could still provide insights into more local movements.

2.5 The choice for the proxies

In a thesis arguing against short-sighted use of proxies for the environment, I should be careful not to do the same. There will be four different proxies included, two associated with pollution indicators and two with ecosystem efficiency.

The pollution variables will be local air pollution and CO_2 emissions. The reason to include local air pollution is the historical significance of it in the field, as observations on declining air pollution in wealthier nations sparked the EKC debate (Krueger et al.,1995; Shafik, 1994; Seldonn & Shung, 1995). CO_2 emissions are included as they form the most-used proxy to research the EKC due the significant impact on climate change (Cole, 2004; Aspergis, 2016; Youssef, et al. 2016). For eco-efficiency measures, the available freshwater resources and the level of biodiversity are used. Water is vital for existence, making it one of the most important and studied eco-efficiency measures. Biodiversity is an environmental factor that until recently was relatively overlooked. It is also usually at odds with other important issues; the need to feed the world has put pressure on many ecosystems on land and under water. Considering that wealthier nations have larger ecological footprints, it is to be expected that they will also burden the local ecosystems more (WWF, 2021).

2.6 Hypotheses

Based on the empirical and theoretical research available, it seems unlikely that the eco-efficiency measures correspond to income changes in the same way as pollution measures. To account for the several components that constitute a sustainable environment, four different indicators are used: the exposure to air pollution, renewable water availability, carbon dioxide emissions per capita and the state of biodiversity in a nation.

Air pollution is expected to have an EKC. In some of the first research into the EKC, forms of air pollution were used as proxies for the state of the environment (Grossman & Kreuger, 1994; Shafik 1995; Cole 2003). The degree of air pollution and economic growth was found to have an inverted U shape form and it formed the basis or the EKC theory. Similar results are therefore expected in this paper.

CO_2 levels are probably the most widely used proxy for the state of the environment in academic literature, featuring in many seminal works (Cole, 1997; Dinda, 2004; Apergis & Ozturk, 2015; Awaworyi Churchill et al., 2018). Although, not entirely conclusive, in most cases an EKC is found. The found turning points come at considerably higher levels of income than in the case of air pollution.

The availability of renewable water resources is an important indicator of the nature's wellbeing and of crucial importance to human life too. This justifies the inclusion of the variable into the study. Research has been more limited on the relationship between water availability and economic growth. Expósito et al. find no turning point in their study (2019), whilst Zhao did find a significant inverted U shape (2017). Thompson (2012) found water scarce and abundant countries to have very varied turning points in their EKC.

For biodiversity and the degree of income the inverted U-shape is not expected or the turning point exists at an income level far from current levels of income. Studies focusing on economic growth and biodiversity levels found a negative relationship between economic growth and biodiversity or no relationship at all (Czech et al., 2012; Dietz & Adger, 2003; Marques et al., 2019). Therefore, the following hypotheses are formulated:

H1: Income and water availability will not show an EKC
H2: Income and biodiversity will not show an EKC
H3: Income and air pollution will show an EKC
H4: Income and CO_2 emissions will show an EKC

3. Methodology

The Environmental Kuznets Curve would suggest an inverted U shape, where initially with an increasing level of income is correlated to an increase in environmental degradation. At a certain level of income, however, the *composition* effect would outweigh the *scale* effect and a threshold would be reached after which an increase in GDP per capita would be accompanied with an increase in environmental wellbeing. To capture this relationship the following formula will be used:

$$E_{it}= F\ (Y_{it},\ Y^2_{it},\ Z_{it}) \tag{1}$$

Here *E* is an environmental factor, *Y* the income per capita, Y^2 GDP per capita squared and Z a set of control variables in country, *i*, and year *t*. The aim of this thesis is to check the effect of changing income on several environmental factors. The environmental factors included are: the amount of renewable water available per capita (H20), average exposure to air pollution (AIR), CO_2 emissions per capita (CO2) and two measures of biodiversity, the number of species under threat in a nation (RLI) and remaining intact habitat for species (SHI).

To reduce the risk of omitted variable bias in which the error term is both correlated with the independent and dependent variable a set of control variables are added. These include the degree of trade, forest coverage and population density. The reasoning for their inclusion is based on prior research (Awaworyi Churchill et al., 2018; Allard et al., 2018; Zhang et al., 2016; Grossman & Krueger, 1996) which will be discussed in more depth in the next section. Having added the control variables, this results into the following model:

$$\ln(E)_{it}= \gamma_0 + \gamma_1 \ln(Y)_{it} + \gamma_2 \ln(Y^2)_{it} + \gamma_3 \ln(T)_{it} + \gamma_4 \ln(P)_{it} + \gamma_5 \ln (FA)_{it} + \mu_{it} \qquad (2)$$

Where T stands for the trade openness of a country, P for the population density and FA for the forest coverage of a nation and μ_{it} captures the error term, the other terms are explained in Eq. (1).

Theory suggests that the scale effect will lead to a negative relationship between environmental sustainability, whilst the composition affect will have a positive relationship. This indicates that the EKC should follow an inverted U-shape with a certain turning point after which the composition effect dominates and environmental degradation decreases with higher income levels. The turning point is calculated using the following expression:

$$Y^*=e^{-\frac{\gamma_1}{2\gamma_2}} \qquad (3)$$

3.1 Control variables

The included control variables are trade, population density and forest coverage. The effect of trade could be ambiguous. Access to a larger market will lead to more potential profits, therefore spurring higher levels of economic activity. These higher production levels put a strain on the local environment (Dinda, 2004). On the other hand, increased trade also increases competition in a country from outside leading to only more efficient businesses surviving. Furthermore, the increased openness of a nation allows for a faster spread of technology, which could also stimulate more environmentally friendly ways of producing goods (Tonali et al., 2016). The ambiguous aspect of trade comes back in research results, where trade has been found to affect the environment positively and negatively (Shazad et al., 2017; Tonali et al., 2016)

Population density is expected to be negatively associated with the environment. An increase in a country's population will lead to more energy consumption, more water consumption and has been found to significantly affect biodiversity negatively (Ohlan, 2015; Dietz & Adger, 2003; Anvi et al., 2015).

Forest area is expected to be positively related with renewable water resources, the air quality, CO_2 emissions and the degree of biodiversity in a nation. Forests cleanse the air and preserve water in the soil (Van der Werf, 2009). In terms of environmental sustainability, it could therefore be considered positive news that the world total forest area is growing (Chen et al., 2019). This greening of the world, however, is mainly caused by global climate change making tundra more suitable for forests and the increased converting of grassland into large plantations. These new trends do not come per se at the benefit of biodiversity. The replacing of wet- and grasslands with monoculture will most likely be disadvantageous for biodiversity levels. More forests will thus benefit air pollution and water availability but whether biodiversity will profit depends on the initial ecosystem.

3.2 Data

The dataset spans from 1990-2017 and includes 144 countries (see Appendix A1). All data is annual panel data. For the environmental indicators, the data on renewable water availability, CO_2 emissions and the exposure to air pollution is borrowed from the World Bank (2020). Biodiversity measures are borrowed from the IUCN and Map of Life (2021). Forest coverage, trade and the GDP per capita are also borrowed from the World Bank. Income is measured in GDP per capita converted to purchasing power parity and measured in dollars. Data on renewable water sources was only available per 5 years and linear interpolation was used to fill the missing years.[1]

Table 3: Descriptive Statistics of the main variables used

Variable	Obs	Mean	Std. Dev.	Min	Max
RLI	2458	.869	.091	.433	.993
AIR	5351	31.115	17.683	5.894	100.784
Y	5351	12467.043	14618.808	285.587	110660.87
H20	5351	18116.987	52791.267	2.757	667300.56
CO2	5351	4.282	5.056	.008	36.089
FA	5351	32.682	22.313	.009	98.575
P	5351	147.349	479.284	1.406	7908.721
T	5351	72.994	47.879	0	437.327
SHI	4,064	90.96	13.322	0.1270	100

Biodiversity

The most used indicator for biodiversity is the Red List Index (RLI), here risk for species in a nation to be extinct on a scale of 0 to 1, where 1 is no risk and 0 is certain extinction (IUCN, 2020). The Red list Index has its shortcomings as it only uses five taxonomies excluding e.g., insects, reptiles, most marine life and almost all flora. The pressure on a species depends on population size and habitat fragmentation. For every recorded species its range is known. This allows the IUCN to calculate the average pressure on organisms in a country. As a robustness check another biodiversity indicator is used called the Species Habitat Index (SHI). The SHI is calculated per species by the Map of Life (2020). The indicator points out the habitat loss of a species per year with the base year being 2000. Using the spread of the species per nation the losses per organism can be calculated.

1 Due to its size, the dataset is not included in the Appendix, but is available upon request

The decision to use nation level

In the field of development economics, the focus has shifted from studies on a national level to more detailed research using grids or subnational regions over the last years. Although this level of detailedness is preferable as it gives a more apt representation of the situation, it could not be done for this paper. This could not be achieved due to data restrictions. Data on environmental factors is still predominantly gathered on a national level. Although in more developed nations, sub national data is more widely available, it would restrict the scope of the research. Developing nations not necessarily follow a similar trajectory as their more developed counterparts and one of the aims of this thesis is to overcome previous limitations in research which focused mostly on OECD nations. As it is especially developing nations who will determine the state of global sustainability it is crucial to include them as much as possible. In the Appendix the included nations can be found (A1).

The decision to use panel data

The preferred approach to estimate the relationship between different sustainability components and their relationship with the income per capita in a nation is by using panel data. Previous studies (e.g., Chung, 2005) often made use of cross-sectional data, but this limits the capability of the paper to provide useful information. Firstly, omitted variable bias between nations is hard to rule out when comparing the differences between countries. Other unobserved effects that the data has not captured could be the cause for the results. Furthermore, the measurement errors between nations could vary drastically. There are several reasons for this difference, one is the political agenda of a nation. Countries who pursue economic growth at the cost of environmental factors might restrict opportunities to collect data on the environment to prevent criticism. Similarly, nations in political turmoil or with ongoing conflicts may also prevent proper data collection. The panel data approach with fixed effects might still be biased on the national level. Changes within a nation might lead to differences in recorded data and this affects the recorded data.

Exogeneity of the environmental sustainability on income per capita

A concern when it comes to the relationship between an environmental indicator and income, is the issue of reverse causality. Potentially it is not the level of GDP per capita influencing the state of the environment, but vice versa. Previous research studied this form of bias, but found no reason for concern (Cole, 2004; Tonali et al., 2016). However, these studies primarily used proxies like air quality and CO_2 for environmental sustainability and their relationship might be different with income than water consumption and biodiversity. For water availability water shortages have no significant effect on economic growth, but this relationship could change due to increasing population pressure and melting snow-caps (Lim et al., 2004; World Bank, 2021).

4. Results

4.1 Tests for evaluation of correct analysis tools

A Hausman test is performed to see whether a fixed or random effects model is preferred. A fixed effects model controls for time invariant variables in a country, like mountains or seas which could affect the observed values. Air pollution is for example harder to reduce in mountainous areas. The p value ($p<.001$) shows that the null hypothesis should be rejected and thus a fixed effects model implemented.

Table 4 Hausman (1978) specification test

	Coef.
Chi-square	54
Test value	58.788
P-value	0

Cross-sectional dependence, unit roots and cointegration

A dataset may contain several characteristics that influence the found results and if not accounted for can lead to false conclusions. An issue with panel data can be the presence of cross-sectional dependence, when all units in the same cross-section are correlated due to some unobservable variable not included in Eq. 2 (Menegaki, 2021). Cross-sectional dependence can be caused by economic proximity, trade unions or other forms through which nations affect one another. To test for the presence of cross-sectional dependence the Pesaran 2004 test is used. This test for cross-sectional dependence is uncommon in earlier works, but nowadays standard in similar research (Awayori Churchill et al.,2018; Dogan et al., 2020). Table 5 shows that we need to reject the null hypothesis of no cross-sectional dependence and account for its presence in further tests.

Table 5: Results for Pesaran (2004) Cross-sectional dependence test

Average correlation coefficients & Pesaran (2004) CD test
Number of groups: 144
Average # of observations: 27.06

Variable	CD-test	p-value	corr	abs(corr)
Y(PPP)	478.950	0.00	0.908	0.913
CO2	81.800	0.000	0.155	0.525
Y (no PPP)	452.390	0.000	0.859	0.859
H20	442.280	0.000	0.841	0.946
P	452.500	0.000	0.861	0.964
Y^2(no PPP)	221.090	0.000	0.863	0.877

T	40.410	0.000	0.157	0.442
RLI	132.500	0.000	0.519	0.829

Notes: Under the null hypothesis of cross-section independence CD ~ N (0,1)

To test the stationarity of the variables included in Eq. (2), it is necessary to for the presence of unit roots. The results of this test are presented in table 6. As the variables contain cross-sectional dependence a Pesaran 2007 test is needed which accounts for this. The findings indicate that in levels all variables do suffer from a unit root as we accept the null hypothesis of the presence of a unit root. If the data is integrated to the first order, the unit roots are no longer present, and the issue of non-stationarity is dealt with.

Table 6 Results unit-root test

	Level		First difference	
	CIPS Zt-bar	*p*-value	CIPS Zt-bar	*p*-value
Y(PPP)	-1.2678	0.1024	25.4531	0.0000
Y^2(PPP)	0.0277	0.5111	-25.3940	0.0000
CO2	4.4228	1.00	-33.7659	0.0000
H2O	4.6223	1.00	-17.7318	0.0000
RLI	14.7309	1.00	-15.5034	0.0000
AIR	11.3698	1.00	-32.4364	0.0000
Trade	-0.5984	0.2748	-32.5392	0.0000
Forest	-12.8724	0.3962	-28.4628	0.0000
Y (no PPP)	11.0899	1.00	-29.1850	0.0000
Y^2(no PPP)	0.5949	0.7240	-28.8522	0.0000

Time trend included constant included

The findings indicate the presence of CSD and the non-stationarity. The variables are therefore integrated into order 1. Therefore, we proceed by checking for a cointegrating relationship between the variables in the model. Per dependent variable a test is run with the independent variables from Eq.2. The results, included in the Appendix (B.3), suggest that a cointegrated relationship exists for every dependent variable and the various explanatory variables.

Fixed effects or Mean Group

In early research it was common to obtain results using fixed effect OLS models. These models were built around two assumptions: 1. Large cross sections, where we can have as few as two time periods; 2. Random sampling of cross-sectional units (Kapoor, 2022). Due to the found cross sectional dependency in the data set, assumption 2 is violated and it is more appropriate to use another method of estimation. Furthermore, fixed effects models only account for heterogeneity in the intercept and error distribution between the countries, but not for the heterogeneity in the slopes (Campello et al., 2019). It is not unthinkable that in this thesis' sample there is a fair degree of heterogeneity caused by the different levels of economic development, culture and geographic positioning. This leads to a bias in the results as the slope coefficients could differ per group. To account for this, one can use the Mean Group (MG) estimator (Awaworyi Churchill et al., 2018, Dogan et al., 2020, Campello et al., 2019). The mean group estimator estimates separate time series regressions for each country. This means that it allows the intercept, the slope, and even the error distribution to differ across countries (Kapoor, 2022). It then averages over the (slope) estimates from the different countries to obtain a global average. In standard fixed effects settings, we only allow the intercept and error distribution to differ across countries (Kapoor, 2022). In general, the MG estimator is 'better' for this panel data set, however the fixed effect model results are also included. For both regressions time dummies have been included rather than a time trend as the countries differ quite substantially from each other and therefore the inclusion of a trend is hard to imagine.

4.2 The main results

In the following section the main results are presented. In Table 7 all the results are presented for both estimators. Both models included time control to account for year specific changes.

Table 7 Results

DV	H20		AIR		CO2		BIO	
Estimator	FE	MG	FE	MG	FE	MG	FE	MG
Y	-0.032	-0.016*	0.19***	1.200**	2.116***	3.088**	0.006	0.03647
	(0.025)	(0.009)	(0.058)	(0.594)	(0.302)	(1.512)	(0.027)	(0.0328)
Y^2	0.0002	0.001*	-0.010***	-0.069**	-0.088***	-0.149*	-0.001	-0.0023
	(0.0015)	(0.001)	(0.003)	(0.032)	(0.0177)	(0.085)	(0.002)	(0.0018)
T	0.002	-0.001	-0.001	0.016***	0.003	0.003	0.001	<0.001
	(0.003)	(0.001)	(0.001)	(0.006)	(0.0340)	(0.022)	(0.001)	(0.001)
FA	0.008	0.045**	0.037	0.586	-0.010	-0.289	0.011	-0.28
	(0.011)	(0.034)	(0.025)	(0.704)	(0.0787)	(1.004)	(0.019)	(1.084)
P	-1.107***	-0.789***	0.088***	-0.181	0.47***	-0.568	-0.04***	-0.051***
	(0.013)	(0.024)	(0.026)	(0.284)	(0.151)	(0.774)	(0.003)	(0.019)
EKC holds	No	Yes	Yes	Yes	Yes	Yes	No	No
Turning point	-	2981$	13360 $	5976$	172301 $	31647$	-	-
Obs.	5307	4807	5788	5070	5551	4010	2928	2397
Time control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: standard errors are reported in parentheses, *, **, *** signify significance at 10%, 5% and 1% level. Intercept and time dummies included in all regressions

The main results are presented in table 7 above. For the EKC to exist both the income level per capita and its square need to be significant. Using the mean group estimator for water availability, initially availability decreases with income, but due the significant square there is a turning point. This is not in line with the first hypothesis that water availability will not show an EKC. The fixed effect regression does not show an EKC. For air pollution and CO_2 emissions, the levels increase with a rise in income at first, but due to significant negative effect of the squared income term, there is a turning point where this increase with income stops and reverses. For biodiversity, here represented by the RLI, this is not the case. For the EKC to hold, the linear income term should be negative and the quadratic term positive. The opposite is the case however, the linear term is insignificant and positive, whilst the quadratic term is insignificantly negative. Considering the turning points, air pollution and CO_2 emissions follow the expected curvature, where air pollution decreases at a lower turning point than the carbon pollution. These findings suggest that renewable water resources also increase after an income of 2981$, which is less than found in other literature (Zhao, 2017).

Looking at each regression in more detail; the amount of available renewable water shows a relationship confirming the EKC. Initially with income rise the available water decreases, but at higher income levels the amount of renewable water increases again due to the significant Y^2 term, if the mean group estimator is used. Population density puts pressure on available water resources whilst the presence of forest significantly boosts water reservoirs.

Air quality is measured in exposure to air particles and with an increase in income the linear term is positive indicating more air pollution with higher levels of income. Again, there is a turning point, as the quadratic income term is significantly negative. At higher levels of income this quadratic term becomes dominant, and the degree of air pollution decreases with income. In the FE model, an increase in population leads to higher level of pollution. In the MG model trade also enhances air pollution.

The level of CO_2 emissions also follows the EKC. Initially levels increase, as the significant positive sign of Y shows. There is a stark difference in the turning point between the FE and MG model. For the MG the turning point is reached at around 30000$, for the FE model this point lies around 170000$. The difference comes mainly from the much weaker effect of the Y^2 effect.

Biodiversity shows no signs of an EKC as the variables Y and Y^2 are insignificant. In general, the role of income seems negligible and population density appear to be the main driver behind species survival chances. The results are similar to Leclère et al., (2020) and Otero et al., (2020). As mentioned in the theoretical framework, in their much-cited research Ulucak and Bilgili did find an EKC, but they did not include population density as a control variable. Performing this thesis' regression analysis without population density as they did, shows similar outcomes as in Ulucak and Bilgili's results (see Appendix B.5). This seems to indicate that their results suffer from omitted variable bias.

The ambiguous role of trade is shown in the results. Trade rarely significantly contributes or harms an environmental factor.

4.3 Robustness checks

Biodiversity and income

One of the unexpected results was the limited role of income on biodiversity. From the regressions, it seems to be the case that population growth has been responsible for the current mass extinction and that the role of income is negligible. In table 7, the Red List Index is used as proxy for biodiversity. Biodiversity however is a complex system with several interpretations. To avoid the results in this paper to solely rely on criteria of the IUCN on e.g., what makes a specie threatened or not, the same regression is run with the Species Habitat Index (SHI) replacing the RLI. The results are strikingly similar, in both cases the squared income variable is insignificantly negative (see Table 8 below). whilst the linear term is insignificantly positive. Furthermore, a higher population density is detrimental for the local biodiversity. Unfortunately, the data used is somewhat misleading, as it is based on the Red List index. As said before, this index does not include many classes of organisms. Insect populations, for example, are dwindling rapidly in the Netherlands, but they are ignored when the RLI is calculated (Hallmann et al., 2018). Other biodiversity (SHI, LPI, EF) indices run into similar problems, and this showcases the shortcomings of current biodiversity data.

Table 8 The different biodiversity estimators

	Dependent variable	
Biodiversity estimator	SHI	RLI
Y	9.106	0.03647
	(5.72)	(0.0328)
Y^2	-.51347	-0.0023
	(0.321)	(0.0018)
Trade	.03785*	<0.001
	(0.02)	(0.001)
Forest	.1.77	-0.28
	(4.58)	(1.084)
Population density	-1.0486*	-0.051***
	(0.321)	(0.019)
EKC Holds	No	No
EKC turning point	-	-

Notes: standard errors are reported in parentheses, *, **, *** signify significance at 10%, 5% and 1% level. Intercept and time controls included in both regressions.

Results per region

The results above describe the findings for a global panel. The world's diversity in culture, economic development and geography does however raise the question whether the found relationships would hold for different continents. It is not carved in stone that other nations will follow developed nation's form of economic and environmental development. Furthermore, less developed countries are also underrepresented in environmental economic studies due to limited data availability. Chung et al. aspired to perform such study using cross-sectional data and identified differences in Asian countries vis a vis the rest of the world (2003). To examine regional differences the world is divided into seven zones based on the World Bank's criteria (World bank, 2020). Eq. 2 is expanded with 7 dummies, one for each zone, taking the value 1 when studied. This practically subdivides the sample into seven subsamples which then can be analyzed.[2]

Table 9 The presence of an EKC per region and indicator

Indicator / Region	AIR	CO2	H2O	BIO(RLI)	Mean GDP per capita
SSA	Yes (938$)	Yes (15795$)	No	Yes (6066$)	1733$
MENA	Yes (4903$)	No	No	No	9285$
EUCA	Yes (3043$)	Yes (19428$)	No	No	9587$
EAP	Yes (10832$)	Yes (44426$)	Yes (1079$)	No	7471$
SAS	Yes (1005$)	Yes (37304$)	No	No	2041$
NA	Yes (38430$)	Yes (75889$)	Yes (32748$)	Yes (59948$)	22483$
LAC	Yes (6554$)	Yes (41291$)	Yes (27311$)	No	5750$

The results presented in the table above show no stark differences with the earlier findings on a global level. Interesting is that the continents with dry climates have no EKC for water availability, whilst the issue of water shortages would seem more pressing in these areas. If a regression is run where the country sample is split between water abundant and water scarce nations, we do observe this trend, where water abundant nation's economic growth is not linked to water consumption in an EKC shape, but this is the case for nations with less water (Appendix B.7). For biodiversity it is somewhat hopeful to see that in Sub-Saharan Africa there is a turning point, although current average income (measured in PPP) is 3410$ and therefore still quite far of the turning point found (6066$). A potential explanation for the regional significance can be the economic importance of wildlife in Sub-Saharan Africa. 6% of the population is employed due to wildlife tourism and income from safaris and other

2 SSA= Sub-Saharan Africa, MENA= Middle east and Northern Africa, EAP= East Asia and Pacific. EUCA= Europe and Central Asia, SAS= South Asia, LAC= Latin America and Caribbean, NA= North America

nature experiences represented over 7% of the GDP in 2016 (Price, 2017). This 'capitalization' of nature could have contributed to prioritize protection of ecosystems.

Climate and the EKC

The different results per region suggest that the relationship between society and the environment is driven by the climate they are in. For example, drier areas will try to reduce their water footprint. To test this, the sample is subdivided into the major climate zones found on earth (SEDAC, 2020). Using the Köppen-Geiger climate classification subsamples were formed and Eq. 2 used to analyze the relationship between environmental factors and driving factors.

The group variable in the dataset is countries and allocating climates to a nation is hard as a country most often does not fall into just one of the categories. For this reason, countries where at least 25% of the population would live in a certain climate would be included in the subsample (e.g the USA will both be in the Subtropical climate sample and the Continental subsample). Another issue is climate change, the increasing global temperatures over time led to changes in local precipitation and temperature. A country with a continental climate in 1970 could be classified as a Mediterranean nowadays. As the climate classification is an irregular performed task it was impossible to include climate as a time variable. The issue might exist that nations fall are assigned the wrong climate zone. However, the fact that the subsamples already allow for a country to fall in multiple climate zones potentially mitigates the effects.

Table 9 The presence of an EKC per climate zone and indicator

Indicator / Region	AIR	CO2	H2O	BIO(RLI)	Mean GDP per capita
Equatorial	Yes (9450$)	Yes (21861$)	No	No	7120$
Equatorial Monsoon	Yes (1638$)	Yes (27036$)	No	Yes (1958$)	8101$
Arid and semiarid	Yes (19617$)	No	Yes (5264$)	No	12240$
Subtropical and Mediterranean	Yes (2531$)	Yes (71987$)	No	Yes (23327$)	16723$
Continental	Yes (32988$)	Yes (29533$)	No	No	18423$
Boreal	Yes (59324$)	Yes (17496$)	No	No	29964$

The results show that what was hypothesized before, depending on the climate, countries do or do not encounter a turning point in the degradation of the environment. For example, countries with less available water do have an EKC, whilst the other climate zones do not. Theoretically, this could be explained by the *composition effect*, where depending on the climate you are in, the necessity to change your water consumption is reached at earlier levels of income, as the consequences of not changing your consumption pattern are different too. Naturally, an Israeli farmer will be quicker to adopt sophisticated irrigation techniques than a Scottish farmer, although their average income is about the same.

In general, an overlap can be observed between the geographical positioning of a continent, which corresponds to a certain climate, and the results. The Middle East and North Africa are arid to semi-arid regions and both in the region regressions as in the climate regressions the results are therefore similar. A striking feature not represented in the tables above is the role of forest coverage on biodiversity. In climate zones where forest are expected to grow, like around the Equator and in regions with land climates the forest benefit biodiversity. In regions where vast forests are not present originally, like on the tundra and the savannah, an increase in the forest coverage leads to a decrease in the biodiversity. A possible explanation for this phenomenon is the greenifying of the world. Human induced changes in the form of new plantations and the thawing of the permafrost have led to forestation in formerly clear areas. The original wildlife suffers from these changes as species diversity increases over time and in new pioneering forests and therefore finds less diversity than there was before.

5. Conclusion

To conclude, the results showed that not for all contributors to environmental sustainability the Environmental Kuznets Curve holds. Water consumption and biodiversity are pillars of human society and life in general but increases in our wealth deplete these natural resources with little indication of a turning point. This study shows that it would be apt to rethink the EKC and perhaps rename the abbreviation to Emissions Kuznets Curve. Therefore, current research would be advised to be careful with using CO_2 emission as a proxy for the environment. As important as this greenhouse gas is, it does not solely define the state of nature. A world with lower carbon emissions could still be a less sustainable place than the status quo.

The issue of everyone using CO_2 emissions, however, ties into the next point, the scarcity of information on other environmental factors. Data on biodiversity is limited, and the available data is all but flawless. This limits research to do analyses in more detailed manner, a similar study to this but on a regional level could be very interesting. This is especially important as there exists many varieties in results between regions and climates, and for policy makers it is therefore key to look at research about areas similar to their own. However, change is on the horizon as data sources are combined, updated, and created and it will be interesting to see what future research with richer data can find (Rewild, 2021; GBIF, 2021; IUCN, 2021).

6. Literature

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Appendix

Appendix A: Countries Included

Afghanistan, Albania, Algeria, Andorra, Angola, Antigua and Barbuda, Argentina, Armenia, Aruba, Australia, Austria, Azerbaijan, Bahamas, The, Bahrain, Bangladesh, Barbados, Belarus, Belgium, Belize, Benin, Bermuda, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Brunei Darussalam, Bulgaria, Burkina Faso, Burundi, Cabo Verde, Cambodia, Cameroon, Canada, Cayman Islands, Central African Republic, Chad, Chile, China, Colombia, Comoros, Congo, Dem. Rep., Congo, Rep., Costa Rica, Cote d'Ivoire, Croatia, Cuba, Cyprus, Czech Republic, Denmark, Djibouti, Dominica, Dominican Republic, Ecuador, Egypt, Arab Rep. El Salvador, Equatorial Guinea, Eritrea, Estonia, Eswatini, Ethiopia, Fiji, Finland, France, Gabon, Gambia, The, Georgia, Germany, Ghana, Greece, Grenada, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hungary, Iceland, India, Indonesia, Iran, Islamic Rep., Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Rep., Korea, Rep., Kosovo, Kuwait, Kyrgyz Republic, Lao PDR, Latvia, Lebanon, Lesotho, Liberia, Libya, Liechtenstein, Lithuania, Low & middle income, Luxembourg, Madagascar, Malawi, Malaysia, Maldives, Mali, Malta, Mauritania, Mauritius, Mexico, Moldova, Mongolia, Montenegro, Morocco, Mozambique, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, , North Macedonia, Norway, Oman, Pakistan, Palau, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Puerto Rico, Qatar, Romania, Russian Federation, Rwanda, Samoa, Sao Tome and Principe, Saudi Arabia, Senegal, Serbia, Seychelles, Sierra Leone, Singapore, Slovak Republic, Slovenia, Small states, Somalia, South Africa, South Sudan, Spain, Sri Lanka, Sub-Saharan Africa, Sudan, Suriname, Sweden, Switzerland, Syrian Arab Republic, Tajikistan, Tanzania, Thailand, Timor-Leste, Togo, Trinidad and Tobago, Tunisia, Turkey, Turkmenistan, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Uzbekistan, Venezuela, RB, Vietnam, West Bank and Gaza, Yemen, Rep., Zambia, Zimbabwe

Appendix B: Regressions and methods

B.1 Results

Regression results for the Fixed Effects Model

lnAIR	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lnforest	.037	.025	1.49	.138	-.012	.086	
lnpopdens	.088	.026	3.44	.001	.038	.139	***
lntrade	-.001	.001	-1.42	.156	-.004	.001	
lnPPP	.19	.058	3.29	.001	.076	.303	***
lnPPP2	-.01	.003	-3.05	.003	-.017	-.004	***
Constant	2.016	.271	7.43	0	1.481	2.551	***

Mean dependent var	3.265	SD dependent var	0.576
R-squared	0.325	Number of obs	5788.000
F-test	31.222	Prob > F	0.000
Akaike crit. (AIC)	-17741.996	Bayesian crit. (BIC)	-17528.762

**** p<.01, ** p<.05, * p<.1*

Regression results

lnH20	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lnforest	.008	.011	0.75	.451	-.013	.029	
lnpopdens	-1.107	.013	-83.52	0	-1.133	-1.081	***
lnTRADE	.002	.003	0.48	.628	-.005	.008	
lnPPP	-.032	.025	-1.27	.204	-.081	.017	

lnPPP2	0	.002	0.18	.855	-.003	.003	
Constant	12.926	.111	116.02	0	12.707	13.144	***

Mean dependent var	8.287	SD dependent var	1.770
R-squared	0.844	Number of obs	5307.000
F-test	857.042	Prob > F	0.000
Akaike crit. (AIC)	-14357.830	Bayesian crit. (BIC)	-14140.797

*** *p<.01, ** p<.05, * p<.1*

lnCO2	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lngdp	2.116	.34	8.58	0	1.85	2.953	***
gdp22	-.0.88	.018	-7.81	0	-.146	-.087	***
lnTRADE	-.003	.034	-0.30	.767	-.045	.033	
lnforest	-.01	.077	0.895	.68	-.121	.185	
lnpopdens	.478	.152	0.37	.002	-.142	.208	***
Constant	-11.526	1.243	-9.27	0	-13.976	-9.075	***

Mean dependent var	0.632	SD dependent var	1.557
R-squared	0.409	Number of obs	5201.000
F-test	40.837	Prob > F	0.000
Akaike crit. (AIC)	-2369.393	Bayesian crit. (BIC)	-2336.447

*** *p<.01, ** p<.05, * p<.1*

Regression results

lnRLI	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lngdp	.004	.009	0.43	.667	-.014	.021	
gdp22	-.001	0	-2.61	.009	-.002	0	***
lnTRADE	.001	.001	0.62	.533	-.001	.002	
lnforest	.01	.006	1.81	.071	-.001	.022	*
lnpopdens	-.04	.003	-14.65	0	-.046	-.035	***
Constant	.054	.045	1.19	.235	-.035	.142	

Mean dependent var	-0.155	SD dependent var	0.118
R-squared	0.296	Number of obs	2888.000
F-test	228.970	Prob > F	0.000
Akaike crit. (AIC)	-17288.231	Bayesian crit. (BIC)	-17252.421

*** *p<.01, ** p<.05, * p<.1*

lnSHI	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lngdp	.085	.308	0.28	.782	-.522	.693	
gdp22	-.017	.016	-1.02	.309	-.049	.016	
lnTRADE	.001	.014	0.06	.956	-.027	.028	
lnforest	.587	.255	2.30	.023	.084	1.091	**
lnpopdens	-.267	.073	-3.66	0	-.411	-.123	***
Constant	4.375	1.713	2.55	.012	.991	7.758	**

Mean dependent var	4.494	SD dependent var	0.241
R-squared	0.237	Number of obs	3463.000
F-test	21.483	Prob > F	0.000
Akaike crit. (AIC)	-2155.615	Bayesian crit. (BIC)	-2124.866

**** p<.01, ** p<.05, * p<.1*

Results for Mean Group type estimations

Coefficient averages computed as outlier-robust means (using rreg)
Mean Group type estimation Number of obs = 4,010
Group variable: newCountryCode Number of groups = 149
Obs per group:
min = 18
avg = 26.9
max = 27
Wald chi2(5) = 7.88
Prob > chi2 = 0.1631

lnCO2	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
lnPPP	3.088	1.512	2.040	0.041	0.125	6.052
lnPPP2	-0.149	0.085	-1.750	0.080	-0.315	0.018
lnTRADE	0.003	0.022	0.150	0.878	-0.040	0.047
lnforest	-0.289	1.004	-0.290	0.774	-2.257	1.679
lnpopdens	-0.568	0.774	-0.730	0.463	-2.085	0.950
__000007_t	0.009	0.012	0.690	0.492	-0.016	0.033
_cons	-17.520	8.453	-2.070	0.038	-34.087	-0.953

Root Mean Squared Error (sigma): 0.0813
(RMSE uses residuals from group-specific regressions: unaffected by 'robust').
Variable __000007_t refers to a group-specific linear trend.
Share of group-specific trends significant at 5% level: 0.322 (= 48 trends)

Note: 34 obs. dropped (panels too small)
Pesaran & Smith (1995) Mean Group estimator
All coefficients present represent averages across groups (newCountryCode)
Coefficient averages computed as outlier-robust means (using rreg)
Mean Group type estimation Number of obs = 5,070
Group variable: newCountryCode Number of groups = 200
Obs per group:
min = 10
avg = 25.4
max = 27
Wald chi2(5) = 17.07
Prob > chi2 = 0.0044

lnAIR	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
lnPPP	1.200	0.594	2.020	0.043	0.036	2.364
lnPPP2	-0.069	0.032	-2.140	0.032	-0.133	-0.006
lnTRADE	0.016	0.006	2.700	0.007	0.004	0.027
lnforest	0.586	0.704	0.830	0.405	-0.794	1.966
lnpopdens	-0.181	0.284	-0.640	0.524	-0.737	0.376

__000007_t	-0.010	0.005	-1.850	0.065	-0.021	0.001
_cons	-5.320	4.463	-1.190	0.233	-14.068	3.429

Root Mean Squared Error (sigma): 0.0206

Mean Group type estimation Number of obs = 4,807
Group variable: newCountryCode Number of groups = 182
Obs per group:
min = 22
avg = 26.4
max = 27
Wald chi2(5) = 1098.77
Prob > chi2 = 0.0000

lnH20	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
lnPPP	-0.016	0.009	-1.680	0.093	-0.034	0.003
lnPPP2	0.001	0.001	1.660	0.097	-0.000	0.002
lnTRADE	-0.001	0.001	-2.170	0.030	-0.003	-0.000
lnforest	0.045	0.034	1.340	0.181	-0.021	0.111
lnpopdens	-0.789	0.024	-32.960	0.000	-0.836	-0.742
__000007_t	-0.002	0.000	-4.230	0.000	-0.002	-0.001
_cons	11.047	0.278	39.750	0.000	10.503	11.592

Root Mean Squared Error (sigma): 0.0173
(RMSE uses residuals from group-specific regressions: unaffected by 'robust').

Pesaran & Smith (1995) Mean Group estimator
All coefficients present represent averages across groups (newCountryName)
Coefficient averages computed as unweighted means
Mean Group type estimation Number of obs = 2,737
Group variable: newCountryName Number of groups = 147
Obs per group:
min = 8
avg = 18.6
max = 19
Wald chi2(5) = 11.78
Prob > chi2 = 0.0379

lnRLI	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
lnTRADE	0.000	0.000	0.700	0.483	-0.000	0.001
lnPPP	0.036	0.032	1.140	0.256	-0.026	0.099
lnforest	-0.286	0.332	-0.860	0.388	-0.936	0.364
lnpopdens	-0.052	0.020	-2.580	0.010	-0.091	-0.012
lnPPP2	-0.002	0.002	-1.280	0.200	-0.006	0.001
__000007_t	-0.002	0.001	-2.010	0.045	-0.004	-0.000
_cons	0.603	1.012	0.600	0.551	-1.380	2.586

Root Mean Squared Error (sigma): 0.0004
Variable __000007_t refers to a group-specific linear trend.
Share of group-specific trends significant at 5% level: 0.456 (= 67 trends)

B.2 The results for Sustainable habitat Index to compare to RLI.
See results RLI in B.1

lnSHI	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lnPPP	.085	.093	0.92	.358	-.097	.268	
lnPPP2	-.017	.005	-3.23	.001	-.027	-.007	***
lnTRADE	.001	.01	0.08	.936	-.018	.02	
lnforest	.587	.061	9.62	0	.467	.707	***
lnpopdens	-.267	.031	-8.54	0	-.328	-.205	***
Constant	4.375	.47	9.32	0	3.454	5.296	***

Mean dependent var	4.494	SD dependent var	0.241
R-squared	0.237	Number of obs	3463.000
F-test	205.248	Prob > F	0.000
Akaike crit. (AIC)	-2153.615	Bayesian crit. (BIC)	-2116.716

**** p<.01, ** p<.05, * p<.1*

Note: 20 obs. dropped (panels too small)
Pesaran & Smith (1995) Mean Group estimator
All coefficients present represent averages across groups (newCountryCode)
Coefficient averages computed as unweighted means
Mean Group type estimation Number of obs = 2,749
Group variable: newCountryCode Number of groups = 149
Obs per group:
min = 6
avg = 18.4
max = 19
Wald chi2(4) = 10.96
Prob > chi2 = 0.0270

lnRLI	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
lnPPP	0.195	0.107	1.820	0.069	-0.015	0.404
lnPPP2	-0.011	0.006	-2.030	0.042	-0.022	-0.000
lnforest	0.132	0.102	1.300	0.194	-0.067	0.331
lnTRADE	0.002	0.001	1.270	0.203	-0.001	0.004
_cons	-1.386	0.640	-2.170	0.030	-2.640	-0.132

Root Mean Squared Error (sigma): 0.0015

Pesaran & Smith (1995) Mean Group estimator
All coefficients present represent averages across groups (newCountryName)
Coefficient averages computed as unweighted means
Mean Group type estimation Number of obs = 3,387
Group variable: newCountryName Number of groups = 148
Obs per group:
min = 8
avg = 22.9
max = 24

Wald chi2(5) = 8.81
Prob > chi2 = 0.1171

lnSHI	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
lnTRADE	0.038	0.022	1.720	0.086	-0.005	0.081
lnPPP	9.106	5.723	1.590	0.112	-2.111	20.324
lnforest	1.774	4.583	0.390	0.699	-7.209	10.756
lnpopdens	-1.049	0.574	-1.830	0.068	-2.174	0.077
lnPPP2	-0.513	0.321	-1.600	0.110	-1.143	0.116
_cons	-38.129	29.788	-1.280	0.201	-96.511	20.254

Root Mean Squared Error (sigma): 0.0478

B.3 The tests

Test for cross-sectional dependence

Average correlation coefficients & Pesaran (2004) CD test
Number of groups: 144
Average # of observations: 27.06

Variable	CD-test	p-value	corr	abs(corr)
lnPPP	478.950	0.000	0.908	0.913
lnCO2	81.800	0.000	0.155	0.525
lnforest	.	.	.	.
lngdp	452.390	0.000	0.859	0.859
lnH20	442.280	0.000	0.841	0.946
lnpopdens	452.500	0.000	0.861	0.964
lnPPP2	221.090	0.000	0.863	0.877
lnTRADE	40.410	0.000	0.157	0.442
lnRLI	132.500	0.000	0.519	0.829

Notes: Under the null hypothesis of cross-section independence CD ~ N (0,1)

Unit root tests

	Level		First difference	
	CIPS Zt-bar	*p*-value	CIPS Zt-bar	*p*-value
Y(ppp)	-1.2678	0.1024	25.4531	0.0000
Y^2(ppp)	0.0277	0.5111	-25.3940	0.0000
CO2	4.4228	1.00	-33.7659	0.0000
H2O	4.6223	1.00	-17.7318	0.0000
RLI	14.7309	1.00	-15.5034	0.0000
AIR	11.3698	1.00	-32.4364	0.0000
Trade	-0.5984	0.2748	-32.5392	0.0000
Forest	-12.8724	0.3962	-28.4628	0.0000
Y	11.0899	1.00	-29.1850	0.0000
Y^2	0.5949	0.7240	-28.8522	0.0000

Time trend included constant included

Cointegration tests

H2O as dependent variable

Statistic	Value	*P*-value

Modified Phillips-Perron t	10.8707	0.0000
Phillips-Perron t	9.7507	0.0000
Augmented Dicke-Fuller t	-18.0133	0.0000

CO_2 as dependent variable

Statistic	Value	*P*-value
Modified Phillips-Perron t	0.2799	0.3898
Phillips-Perron t	-50.0623	0.0000
Augmented Dicke-Fuller t	-48.4605	0.0000

AIR as dependent variable

Statistic	Value	*P*-value
Modified Phillips-Perron t	-2.8638	0.0021
Phillips-Perron t	-53.1636	0.0000
Augmented Dicke-Fuller t	-57.5566	0.0000

RLI as dependent variable

Statistic	Value	*P*-value
Modified Phillips-Perron t	9.5234	0.0000
Phillips-Perron t	-25.5236	0.0000
Augmented Dicke-Fuller t	-27.7558	0.0000

B.4 Water demand, wealth and climate

For arid and semi-arid climate

Mean Group type estimation   Number of obs   =   589

Group variable: newCountryCode Number of groups = 35

Obs per group:

min = 11

avg = 16.8

max = 17

Wald chi2(5) = 78.13

Prob > chi2 = 0.0000

lnH20	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
lnPPP	0.349	0.136	2.560	0.010	0.082	0.617
lnPPP2	-0.020	0.008	-2.550	0.011	-0.036	-0.005
lnforest	-0.064	0.040	-1.620	0.106	-0.142	0.014
lnpopdens	-0.590	0.077	-7.680	0.000	-0.740	-0.439
lnTRADE	-0.002	0.001	-1.870	0.062	-0.004	0.000
__000007_t	-0.011	0.002	-4.900	0.000	-0.015	-0.007
_cons	7.691	1.121	6.860	0.000	5.493	9.889

Root Mean Squared Error (sigma): 0.0035

B.5: Importance of including population density

Tables with population density included in the results section (see table 7)

For the RLI using Mean Group estimation

Mean Group type estimation Number of obs = 2,749

Group variable: newCountryCode Number of groups = 149

Obs per group:

min = 6

avg = 18.4

max = 19

Wald chi2(4) = 10.96

Prob > chi2 = 0.0270

lnRLI	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
lnPPP	0.195	0.107	1.820	0.069	-0.015	0.404
lnPPP2	-0.011	0.006	-2.030	0.042	-0.022	-0.000
lnforest	0.132	0.102	1.300	0.194	-0.067	0.331
lnTRADE	0.002	0.001	1.270	0.203	-0.001	0.004
_cons	-1.386	0.640	-2.170	0.030	-2.640	-0.132

For SHI using Fixed Effects Model

lnSHI	Coef.	St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
lngdp	-.201	.088	-2.30	.022	-.373	-.029	**
gdp22	-.003	.005	-0.65	.517	-.013	.006	
lnTRADE	.001	.01	0.14	.885	-.018	.021	
lnforest	.705	.06	11.73	0	.587	.823	***
Constant	4.444	.475	9.36	0	3.513	5.375	***

Mean dependent var	4.494	SD dependent var	0.241
R-squared	0.220	Number of obs	3463.000
F-test	233.237	Prob > F	0.000
Akaike crit. (AIC)	-2079.961	Bayesian crit. (BIC)	-2049.211

**** p<.01, ** p<.05, * p<.1*

B.6 Forests and Biodiversity; differences per region

Savannah regions

Mean Group type estimation Number of obs = 299
Group variable: newCountryCode Number of groups = 16
Obs per group:
min = 14
avg = 18.7
max = 19
Wald chi2(5) = 14.35
Prob > chi2 = 0.0135

lnRLI	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
lnPPP	0.074	0.169	0.440	0.662	-0.258	0.405
lnPPP2	-0.005	0.010	-0.530	0.597	-0.026	0.015
lnforest	0.257	0.153	1.680	0.093	-0.043	0.556
lnpopdens	-0.327	0.313	-1.050	0.296	-0.941	0.286
lnTRADE	0.000	0.002	0.080	0.938	-0.003	0.003
_cons	-0.121	1.072	-0.110	0.910	-2.223	1.981

B.7 the difference between water abundant and water scarce nations and their EKC

Note: 19 obs. dropped (panels too small)
Pesaran & Smith (1995) Mean Group estimator
All coefficients present represent averages across groups (newCountryCode)
Coefficient averages computed as unweighted means
Mean Group type estimation Number of obs = 1,443
Group variable: newCountryCode Number of groups = 61
Obs per group:
min = 7
avg = 23.7
max = 28
Wald chi2(5) = 28.71
Prob > chi2 = 0.0000

lnH20	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
lnPPP	7.983	4.123	1.940	0.053	-0.098	16.065
lnPPP2	-0.453	0.239	-1.900	0.057	-0.921	0.014
lnforest	-2.187	4.395	-0.500	0.619	-10.800	6.426
lnTRADE	-0.025	0.043	-0.580	0.561	-0.110	0.059
lnpopdens	-2.352	1.576	-1.490	0.136	-5.442	0.737
_cons	-15.691	11.414	-1.370	0.169	-38.063	6.680

Root Mean Squared Error (sigma): 0.0383

Note: 21 obs. dropped (panels too small)
Pesaran & Smith (1995) Mean Group estimator
All coefficients present represent averages across groups (newCountryCode)
Coefficient averages computed as unweighted means
Mean Group type estimation Number of obs = 3,824
Group variable: newCountryCode Number of groups = 151
Obs per group:
min = 8
avg = 25.3
max = 28
Wald chi2(5) = 35.00
Prob > chi2 = 0.0000

lnH20	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
lnPPP	-0.142	0.303	-0.470	0.640	-0.735	0.452
lnPPP2	0.011	0.018	0.610	0.544	-0.024	0.045
lnforest	0.657	1.058	0.620	0.534	-1.416	2.730
lnTRADE	0.006	0.006	1.130	0.258	-0.005	0.017
lnpopdens	-0.751	0.165	-4.550	0.000	-1.074	-0.427
_cons	10.540	4.520	2.330	0.020	1.682	19.399

Root Mean Squared Error (sigma): 0.0130

Appendix C: The different components of EPI

EPI	EPI	Environmental Performance Index	EPI
PolicyObjective	HLT	Environmental Health	Health
IssueCategory	AIR	Air Quality	Air Quality
Indicator	PMD	PM2.5 exposure	PM2.5
Indicator	HAD	Household solid fuels	Household solid fuels
Indicator	OZD	Ozone exposure	Ozone
IssueCategory	H2O	Sanitation & Drinking Water	Sanitation & Drinking Water
Indicator	USD	Unsafe sanitation	Sanitation
Indicator	UWD	Unsafe drinking water	Drinking water
IssueCategory	HMT	Heavy Metals	Heavy Metals
Indicator	PBD	Lead exposure	Lead
IssueCategory	WMG	Waste Management	Waste Management
Indicator	MSW	Controlled solid waste	Solid waste
PolicyObjective	ECO	Ecosystem Vitality	Ecosystem Vitality
IssueCategory	BDH	Biodiversity & Habitat	Biodiversity
Indicator	TBN	Terrestrial biome protection (national weights)	Terrestrial biomes (nat'l)
Indicator	TBG	Terrestrial biome protection (global weights)	Terrestrial biomes (global)
Indicator	MPA	Marine protected areas	Marine protected areas
Indicator	PAR	Protected Areas Representativeness Index	Protected Areas Rep. Ind.
Indicator	SHI	Species Habitat Index	Species Habitat Index
Indicator	SPI	Species Protection Index	Species Protection Index
Indicator	BHV	Biodiversity Habitat Index	Biodiversity Habitat Index
IssueCategory	ECS	Ecosystem Services	Ecosystem Services
Indicator	TCL	Tree cover loss	Tree cover loss
Indicator	GRL	Grassland loss	Grassland loss
Indicator	WTL	Wetland loss	Wetland loss
IssueCategory	FSH	Fisheries	Fisheries
Indicator	FSS	Fish Stock Status	Fish Stock Status
Indicator	RMS	Marine Trophic Index	Marine Trophic Index
Indicator	FGT	Fish caught by trawling	Fish caught by trawling
IssueCategory	CCH	Climate Change	Climate Change
Indicator	CDA	Adjusted emission growth rate for carbon dioxide	CO2 growth rate
Indicator	CHA	Adjusted emission growth rate for methane	CH4 growth rate
Indicator	FGA	Adjusted emission growth rate for F-gases	F-gas growth rate
Indicator	NDA	Adjusted emission growth rate for nitrous oxide	N2O growth rate
Indicator	BCA	Adjusted emission growth rate for black carbon	Black Carbon growth rate
Indicator	LCB	Growth rate in carbon dioxide emissions from land cover	CO2 from land cover
Indicator	GIB	Greenhouse gas intensity growth rate	GHG intensity trend
Indicator	GHP	Greenhouse gas emissions per capita	GHG per capita
IssueCategory	APE	Pollution Emissions	Pollution Emissions
Indicator	SDA	Adjusted emission growth rate for sulfer dioxide	SO2 growth rate

Indicator	NXA	Adjusted emission growth rate for nitrous oxides	NOx growth rate
IssueCategory	AGR	Agriculture	Agriculture
Indicator	SNM	Sustainable Nitrogen Management Index	Sustainable N Mgmt Index
IssueCategory	WRS	Water Resources	Water Resources
Indicator	WWT	Wastewater treatment	Wastewater treatment