DETERMINANTS OF A WIN-WIN IN ENVIRONMENTAL AND ECONOMIC GROWTH TRENDS OF NATIONS: 2000-2010

by

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B.Sc. Redeemers' University, 2014

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF

THE REQUIREMENTS FOR THE DEGREE OF

Master of Science

in

Environmental Science

Thompson Rivers University

Fall Convocation 2018

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ABSTRACT

The consequences surrounding the rise in economic growth of a nation at the expense of a deteriorating environmental quality for any given nation in the long-run could reflect deterioration of human health, quality of life and a further ecosystem destruction which reflects a win-loss situation. This research identifies those nations that have had progress in their economic growth and environmental performance simultaneously over the recent decade in order to identify the nations in a win-win situation. With the use of the environmental performance trend data available from Yale University and Gross Domestic Product per capita from the World Bank database, we provide insights into nations which had a win-win in economic growth and environmental performance trends simultaneously between 2000-2010 and which did not. Also**,** we explore nations which had a high win-win trend using thresholds and some of the underlying factors that can help to explain differences in performances across nations. This study employs the K-means clustering technique to identify the different clusters of nations within win-win or other pre-defined clusters for over 200 nations. The environmental performance is divided into environmental health which focuses on human health and ecosystem vitality which focuses on the health of the ecosystem. Within this period, low-income, middle-income and high-income nations had an overall win-win situation in environmental issues that affect human health especially the child mortality indicator in comparison to its water and air quality counterparts. Nations had more of a win-loss situation in environmental issues that affect the ecosystem which connotes win for the economy but a declining ecosystem indicator. The statistically significant variables found to impact the likelihood of win-win in the environmental health category using logistic regressions consists of the initial GDP, initial non-income HDI, average investment spending and improvements in political stability. The explanatory power of the independent variables is strongest for win-win in child mortality and economic growth but not much power to explain for water and air quality situation. On the other hand, having a higher likelihood of a win-win case for the health of the ecosystem and economic growth included improved governance effectiveness, initial income-level, average investment spending and the initial environmental performance level of a nation which all varied by magnitude in its influence on biodiversity, fisheries, forestry, agriculture, air quality, climate change and water use indicators.

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ACKNOWLEDGEMENTS

To my supervisor, Dr. Peter Tsigaris, for accepting to be my supervisor. I have grown and learnt so much over the last two years and I could not have achieved this without your support, encouragement, investment and dedication to me and my work, thank you. To Professor Wendy Gardner, thank you so much for the guidance and help you rendered in helping me navigate my path in this program to have a clearer understanding of what was required of me. To Professor Joel Wood and Professor Terry Kading for their valuable suggestions and comments which lead to an improvement in my manuscript. Finally, I would like to thank the external examiner Professor Jesus Crespo Cuaresma for his thoughtful assessment and contributions to my thesis and great suggestions for further research.

DEDICATION

To my father and mother, who approved and let me to apply to this program which was very distant from home, thank you for this opportunity to follow my passion. I love you so much and thank you for supporting me financially, emotionally and spiritually, God bless you richly. I dedicate this thesis to my Lord God Almighty, who is the source of all my wisdom and the Author and Finisher of my faith.

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CHAPTER 1. INTRODUCTION

Researchers have sought to explain and estimate the relationship between economic growth and environmental performance since the seminal paper by Grossman and Krueger (1995). Some have attributed the economic growth of a nation as the major factor in improving its environmental performance over time (Dinda, 2005) while other studies have found the opposite result (Costantini and Monni, 2008; Stern, 2004). Such studies have become increasingly prevalent because of the impact that the activities of economic growth have on the environment and its impacts on the quality of life of people in that environment.

A deteriorating environment is characterized by a lower air quality, less safe drinking water, diseases, more deaths, higher depletion and scarcity of natural resources and more unstable climate conditions, all of which have adverse effects on human health and the ecosystem. These conditions are a result of increased economic activities some of which include increased land use, mining, fishery, electricity generation, agriculture, and manufacturing, all of which are geared towards increasing the standard of living on nations. These resulting environmental issues are some of the consequences of a lack of balance between economic and environmental policies and regulations.

Citizens have become increasingly aware of their right to a high-quality environment, from the basics like access to clean water to nature and a green environment (Criado et al., 2011). It has been of great importance to increase research and add to the current knowledge in pursuit of progress in environmental sustainability (Gallego et al., 2014). A well-known pattern is that some nations with very high economic growth often have declining environmental performances in certain environmental issues like climate change, and forestry (Hsu, 2016) while some developing nations perform well in certain environmental issues like agriculture (Hsu et al., 2013).

Can nations achieve growth simultaneously in economic and environmental performance in the long-run, as opposed to the Environmental Kuznets Curve theory which posits that the relationship between income per capita and environmental deterioration is positive for low income and negative for high income nations? Can developing nations achieve high performances in both the economy and environment? What about rich nations? Can they only aim at improvements of environmental performance given that their growth has slowed down due to diminishing returns? There is still room for more research to be done to add to the current knowledge of the relationship between the growth of economic and environmental performance in the long run.

This study seeks to identify those nations that have made progress in their economic growth and environmental performance simultaneously over a decade in order to identify behavioral traits, patterns and other factors that have led to their win-win situation. It will explore not only win-win situations but identify nations which are clustered in high performances in both the economy and the environment. In addition, this study will attempt to determine the factors which increases the likelihood of high performances in both areas simultaneously relative to the likelihood that it does not lead to high economic growth and environmental performance.

This study will use the Gross Domestic Product (GDP) per capita growth rate for over 200 nations as a measure of increases in the standard of living of nation and the 2012 Pilot trend Environmental Performance Index of ten different policy categories compiled by researchers at Yale University to examine the trends in the performances of nations for the period of 2000 – 2010. This will reveal clusters of nations that have had a win-win situation, including nations with high performances in both areas, reflecting improvements in environmental health and a growing economy and factors that lead to this win-win situation. It will provide relevant information to policy-makers and the public that will help them make better choices geared towards improving the quality of life from an economy and environment.

There is a vast body of literature over the years from studies conducted on economic growth and environmental performance. A prominent theory which was first studied by Grossman and Krueger (1995) which is called the Environmental Kuznets Curve (EKC) hypothesis has been used in several studies. Also, the Environmental Performance Index (EPI) developed by Yale University is also widely applied in several studies. The remainder of this chapter will review findings from the studies which implemented the EKC theory, the EPI Index, other independent approaches and the objectives of this thesis.

Environmental Kuznets Curve

The EKC is hypothesized as following an inverted U-shape for the relationship between income per capita and environmental degradation (Grossman and Krueger, 1995).

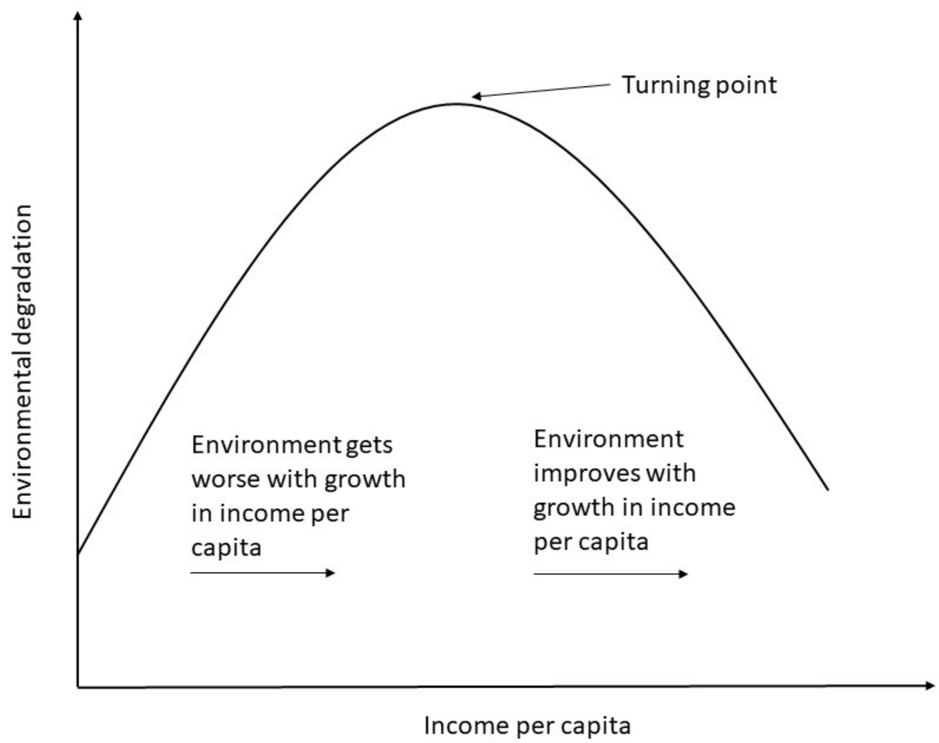

Figure 1.1: The Environmental Kuznets curve (Author's drawing).

As seen in Figure 1.1 above, the EKC hypothesis posits that at very low levels of income per capita that environmental degradation is low, but as income increases that environmental degradation gets worse until income reaches a 'turning point' at which level of degradation begins to reduce with increases in the standard of living. This theory has been used to evaluate different environmental issues and the results have mostly differed for different environmental issues, in different regions and across time (Yandle et al., 2002).

Grossman and Kreuger used panel data from Global Environmental Monitoring System (GEMS) on ambient pollution levels of urban air and water quality for several countries to test the relationship between national income and environmental quality. The authors estimated several reduced-form equations that relate to the level of pollution in a location (air and water) to a flexible function of the current and lagged income per capita in the country and to other covariates. They used the reduced-form estimates approach because it gives the net effect of a nation's income on pollution as opposed to the structural equations.

The results showed increases in GDP per capita may be associated with deteriorating environmental quality in very poor countries, air and water quality appear to gain from increasing GDP to which a critical level has been reached. Also, the turning points for the different pollutants vary but, in most cases, occur at less than $8000 (1985 dollars). Their findings are consistent with those in other studies like the World Bank Development Report (2012) which finds an inverted U-shaped relationship between per capita and income and concentrations of sulfur dioxide in the air.

Shafik (1994) proposed that at a theoretical level, it is not possible to predict how environmental quality will evolve with changes in per capita incomes, particularly where public goods are involved. He suggests that, while there is no inevitable pattern of environmental transformation with respect to economic growth at an aggregate level, there are clear relationships between specific environmental indicators and per capita incomes. He focused on the relationship between environment quality and per capita income, taking into account these other determinants of environmental quality. Income per capita serves to measure directly the relationship between economic growth and environmental quality and measures indirectly the endogenous characteristics of growth. Features such as the impact of rising industrialization and urbanization at middle-income levels and the growing importance of services in high income economies are typical patterns that are proxied by per capita income.

Indicators of environmental quality were used as dependent variables for 149 countries for the period 1960-1990. The environmental quality indicators analysed were the lack of clean water, lack of urban sanitation, ambient levels of suspended particulate matter (SPM), ambient sulfur oxides (SO_2), change in forest area between 1961-1986, the annual rate of deforestation between 1962-1986, dissolved oxygen in rivers, fecal coliforms in rivers, municipal waste per capita, and carbon emissions per capita. To analyse this model, three basic models were tested which include log linear, quadratic, and cubic in order to explore the shape of the relationship between income and each environmental indicator.

The results show that access to clean water and urban sanitation are indicators that improve with higher per capita incomes. Data for deforestation, most of which were not available, were poor at capturing important differences between types of forest. The disappointing results for both the change in forest area between 1962-1986 and the annual rate of deforestation between 1961-1986 showed that none of the income terms were significant in any specification. This led to the conclusion that per capita income appears to have very little bearing on the rate of deforestation.

Shafik's findings also show that the two measures of river quality tend to worsen with rising per capita income. He pointed out that the initial worsening of fecal content was probably associated with growing urbanization and consequent pressures on sanitation, hence, the improvement results when urban sanitation services are introduced. Suspended particulate matter (SPM), which causes respiratory illness and mortality, is largely the result of energy use. For local air pollution, there's an initial deterioration of environmental quality as industrialization and energy intensity increases, followed by an improvement as cleaner technology are used and fuel switching occurs. Technology, proxied by the time trend, appears to have played a favourable role in making improved local air quality possible at an earlier stage of development. He suggests that it is possible to solve some environmental problems but that it is not necessarily automatic. The econometric results from this study indicate that most societies adopt policies and make investments that reduce environmental damage associated with growth. This author's work showed how ten different indicators react to rising income for low, middle and high-income countries. Some indicators improved while other worsened with rising income.

Research conducted by Stern (2004, 2017), the author presents a critical history of the Environmental Kuznets Curve (EKC). He also reviewed the development of the EKC concepts, the theory behind the EKC and the econometric methods used in EKC studies. Stern highlighted the more important recent developments that have changed the view of the EKC and alternative approaches that are being used such as decomposition of emissions and efficient frontiers. The EKC, which is named for Kuznets who hypothesized that income inequality first rises and then falls as economic development progresses, was a concept that emerged in the early 1990s with Grossman and Krueger's (1991) pathbreaking study of the potential impacts of NAFTA and the concept's popularization through the 1992 World Bank Development Report. However, Stern (2004) argues that if the EKC hypothesis were true, then rather than being a threat to the environment, economic growth would be the means to eventual environmental improvement.

But contrary to the claims of the EKC concept, Stern (2004) went further to point out the weaknesses of the EKC. He identified that most of the EKC literature are econometrically weak which is seen in little or no attention being paid to the statistical properties of the data used such as serial dependence or stochastic trends in time-series. Also, little consideration has been paid to issues of model adequacy such as the possibility of omitted variables bias. He also pointed out that when diagnostic statistics and specification tests are considered, and appropriate techniques are used, the EKC does not exist and states that instead, we get a more realistic view of the effect of economic growth and technological changes on environmental quality. The economic factors that drive changes in environmental impacts and may be responsible for rising or declining environmental degradation over the course of economic development include proximate variables such as scale of production, composition effect, technique effect and changes in input mix. Other underlying causes such as environmental regulation, awareness, and education (Stern, 2017) were also pointed out. Table 1.1 below presents these proximate factors and how they impact environmental degradation.

			EKC effects	Variables	Examples
Political and institutional framework	Environmental regulation and innovation policy		Scale effect	Production	Rising emissions with growing economy
			Composition effect	Output mix	Lower emissions moving to a service sector relative to industrial production
		Technique effect	Input mix	Mix of inputs labour and capital	Robots replacing humans
			State of technology	Production efficiency	Less polluting inputs per unit of output
			Emissions specific changes in process	Inputs usage	Green energy

Table 1.1: Factors that influence the environmental quality of nations (Author's interpretation of Stern (2004, 2017).

Stern (2004) provided a summary of several studies of sulfur emissions and concentrations in the order of estimated income turning point. He found that there is a monotonic relation between sulfur emissions and income just as there is between carbon dioxide and income for recent studies that used more representative samples. The estimated turning points from these studies ranged from $3,137 by Panayotou (1993) to $101,166 by Stern and Common (2001) for sulfur emissions. Stern (2004) concluded from the EKC literature that concentrations of pollutants may decline in nations from middle income levels, while emissions tend to be monotonic in income.

The econometric criticisms of the EKC which are heteroskedasticity, simultaneity, omitted variables bias, and cointegration issues was discussed by Stern (2004). The majority of studies have found the EKC to be a fragile model suffering from severe econometric misspecification (Millimet et al., 2003; Sobhee, 2004). Stern also proposes that the use of more appropriate methods tends to indicate higher turning points and possibly a monotonic curve for emissions of major pollutants. A better model may result from including additional variables to represent either proximate or underlying causes of change in emission. A detailed theoretical and empirical review of the EKC concludes that the existence of a simple and predictable relationship between pollution and per capita income is not robust. The inverted U-curve becomes monotonic or disappears when the model is adjusted for several tests and when more variables are added to it.

Dasgupta et al. (2002) shows evidence that developing countries are also performing better due to informal or decentralized regulation. Also, liberalization of developing economies has encouraged more efficient use of inputs and less subsidization of environmentally damaging activities. Other changes include multinational companies raising standards in the countries in which they invest, better methods of regulating pollution and better information on pollution being available. This has encouraged government to regulate and empower local communities, indicating that the regulatory capacity of developing countries has been strengthened.

Mckitrick and Wood (2017) closely examined the relationship between four common air pollutants and income across Canadian by using data on local pollution concentrations and provincial-level and metropolitan-level macroeconomic variables. The purpose was to identify the scale effect, composition effect, and technique effect while controlling for unidentified characteristics of individual monitoring stations. These four air pollutants include the annual average concentrations of sulfur dioxide (SO_2), nitrogen dioxide (NO_2), carbon monoxide (CO) and ground-level Ozone (O_3) at monitoring stations across the country from 1984 to 2010. By use of panel methods and pollution concentration data from individual monitoring stations, their study allowed for a much larger sample size than previous Canadian studies. The econometric modelling approach used in their study separates and identifies the relative magnitudes of the scale, composition, and technique effects. Their results show many similarities in the income–pollution relationship for concentrations of SO_2, NO_2, and CO. For all three pollutants, the relationship with income switches from negative to positive when time fixed effects are accounted for which reflects the improvement in technique over time. A positive effect of increases in the scale of the economy was completely offset by improvements in technology and changes in the composition of output. The results for ground-level ozone were similar to the other pollutants when choosing the measure used to assess the Canada-Wide Standard (CWS) but different when using annual average concentrations of ozone. The authors point out that this difference may be due to the focus of government policy to reduce short-term, rather than long-term, exposure to ozone. The results further revealed no scale effect for CO after controlling for changes in composition and technique, no composition effect for SO_2 but composition effects for CO and NO_2 exist. There was no relationship with income identified when looking at annual average concentrations of O_3 but when the CWS measurement of ozone concentrations was used instead, the results were similar for the other three pollutants which comprised of a positive scale effect, a negative composition effect, and a negative technique effect.

In another context, Costantini and Monni (2008) combined the Resource Curse hypothesis and EKC to test the causal relationship between economic growth, human development and sustainability. Sample data of 14 nations with resource curse and another 14 nations with resource blessings from 1975-2003 on economic growth and genuine savings were used. The authors formulated an integrated model which was modified to reflect the role of human development in the EKC and the quality of institutions on the Resource Curse hypothesis (RCH). The aim of the study was to provide a link between the RCH modified with the role of institutions on one side and the relationship between economic growth and sustainable development on the other. The findings maintain that natural resource endowment could be a source of low economic growth rates if the institutions in a country do not have the ability to manage the resources in the right way. They pointed out that investment policies geared towards human capital formation are effective actions in reaching a higher development level and consequently in the quality of institutions. The authors also deduced that an economy based on resource exploitation without appropriate institutions will run into Dutch disease or rent-seeking effects (which is the negative impact put on an economy by anything that gives rise to a sharp inflow of foreign currency) with reduced economic growth and lower Human Development Index (HDIs). They affirmed that Human Development should be the first objective of international development policies whereas an increase in human well-being is necessary to provide a sustainability path. Their study expands the traditional EKC to show how an increase in Human Development and quality of institutions also plays a significant role in affecting the environmental quality of nations.

A study conducted by Criado et al. (2011), shows that stabilizing pollution levels in the long run is a pre-requisite for sustainable growth. These authors developed a neoclassical growth model with endogenous emission reduction in order to analyse the conditions under which an economy may achieve sustainable growth. This means balanced growth paths characterized by growing per capita incomes and non-declining environmental quality predicting that, along optimal sustainable paths, pollution growth rates are positively related to output growth (scale effect) and negatively related to emission levels (defensive effect). Panel data for 25 Eastern and Western European countries over the period 1980-2005 was used to test the existence of both the scale and the defensive effect for two air pollutants, sulfur oxides (SO_X) and nitrogen oxides (NO_X).

Based on the framework implemented by Criado et al. (2011), sustainability requires satisfying a general condition of pollution convergence. By considering the question, "How do pollution dynamics interact with output dynamics along sustainable growth paths?", the authors considered a growth model with endogenous pollution abatement, to show that the optimal path is characterized by a precise dynamic relationship between pollution growth rates, emission levels, and output growth rates, which induces pollution convergence in the long run. This dynamic law was tested empirically for the two major air pollutants SO_X and NO_X using panel data from European countries.

Criado et al. included an additional element to the model by also predicting a positive interaction between pollution growth and income growth, added to a negative growth-level relationship in pollution. This analysis was referred to as a convergence test in which β -convergence in pollution is conditional on country-specific output dynamics. All these specifications allow for structural dissimilarities within groupings of countries through a group-specific dichotomous variable. Their results were consistent with the predictions of the theoretical model and confirm the existence of scale effects and defensive effects for SO_X and NO_X. Findings showed that the path followed since 1985 by the NO_X emissions per capita is fully compatible with the convergence equation predicted by the theoretical model, but with a stronger evidence holding within the European Union (EU15) countries. The defensive effect reflects the effectiveness of abatement expenditures in limiting pollution growth. Regression estimates support the model predictions, identifying a clear scale effect linked to GDP growth and a negative effect captured through the impact of the past pollution level component.

Taylor and Brock (2010) set out to provide a cohesive theoretical explanation for three features of the pollution and income per capita data which includes emissions, emission intensities and pollution abatement costs. They established that the EKC and the core model of modern macroeconomics which is the Solow model are intimately related. By introducing a very simple growth model closely related to the one-sector Solow model, the authors show how this amended model generates predictions closely in line with U.S. and European evidence. They showed this by amending the Solow model to incorporate technological progress in abatement which results in the EKC being a necessary by product of convergence to a sustainable growth path. This was an alternative empirical method tightly tied to theory to estimate their model on carbon emissions from 173 countries over the period of 1960–1998.

Taylor and Brock used the Green Solow model to provide a very simple explanation for all three puzzles. They borrowed techniques used in the macro literature on income convergence to derive a simple linear estimating equation linking growth in emissions per capita over a fixed time period to emissions per capita in an initial period and a limited set of controls. These controls include typical Solow type regressors such as population growth and the savings rate, but also include a measure of pollution abatement cost. An augmented Solow model was developed where exogenous technological progress in both goods production and abatement leads to continual growth with rising environmental quality. Collection of data on carbon emissions per capita, population growth rates and the investment share of GDP for a group of 173 countries from 1960 to 1998 was used to conduct their empirical work.

The results show that relationship between income and pollution is complex even when using this simple model. The EKC and the Solow model, are intimately related identifying the forces of diminishing returns and technological progress by Solow as fundamental to the growth process, may also be fundamental to the EKC finding. Because of diminishing returns, development starts with rapid economic growth, emissions rise with output growth but fall with ongoing technological progress in abatement. The findings also show that as countries mature and approach their balanced growth path, economic growth slows and the impact of this slower growth on emissions is now overwhelmed by the impact of technological progress in abatement and emission levels decline. This interplay of diminishing returns and technological progress generates a time profile of rising and then falling emission levels as income per capita grows along a path of sustainable growth. The authors deduced that a tightening of pollution policy raises costs and lowers the level of pollution, but not its long run rate of growth, showing that, environmental policy has a level and not growth effect in the model.

Environmental Performance Index

The Environmental Performance Index (EPI) is a composite index composed by Yale university that ranks nations on their environmental quality for two broad objectives of Environmental Health and Ecosystem Vitality (Hsu, 2016). However, the 2012 pilot Trend Index ranks countries on the basis of improvement or decline from 2000 to 2010 (Emerson et al., 2012). The EPI is a composite index that includes multiple tiers of indicators to assess country-level environmental performance with a score from 0 to 100 and a ranking relative to other countries. The policy categories represent core areas of environmental policy concern for which measurable indicators can be assessed. For the purposes of evaluating the trends in the different country's performances, the ten policy categories from the 2012 EPI and Trend EPI are used in this study.

The Environmental Health objective measures the impacts on human health in three policy categories of Air, Water and Human Health (Hsu, 2016). The Ecosystem Vitality measures the impacts on the ecosystem and natural resources in seven policy categories of Air, Water, Fisheries, Forests, Climate Change and Energy, Biodiversity and Habitat, and Agriculture (Hsu, 2016) as seen in figure 1.2.

Hsu et al. (2013) used the 2012 EPI and trend EPI index proximity-to-target methodology and simple regression analysis to assess how nations have progressed in the environmental issues identified in the Millennium Development Goal (MDG7). Using data from international organizations, research institutions, government agencies and academia, they created a paired down Rio index and Rio trend index highlighting the policy categories of the MDG7 which includes; Water (effects on human health), Biodiversity and Habitat, Forestry, Fisheries, and Climate Change and Energy, demonstrating how these nations have improved or declined in those areas. Additional explanatory factors used were GDP per capita, Human Development Index (HDI), non-income HDI, Control of Corruption and Voice and Accountability. Simple linear regression results show that progress in those environmental issues identified are uneven and they vary by country, region and issue. The results also show that income only accounts for a certain percentage of environmental change in nations and that other factors also play a role.

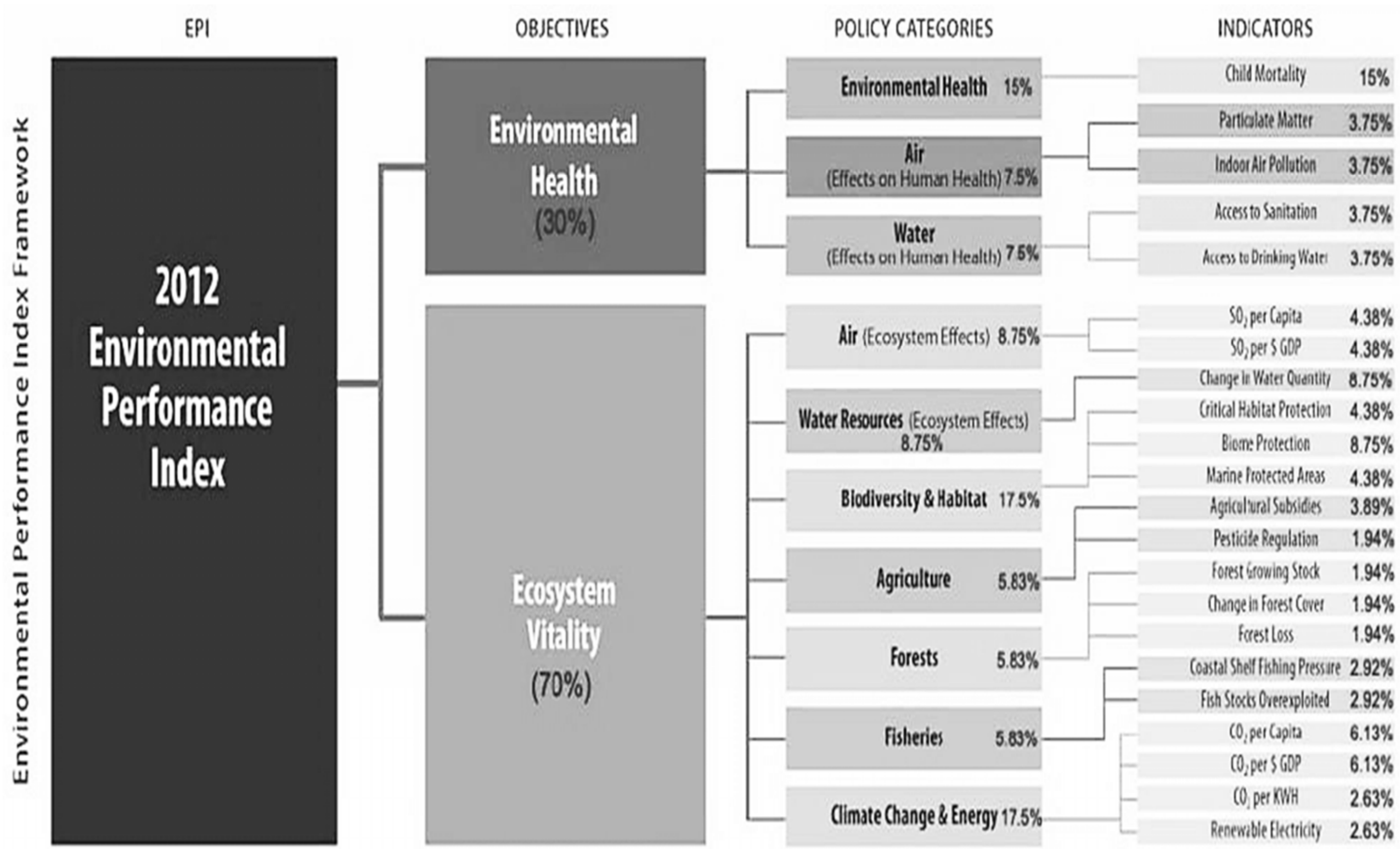

Figure 1.2: The 2012 Environmental Performance Index (EPI) (Emerson et al., 2012).

The EPI assesses social and economic driving forces, pressures on the environment, states of the environmental changes and impacts on human health and ecosystems (Hsu, 2016). A brief description of its methodology is presented below:

EPI Pilot Trend Methodology

The method employs a multi-step process to produce indicators on a consistent scale to allow for comparison across sectors (Hsu et al., 2013). The policy indicators are based on a proximity-to-target methodology as shown in Figure 1.3. Each country's performance on any given indicator is measured based on its position and within a range determined by the lowest performing country (poor performance benchmark, equivalent to 0 on a scale from 0-100) and the target (top performance benchmark, equivalent to 100). The proximity-to-target score ($PT_{S,i,t}$) of each nation for each time period is:

$$PT_{S,i,t} = \frac{T_P - L_P - (T_P - I_{i,t})}{T_P - L_P} * 100$$

Where L_P is the poor performance benchmark, T_P is the top performance benchmark or the target and $I_{i,t}$ is the indicator of nation i at time t = 2000 – 2010. The proximity to target shows how far the indicator score is from the poor performance benchmark as a fraction of the distance between poor and top performances. If it is not far from the target, then the $PT_{S,i,t}$ will be closer to 100 and if it far from the target it will be closer to 0.

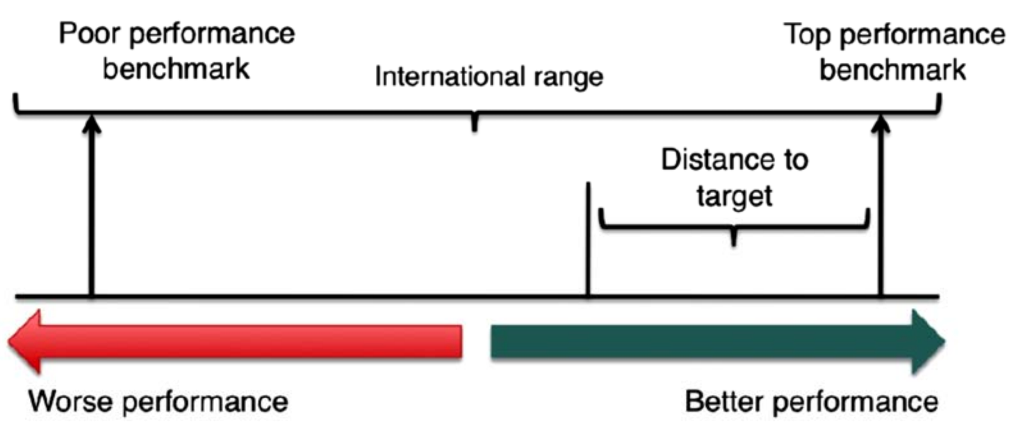

Figure 1.3: Performance benchmark for nations (Hsu et al., 2013).

Then for each indicator, a simple linear regression model of the annual proximity-to-target scores is used to determine a rate of improvement or decline for each indicator. The slope of the trend line determines the scale. 0 slope reflects “no change”, a positive slope reflects improvement and a negative slope indicates decline. This is done for every nation and for every indicator. Then these slopes for each indicator are ranked from “best improvement” receiving a score of 50 and defined by the 95% percentile of the slopes, 0 slope reflecting “no change” again and -50 is for the “worst trend decline”. Forest Loss, Forest Growing Stock, Forest Cover, and Change in Water Quantity have trend scores that range from -50 to 0 as they are change indicators (See Appendix A for EPI indicators framework and exploration).

The 2012 EPI trend ranks a range of 170 - 230 countries on the change in their environmental performance over the last decade in two broad policy objectives which are Environmental Health and Ecosystem Vitality which are defined below:

Environmental Health trend (human health effects): This objective measure which countries are improving and those declining in policy categories associated with environmental stresses to human health (See Appendix B for definitions of each indicator in the policy categories). The policy categories are:

- Air Pollution (effects on human health): This policy category consists of two indicators namely indoor air pollution (INDOOR) and particulate matter (PM25).
- Water (effects on human health): This policy consists of two indicators which are; access to drinking water (WATSUP) and access to sanitation (ACSAT).
- Environmental Burden of Disease: This policy consists of child mortality (CHMORT).

Ecosystem Vitality trend (ecosystem effects): This objective measure which countries are improving and those declining in policy categories associated ecosystem health and natural resource management. The policy categories are:

- Air Pollution (effects on human ecosystem): This policy consists of sulfur dioxide emissions per capita (SO2CAP) and sulfur dioxide emissions per GDP (SO2GDP).
- Water (effects on ecosystem): This policy consists of change in water quantity (WATUSE).
- Biodiversity and Habitat: This policy categories consists of biome protection (PACOV), marine protection (MPAEEZ) and critical habitat protection (AZE).
- Forests: This policy category consists of forest loss (FORLOSS), forest cover change (FORCOV) and growing stock change (FORGROW).
- Fisheries: This policy category consists of coastal shelf fishing pressure (TCEEZ) and fish stocks overexploited (FSOC).
- Agriculture: This consists of agricultural subsidies (AGSUB) and pesticide regulation (POPs).
- Climate Change: This consists of CO2 emissions per capita (CO2CAP), CO2 emissions per GDP (CO2GDP), CO2 emissions per electricity generation (CO2KWH) and renewable electricity (RENEW).

Gallego et al. (2014) uses the HJ biplot methodology and regression analysis to examine the impacts of socio-economic factors such as GDP per capita and education and institutional factors such as government effectiveness, control of corruption and political ideology jointly on environmental performance in countries worldwide. They used a sample of 149 nations and the 2008 EPI index as a measure of environmental performance. The HJ biplot methodology gave a graphical representation of the countries' environmental performance in relation to environmental health and ecosystem vitality to show how the economic and institutional factors affect them. The regression results show that higher levels of income and education are strongly linked to the environmental performance of these nations whereas governance effectiveness has little to no effect on environmental performance. Testing a model where GDP was used in its quadratic form gave results which conform with the EKC hypothesis which states that in the early stages of economic development, environmental performance issues increases along with income level, but then decreases in relation to GDP at higher levels.

A similar study yielding a different result was recently conducted by Mavragani et al. (2016). The authors applied factor analysis methodology to an empirical model to test the relationship between environmental performance, economic development, governance and openness of market. They used a sample data of 78 countries including all G20 and EU members as a representative of countries accounting for over 90% of global trade and investment. They used the 2014 EPI index as a measure for environmental performance. The also used the Open Market Index (OMI) proposed by the International Chamber of Commerce (ICC) as a measure for openness of market, World Governance Indicators (WGI) indicators which include Rule of Law, Voice and Accountability, Political Stability and Government Effectiveness as a measure of governance indicators. Results show a positive correlation between a country's economic growth, the openness of an economy, high levels of effective governance and its environmental performance.

Independent Approach

Using data from the Economics of Ecosystems and Biodiversity (TEEB) study, Costanza et al. (2014) provided an updated estimate of the value of ecosystem services from the earlier estimate in 1997 by generating global aggregates of the value of ecosystem services using an accounting approach. These authors estimated the value of 17 ecosystems services for 16 biomes and an aggregate global value given in monetary terms using a simple benefit transfer method. The authors selected 665 value data points from over 300 publications which were screened in the Ecosystem Services Value Database (ESVD). They also provided a comparison of the study conducted by DeGroot et al. (2012) results with the Costanza et al., (1997) results to estimate the changes in the flow of ecosystem. They also estimated the global changes in ecosystem services values from land-use change over the period 1997-2011. The purpose of their study was to raise awareness about the magnitude of these services relative to other services provided by human-built capital at that point. Their results showed that global land use changes between 1997 to 2011 have resulted in a loss of ecosystem services of between $4.3 and $20.2 trillion/yr. This study brings to light the benefits of ecosystem services by how they interact with the other forms of capital which are human, social and built capital, to contribute to the services of a nation. This study connects to the huge policy objectives of the EPI index whose goal is to promote ecosystem vitality and environmental health.

Another outstanding work that examines nations in a path for sustainable development was done by Moran et al. (2008). The Human Development Index (HDI) was used as an indicator for human development and the ratio of national footprint per capita to global biocapacity per capita as an indicator for ecological sustainability. They established the minimum criteria of sustainable development to be HDI≥0.8 and Footprint to Biocapacity as ≤1.0. Sample data of 93 countries were used with data span of period of 1975-2003 for these indicators. Comparing the trends in HDI and Ecological Footprint for the period of 1975-2003 revealed that only one country met the minimum criteria for both indicators in the most recent year while most nations had exceeded the Ecological Footprint requirement without reaching the Human Development requirement. They identified the factors that determined the gap between the footprint and biocapacity as the need for nations to prioritize ecosystem vitality by protecting ecosystems from climate change an eliminating the use of toxic chemicals that degrade ecosystems. This also involves the protection of soil from erosion and degradation, preserving croplands from agriculture, protection of river basins, wetlands and watersheds to secure freshwater supplies and maintaining healthy forests and fisheries.

Thesis Objectives

The approach to this thesis is built from the observations and reviews of previous studies which used the EKC theory, EPI index and other methods to help explain the relationship between economic growth and environmental performance. These reviews have helped frame the scope of this study by identifying knowledge gaps which will also contribute to the current body of knowledge on progress in economic and environmental performances and sustainability.

Most EKC studies focus on how economic growth impacted various air pollutions indicators and carbon emission (Stern, 2004) but there is a knowledge gap with the new EPI index presenting different policy categories for environmental indicators (Hsu, 2016) to be evaluated. The evaluation of the impacts of the growth rate of output on other environmental indicators like agriculture, fisheries and biodiversity also has limited research. There has been a more frequent use of the EPI index in recent years in identifying how nations have performed in the environmental issues identified in the MDG7 (Hsu et al., 2013) which impacts policy formation. A further step in research will be to see how nations respond in all the environmental issues pointed out in the EPI index and not just the MDG7 when associated with their average growth rate.

Another knowledge gap is identifying the factors common to those countries that have a high performance in both growth rate of per capita income and environmental quality simultaneously. The use of the EPI aggregate as an indicator for environmental performance (Mavragani et al., 2016) rather than considering the various policy categories of environmental health and ecosystem vitality to see if the results differ has not been vastly studied. There is also limited knowledge in considering the long-run period as opposed to individual years which can help reveal trends that will be useful to assess the progress and contributions of national environmental assets over time to devise more specific and measurable policy goals and targets (Moran et al., 2008).

This research is peripheral to the Environmental Kuznets literature, peripheral to the macroeconomic growth convergence literature, and peripheral to the ecological economics literature by taking a different approach to inquiry about economy and the environment. Looking at the 2000-2010 decade which is a turbulent period for the economy given events such as the September 11, 2001 terrorist attack on USA, the response of governments around the world to such an event as well as the influence of the 2008 great recession adds an element of economic and political uncertainty with the economy area. Nations during that period achieving growth in both the economy and the environment simultaneously is not as easy given such a decade.

This study aims to investigate the trends in the performances of over 200 nations for the 10 environmental policy categories associated with their average GDP per capita growth rate respectively. The aim is to discover clusters of nations which had a win-win trend relative to those which did not as well as those nations which had very high performances in both areas simultaneously and the factors which influence the likelihood of such performances. Examining the impact of economic growth for the environmental performances of nations for different policy targets will add more information and build on the existing literature.

According to the classification in Figure 1.4 of this study, nations in the win-win category are those nations that have progress in their economic growth and environmental quality simultaneously over a long period of time. They are located in the upper right quadrant of the figure. According to the EKC theory these would be nations with a high standard of living mostly operating on the left-hand side of the EKC curve where increases in the nations income per capita or standard of living leads to improvements in the environmental quality. Within this quadrant, clusters of nations with high performance trends in both areas will be identified sometimes using thresholds. The loss-win category which is the bottom right quadrant indicates nations that have progress in their economic growth but a decline in their environmental performance over the decade illustrating trade-offs between economy and the environment. The win-loss category is the top left quadrant and it indicates nations that have a decline in their economic growth but still progress in their environmental quality which according to the EKC theory would be located to the left side with nations that have a low income per capita. The loss-loss category which is the bottom left quadrant indicates nations that have a decline in both indicators simultaneously over the decade.

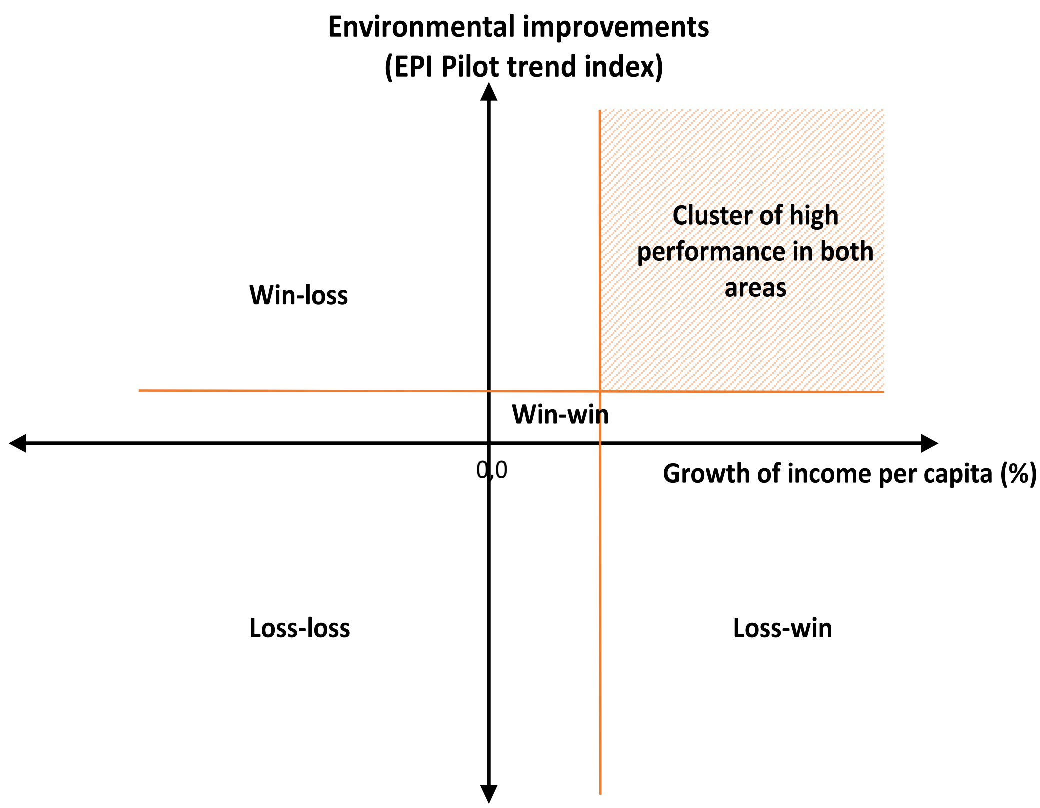

Figure 1.4: Classification of trends in economic growth and environmental performance for the design of this study. Win-win is the top right quadrant with an additional high win-win cluster. The loss-win is the bottom right quadrant. The win-loss is the top left quadrant and the loss-loss is the bottom left quadrant.

The threshold for high performance for the growth rate of per capita GDP is set at 2 percent, although somewhat arbitrary, it is based on the long run growth rate of the industrialized nations (i.e., U.S.A, Canada, England, Japan, Germany, etc.) over the last century. Hence these high economic growth nations are most likely developing and emerging nations which according to EKC should be in the win-loss of Figure 1.3 and not in the win-win. The threshold for high performance in the environmental policy categories will be determined separately for each policy category based on their trend scores which is set differently by Yale University.

In addition to the classification discussed above, this study will explore also the factors that influence the likelihood of achieving high performances in both areas simultaneously. The control variables possibly associated with the likelihood of such high-performance clusters in both areas includes the initial GDP per capita and initial non-income HDI (i.e., education and health). Explanatory factors likely impacting the likelihood of high performance nations in both areas simultaneously relative to other nations that are not in that cluster of nations include change in government effectiveness and political stability which are mostly governance indicators over the period. Also, the investment spending as a fraction of the size of the economy which is considered one of the engines of economic growth will be considered. The 2012 Environmental Performance trend index policy categories mentioned previously would be used as the indicator for environmental performance.

In what follows: Chapter 2 will employ the K-means cluster analysis to identify various clusters of nations for the average growth rate GDP per capita and each of the 10 environmental trend policy categories as per Figure 1.3 above without having thresholds for the variables for a sample of 150 - 230 nations. This research uses six clusters to place the data points of the nations which will appear in different locations on Figure 1.3. The aim is to determine the type of nations in a win-win situation and those which are not. These clusters will also be correlated with the human development index which is composed of GDP per capita, education and health indicators of the nation in an attempt to determine the kind of nations in a win-win.

Chapter 3 uses logistic regressions to determine which factors are important to increase the likelihood of achieving simultaneous high performance in both areas of the economy and the environment. Performance thresholds are set so that the nations being explored are those that had to achieve a relatively high performance in growth rate of GDP per capita and environmental performance. For example, high economic performance was set at an average growth rate of more than 2 percent per year which is in line with historical average growth rates of developed nations. EKC theory would predict that these fast-growing nations would be causing environmental degradation and not environmental improvements. The results of achieving high performance in both factors will be compared with the results of high performance in a single factor which should be easier to achieve (higher likelihood) by nations than having very good performances in both factors simultaneously.

Chapter 4 provides insights into policy considerations based on the results, suggests possible future extensions and discusses limitations of the study.

CHAPTER 2. CLUSTER ANALYSIS EVALUATION OF THE GROUPS OF NATIONS WITH A WIN-WIN TREND IN ENVIRONMENTAL PERFORMANCES AND GDP.

Introduction

There have been well-known indices developed over the years to assess the performance of nations in environmental issues in order to drive informed policy-making towards sustainability. Some of these indices include the Environmental Sustainability Index (ESI) (Esty et al., 2005), Environmental Performance Index (EPI) (Emerson et al., 2012), Ecological Footprint (EF) (Wackernagel and Rees, 1998), and Global Green Economy Index (GGE) (Tamanini et al., 2014) which all evaluate environmental performances of nations using different measures.

The ESI was created to evaluate the environmental sustainability of countries relative to the paths of other countries (Esty et al., 2005) while the EPI is a method of ranking the environmental performance of a state's policies numerically (Emerson et al., 2012) and has been widely used in several studies. For example, the 2012 pilot trend EPI which was compiled to allow countries to examine changes in performance on who is improving and declining from 2000 to 2010 was used by Hsu et al. in 2013 to gauge the improvement or decline in the environmental policy targets set forth in the United Nations Millennium Development Goals (MDGs). The Ecological Footprint (EF) which monitors ecological resource use is also widely used by scientists, businesses, governments, individuals, and institutions to advance sustainable development (Wackernagel et al., 1990).

The environmental performance for high-income, middle-income and low-income nations had changed significantly both positively and negatively over the years evident in the various indices. For example, the 2012 EPI showed the ranking for the top 5 nations to be Switzerland, Latvia, Norway, Luxembourg and Costa Rica (Emerson et al., 2012). At the low end of the 2012 EPI rankings are South Africa, Kazakhstan, Uzbekistan, Turkmenistan and Iraq. Switzerland's top ranking was in large part due to its high performance in air pollution control both on human health and the ecosystem, access to drinking water and the biodiversity and habitat indicators and was not due to its level of income. These results were interesting to see because some middle-income countries, such as Latvia (per capita GDP $12,938) and Costa Rica (per capita GDP $10,238) also achieved high environmental outcomes. This result, although anecdotal, finds a contradiction for the EKC theory by suggesting that income alone does not determine good environmental performance. In the 2014 EPI ranking, the top five countries were Switzerland, Luxembourg, Australia, Singapore, and the Czech Republic. The bottom five countries in 2014 were Somalia, Mali, Haiti, Lesotho, and Afghanistan (Hsu et al., 2014). In 2014, developed nations like the United Kingdom was ranked in 12th place, Japan 26th place, the United States 33rd, while some developing nations like Brazil 77th, China 118th, and India came in 155th. The different results for some of the nations in the top ranks and bottom ranks between 2012 and 2014 is interesting to see which can be further investigated. It reveals that both the high and low performance of nations for environmental issues can be influenced by certain factors over the years which could affect their sustainability other than income. The above analysis is static showing performances in a given year, however the 2012 pilot trend EPI focuses majorly on the ranking of nations on the performance trends for numerous environmental indicators in health and ecosystem vitality from 2000 to 2010. Furthermore, there's a gap in identifying the trends for these environmental indicators associated with their GDP per capita growth rates over the same decade.

The GDP per capita growth rate which is also a well-known concept widely used in the theory of economic development is an important indicator of economic health of the average person of a nation and reflects progress in the standard of living of a nation via new businesses, jobs and personal income. However, many economists, and in particular ecological economists, have cast doubt in GDP as a measure of standard of living of a nation and prefer to use Genuine Progress index (GPI). The GPI accounts for the impact of positive and negative environmental and other externalities from the production of goods and services (Lawn, 2003; Kubiszewski et al., 2013). Arrow et al. (2004) uses the genuine wealth growth rate per capita which accounts for the depreciation of natural capital to measure progress in the standard of living of nation. They find that the GDP per capita growth rate overstates the increase in the standard of living of nations and a better measure to use is the genuine wealth growth rate per capita.

The EPI policy categories are outcome-oriented indicators and are used as a benchmark index by policy makers, environmental scientists, advocates and the general public (Hsu et al., 2013) which makes it a reliable index for assessment. Have the nations with the high performance in environmental indicators also improved, declined or remained unchanged in their GDP growth simultaneously?

The resulting trends for 2000 to 2010 for environmental performance and GDP per capita growth rate can reveal vital information about nations from their past performance which may be useful in making assessments and projections. It will reveal the behavioral traits and patterns of nations that progressed and the direction in which these nations have moved over the decade. Was a high-performance trend sustainable for nations across all indicators? What kind of nations maintained high performances and in what categories? Is income the only factor impacting a win-win trend? This study will employ the k-means clustering analytical technique to identify different groups within the trends of nations that have progressed in the 2012 pilot trend EPI policy categories associated with their average GDP per capita growth rate to assess nations in a win-win relative to those which are not.

Methods

The goal of this chapter is to identify and group nations into the win-win, win-loss, loss-win and loss-loss categories for the average growth rate of GDP per capita and each of the 10 EPI trend policy categories as per Figure 1.3 without having thresholds for the variables from 2000 – 2010 for over 200 nations. It also employs cluster analysis which is a multivariate analytical technique to find useful groupings that are tightly knit in a statistical sense and distinct from each other within the different categories as per Fig 1.3 but especially the win-win category. The results from organizing the data into homogeneous groups can provide either immediate insights or a foundation upon which to construct other analyses (Kettenring, 2006) (See Appendix C for more background information on cluster analysis).

k-means clustering

This study specifically employs the K-means clustering technique which is a non-hierarchical clustering method to identify various clusters of nations within the win-win, win-loss, loss-win and loss-loss categories. The k-means cluster analysis is done by a mechanical algorithm which will subdivide the two data points of each nation into clusters based on nearest mean values. The algorithm minimizes the distance between the data points in each cluster to obtain the optimal division of these points into clusters. The k stands for the number of clusters in the data and is set by the researcher in such a way to minimize the sum of square of errors. The aim is to determine the type of nations in the win-win category and clusters of nations that have high performances in both areas of economy and environment simultaneously. The K-means cluster analysis is a data mining technique that is used in marketing research, computer science, geography, astronomy and agriculture studies but is not frequently used with economic research. These clusters will also be correlated with the human development index (HDI) which is composed of GDP per capita, education and health indicators in an attempt to determine what kind of nations achieve a win-win situation relative to those which did not.

Each data point is assigned to its nearest cluster determined by the Euclidean distance;

$$d(x_{i,}x_j) = \sqrt{\sum_{i=1}^{m}(x_{il}, x_{jl})^2} = \|x_i - x_j\|$$

and the new centroids for the clusters are computed. By recalculating the Euclidean distance from each subject to each centroid, the observations are moved to the clusters they are closest to. This process is repeated until the centroids remain relatively stable (Rosie, 2007).

Data collection

All data on 2012 Environmental Performance trend index for the 10 policy categories on environmental health and ecosystem vitality were collected electronically from Yale web portal (www.epi.yale.edu). All data on GDP per capita for a range of 170 – 230 nations were electronically retrieved from Gap minder Compiled by Mattias Lindgren for the period of 2000 – 2010 used to compute the growth rate.

The policy categories represent core areas of environmental policy concern for which measurable indicators can be assessed. For the purposes of evaluating the trends in the different country's performances, the ten policy categories from the 2012 EPI and Trend EPI are used in this study. The Environmental Health objective measures the impacts on human health in three policy categories of Air, Water and Human Health (Hsu, 2016). The Ecosystem Vitality measures the impacts on the ecosystem and natural resources in seven policy categories of Air, Water, Fisheries, Forests, Climate Change and Energy, Biodiversity and Habitat, and Agriculture. We have a total of 10 policy categories, 3 from Environmental Health and 7 from Ecosystem Vitality (Figure 1.2).

The Software used to run cluster analysis was the NCSS 11, by NCSS, LLC. It is a statistical software which provides statistical tools used to analyze and visualize your data. All the data was imported, filtered and transformed using the software. The optimum number of clusters (K) determined for each policy category is six (6) based on the elbow method by Thorndike (1953) which defines clusters such that the total intra-cluster variation or total within-cluster sum of square (WSS) is minimized. The optimum number of clusters should be chosen such that adding another cluster doesn't improve the total WSS. The total WSS measures the compactness of the clustering which should be as small as possible. The Elbow method looks at the total WSS as a function of the number of clusters.

These clusters will also be correlated with the human development index which is composed of GDP per capita, education and health indicators of the nation for the year 2000. The HDI 2000 was also electronically retrieved from the United Nations Development Programme (UNDP) website.

Results

Win-win for any cluster is characterized by the nations that fall in the area of positive values for x and y axes for average GDP per capita growth rate and the environmental trend policy categories. Nations that are above the (0,0) coordinate have achieved a win-win. According to the standard set up in the pilot trend index by Yale university, the trend scores for all environmental policy categories ranges from -50 to 50 with -50 being the lowest trend score and 50 being the highest trend score. The exceptions for these categories with a different trend score includes Forestry (-50 to 0), and Water (ecosystem effects, -50 to 0) which are change variables (See Appendix D for list of countries, codes and HDI ranks).

Environmental Health: Child Mortality trend, Growth and HDI 2000

Fig 2.1 shows the trends of nations in their association between Child Mortality (EH) and the average GDP per capita over the decade. The win-win category which is the upper right quadrant contains nations that score well on both indicators. Over 80% of nations are in a win-win and are clusters 1, 2, 3, and 6 (Table 2.1, Figure 2.1). Cluster 3 has 29 nations with a win-win and has the highest improving EH trend of nations and a very high average growth rate of the economies. It is composed mostly with low (41.4%) and medium (44.8%) HDIs and only a few high (10.3%) and very high (3.5%) HDI nations and consists of mostly Middle-eastern and North-African countries. This may only be explained by the EKC model with a turning point of income per capita that is very low. Cluster 6 is also a win-win with the highest average GDP trend but also high

EH trend consisting of only 8 nations with mainly medium HDIs (62.5%) some of which include China (CHN), Azerbaijan (AZE), and Equatorial Guinea (GNQ). This also suggests that the EKC turning point is very low. Clusters 1 and 2 has the most nations in the win-win trend. Cluster 1 has 43 nations with a high win-win trend which consists of low, medium, high and only a few very high HDI nations made up of some Central Asian and Eastern Europe countries. Cluster 2 has 77 nations with a win-win trend but closer to the origin of not having win-win and not as high as cluster 3 and 6. Cluster 2 consists of nations with very high HDIs (37.7%) some of which include Great Britain (GBR), Italy (ITA), and Belgium (BEL) as well as high (15.6%). Cluster 4 is a loss-win situation for only 9 nations with relatively medium and high HDIs. This is worrisome as this indicates improvements in economic performance is trade-off with respect to increased child mortality. It is only 9 nations and most of these nations are from Eastern Europe including Russia (RUS), Cuba (CUB) and Slovenia (SVN). Cluster 5 shows a win-0 situation for 14 nations of mostly low HDI nations and indicates a declining Child Mortality trend with no change in average GDP growth rate over the years suggesting a priority is given to reducing child mortality than to economic growth.

Table 2.1: The mean and p-values for Child Mortality trend and the Average GDP per capita growth rate for the 6 clusters of nations in the different categories. The HDI 2000 shows the rank of the nations in percentage for each cluster.

	Cluster					
Variables	1	2	3	4	5	6
	Win-Win	Win-Win	Win-Win	Loss-Win	Win-0	Win-Win
EH-EH mean	15.70	12.32	40.73	-13.91	38.91	26.58
p-values	<0.001	<0.001	<0.001	0.012	<0.001	<0.001
Av growth mean	4.07	1.05	4.38	4.12	-0.32	9.58
p-values	<0.001	<0.001	<0.001	<0.001	0.610	<0.001
HDI 2000 (%)						
Very high	7.0	37.7	3.5	11.1	0.0	12.5
High	32.6	15.6	10.3	55.6	14.3	0.0
Medium	32.6	19.5	44.8	33.3	21.4	62.5
Low	27.9	27.3	41.4	0.0	64.3	25.0
Count	43	77	29	9	14	8

This policy category shows an overall positive trend for over 80% of nations with medium and low HDI nations taking the lead in the win-win for the highest Child Mortality trend and GDP growth over the decade. For this category, EKC holds with a low turning point of income per capita. Reduction in child mortality seems to be a priority for most developing and underdeveloped nations.

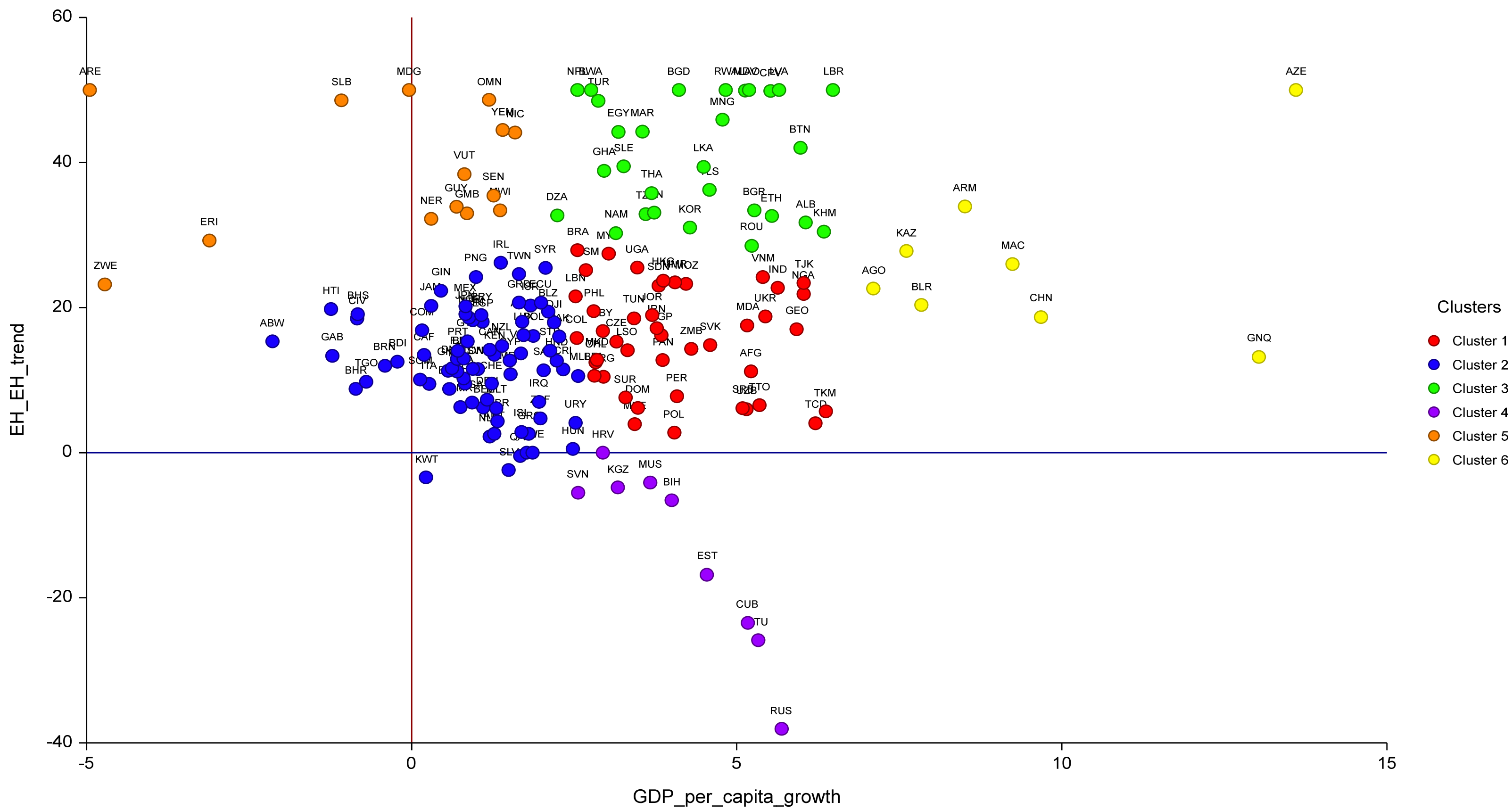

Figure 2.1: The distribution for the 6 clusters of nations in Child Mortality trend and the Average GDP per capita growth rate in the win-win (upper right), win-loss (bottom right), loss-win (upper left) and loss-loss (bottom left) categories.

Environmental Health: Air Pollution, Growth and HDI 2000

Fig 2.2 shows the trends of nations in their association between Air Pollution and the average GDP per capita over the decade. The win-win category which is the upper right quadrant are nations with good performance trends which consists of clusters 3, 4 and 6 (Table 2.2, Figure 2.2). Cluster 4 has a total of 34 nations with a very high win-win trend especially in the improvements of air pollution (trend) while the GDP per capita growth rate is spread from no growth to high growth rates. Cluster 4 are mostly nations with high (32.4%), medium (23.5%) and low (29.4%) and only few very high (14.7%) HDIs. They consist of some Latin American, Eastern Europe and Sub-Saharan African countries like Mexico (MEX), Malaysia (MYS), Slovak Republic (SVK), Zambia (ZMB) and Cameroon (CMR). This cluster supports the EKC theory if the turning point of income per capita is low as was the case with child mortality for developing nations. Clusters 3 and 6 has the most nations in the win-win situation as well. Cluster 3 has 32 nations in the win-win trend with medium and low HDIs which consists of some East European countries. Many nations in Cluster 3 show no change in air pollution trend achieved with a very high growth rate of GDP per capita. This shows again that EKC is not holding since very high growth of the economy for emerging nations should be accompanied with a deteriorating environment assuming the turning point is not very low for air pollution. Cluster 6 also has a win-win with 81 nations with both very high, medium and low HDIs which consists of mostly European and some Sub-Saharan countries. Cluster 6 nations relative to those in cluster 4 have a lower GDP per capita growth rate indicating that environmental improvements do not always need high economic growth rates. Cluster 1 has 15 nations in a 0-loss situation indicating no change in its air pollution trend but a reduction in their standard of living. These are mostly low HDIs nations. Cluster 2 with only 4 nations have the highest average GDP trend. Two show improvements in air pollution while the other two show a deterioration. The 4 nations have low and medium HDIs and are China (CHN), Azerbaijan (AZE), Equatorial Guinea (GNQ) and Armenia (ARM). Cluster 5 is a loss-win situation for 11 nations with relatively low and high HDIs. whose economic performance is occurring at the expense of the environment and is consistent with the EKC theory.

Table 2.2: The mean and p-values for Air Pollution (human health) trend and the Average GDP per capita growth rate for the 6 clusters of nations in the different categories. The HDI 2000 shows the rank of the nations in percentage for each cluster.

Variables	Cluster 1	2	3	4	5	6
	0-Loss	0-Win	Win-Win	Win-Win	Loss-Win	Win-Win
EH-Air mean	-1.17	3.09	2.06	25.24	-17.74	1.20
p-values	0.516	0.493	0.009	<0.001	<0.001	0.002
Av growth mean	-1.57	11.21	4.80	2.91	3.53	1.59
p-values	0.001	0.003	<0.001	<0.001	<0.001	<0.001
HDI 2000 (%)						
Very high	20.0	0.0	4.8	14.7	0.0	34.6
High	26.7	0.0	26.2	32.4	45.5	11.1
Medium	6.7	75.0	38.1	23.5	18.2	29.6
Low	46.7	25.0	31.0	29.4	36.4	24.7
Count	15	4	42	34	11	81

For this category, we see more nations with low, medium and high HDIs in a higher win-win trend than the nations with very high HDIs. cluster 5 supports the EKC theory if the turning point is high for those nations but the turning point has to be low for the other cases to confirm to the EKC model.

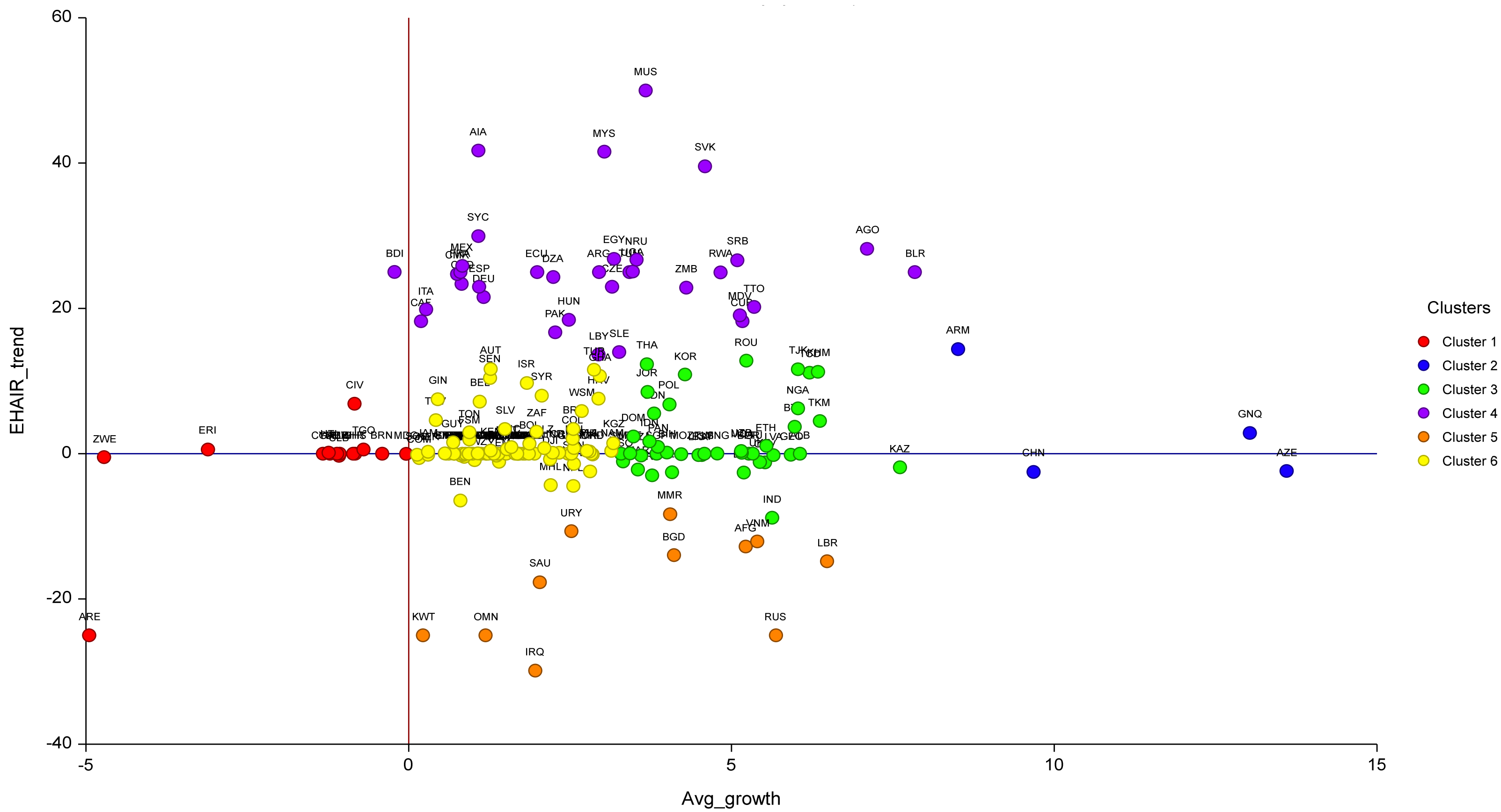

Figure 2.2: The distribution for the 6 clusters of nations in Air Pollution trend (effects on human health) and the Average GDP per capita growth rate in the win-win (upper right), win-loss (bottom right), loss-win (upper left) and loss-loss (bottom left) categories.

Environmental Health: Water Quality trend, Growth and HDI 2000

Fig 2.3 shows the trends of nations in their association between Water Quality and the Average GDP per capita over the decade. Clusters 1, 2, 5 and 6 have nations in the win-win category (Table 2.3, Figure 2.3). Cluster 5 has 23 nations with very high win-win and also the highest improved Water Pollution trend which consists of nations with mostly medium (56.5%) HDIs which consists of some Latin American countries and a few low (17.4%), high (17.4%) and very high (8.7%) HDI nations as well. High environmental performance with high economic growth for emerging nations is consistent with the EKC theory too if the turning point income is low as well. Clusters 1 and 2 has a total of 81 nations with a good win-win trend but not as high as cluster 5 and consists of nations spread between having low, medium and a few high HDIs and consists of mostly Middle Eastern and some Sub-Saharan African countries. Cluster 1 has high environmental performance but lower economic performance relative to that of cluster 2 on average. Cluster 6 has only 4 nations with a very high win-win trend and the highest average GDP growth trend with nations same as the Child Mortality and Air Pollution indicators in their highest average GDP trend. Cluster 4 is a win-loss situation for 22 nations with mainly low HDIs and is consistent with EKC theory provided the turning point income is high. Cluster 3 shows a 0-win situation for 53 nations of mostly very high HDIs which indicates no change in water quality as if affects human health even while their economies progressed.

Table 2.3: The mean and p-values for Water Quality trend (human health) and the Average GDP per capita growth rate for the 6 clusters of nations in the different categories. The HDI 2000 shows the rank of the nations in percentage for each cluster.

	Cluster					
Variables	1	2	3	4	5	6
	Win-Win	Win-Win	0-Win	Win-Loss	Win-Win	Win-Win
EH-Water mean	19.50	5.36	0.65	3.70	34.26	12.39
p-values	<0.001	<0.001	0.163	0.011	<0.001	0.090
Av growth mean	1.60	4.97	1.74	-0.75	3.92	11.21
p-values	<0.001	<0.001	<0.001	0.038	<0.001	0.003
HDI 2000 (%)						
Very high	8.1	2.3	49.1	4.5	8.7	0.0
High	16.2	29.5	20.8	18.2	17.4	0.0
Medium	40.5	31.8	13.2	13.6	56.5	75.0
Low	35.1	36.4	17.0	63.6	17.4	25.0
Count	37	44	53	22	23	4

In this category, we see nations with very high and high HDIs having no change to minimum increase in their water quality even while their economies continue to improve while nations with low to medium HDIs generally have a good water quality trend continuously. These findings are in in contrast with empirical evidence of EKC on water quality indicators.

In summary, for the three human health categories, a win-win is more likely for all nations both developing and developed as these categories have a more direct effect on our health and hence a policy priority. We now turn to ecosystem vitality in which deterioration of environment does not have a direct impact on our health but trade-offs impact future generations.

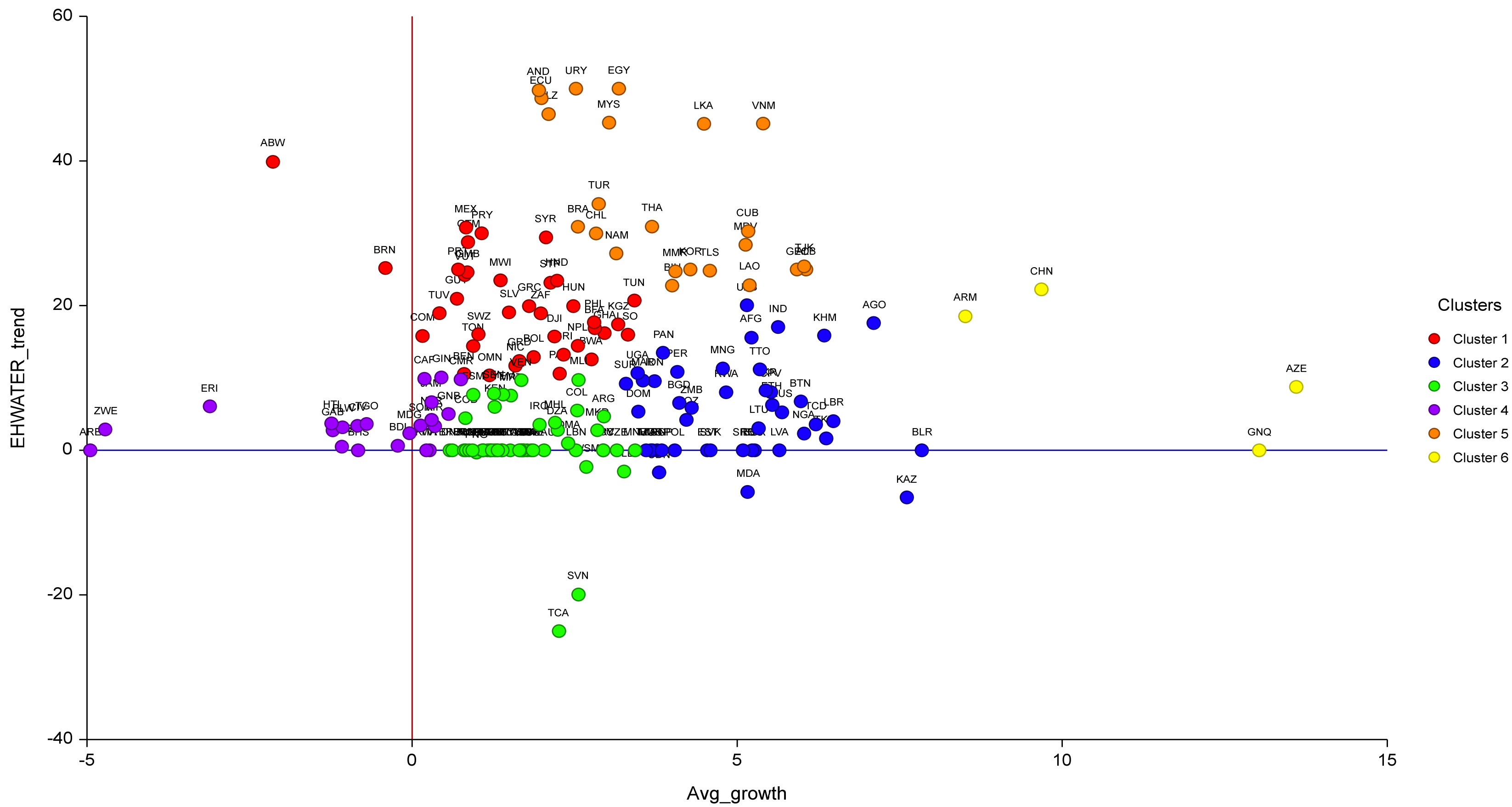

Figure 2.3: The distribution for the 6 clusters of nations in Water Quality trend (effects on human health) and the Average GDP per capita growth rate in the win-win (upper right), win-loss (bottom right), loss-win (upper left) and loss-loss (bottom left) categories.

Ecosystem Vitality: Biodiversity and Habitat, Growth and HDI 2000

This category shows the trends of nations in their association between Biodiversity and Habitat (BH) and the Average GDP per capita over the decade. This category had no nation below 0 which indicates no declining performance in BH trend. Clusters 1, 3, 4, 5 and 6 have nations in the win-win category (Table 2.4, Figure 2.4). Cluster 6 has 16 nations with very high win-win and the most improved BH trend consisting of very high (55.6%) HDI nations like France (FRA), Taiwan (TWA), Belgium (BEL) and a few high (33.3%) and medium (22.1%) HDI nations. This is consistent with the EKC theory that environmental improvements will occur with further economic growth of from developed nations assuming they have past the turning point. Cluster 4 also has 18 nations with a win-win but not as high as cluster 6 consisting of a mix of low to very high HDI nations like Canada (CAD), Australia (AUS), Uganda (UGA) and Guatemala (GTA). Here the low HDI nations are not consistent with what the EKC model predicts except if their turning point is low. These nations should be deteriorating their ecosystem as their standard of living increases if the turning point is high. Since no nation had a negative BH trend over the decade, we conclude that Clusters 1, 5 and 3 with a total of 101 nations have a win-win trend but with very low performances while most of the nations remained unchanged in their BH trend. They consist of mainly medium and low HDI nations and only a few high and very high HDI nations and includes mostly Sub-Saharan an Caribbean countries and some East Asian countries as well. Cluster 2 has 13 nations in a loss-0 situation which showed a declining trend in the Av GDP and no change in their BH with mainly medium and low HDI nations.

Table 2.4: The mean and p-values for Biodiversity and Habitat trend and the Average GDP per capita growth rate for the 6 clusters of nations in the different categories. The HDI 2000 shows the rank of the nations in percentage for each cluster.

Variables	Cluster 1	2	3	4	5	6
	Win-Win	Loss-0	Win-Win	Win-Win	Win-Win	Win-Win
EV-BH mean	1.63	37.07	3.85	2.60	2.34	34.65
p-values	0.003	<0.001	0.072	<0.001	<0.001	<0.001
Av growth mean	5.50	0.34	10.81	2.72	0.38	4.92
p-values	<0.001	0.529	<0.001	<0.001	0.013	<0.001
HDI 2000 (%)						
Very high	3.0	61.5	20.0	20.3	27.9	55.6
High	15.2	15.4	0.0	25.7	16.4	33.3
Medium	39.4	15.4	60.0	35.1	14.8	22.1
Low	42.4	7.7	20.0	18.9	41.0	0.0
Count	33	13	7	18	61	16

In this category, we see few nations with very high HDIs in a win-win situation in Biodiversity and Habitat. Overall this was an unexpected result since nations of the world improved or had no change in biodiversity and habitat while their economies grew.

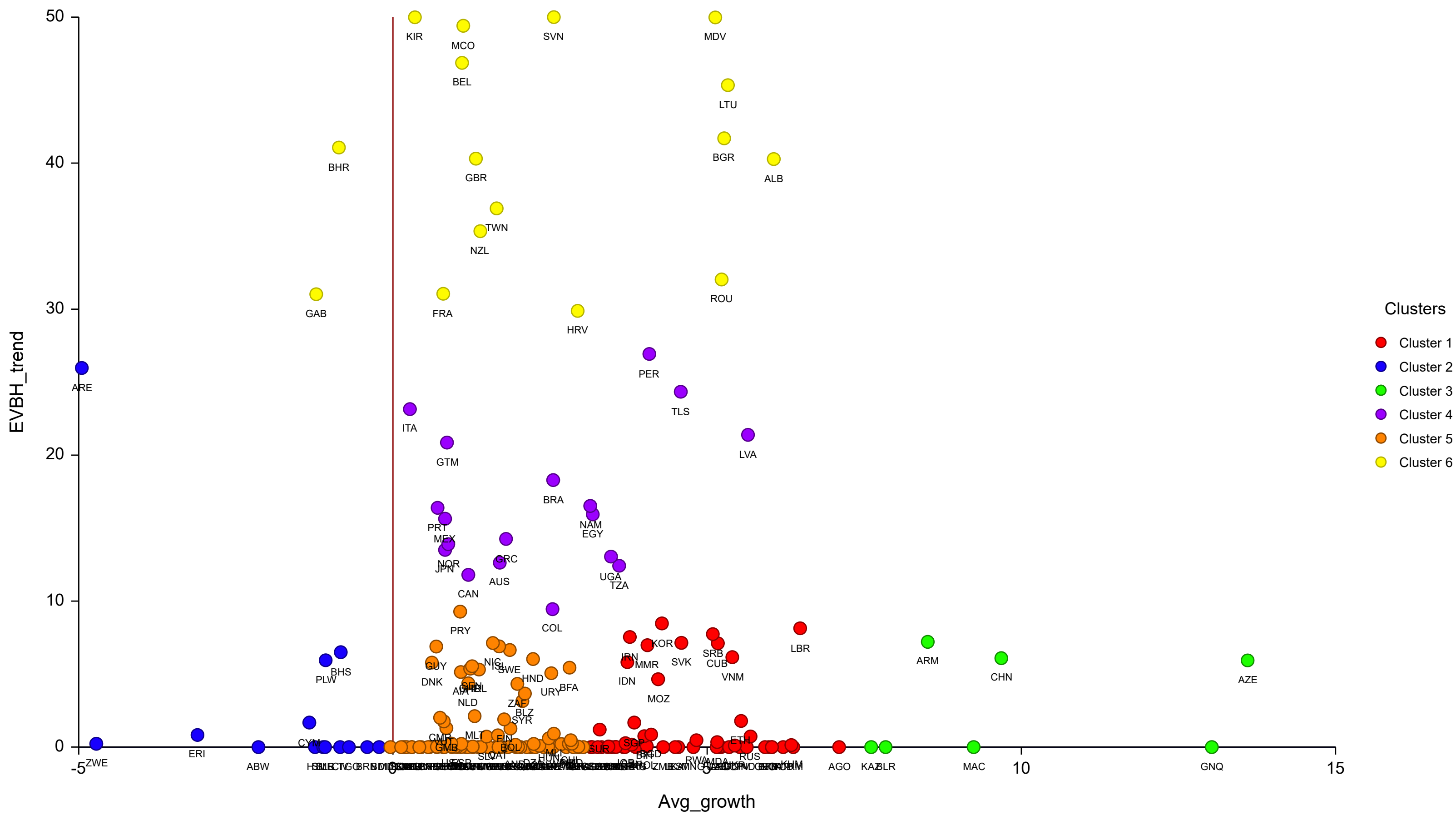

Figure 2.4: The distribution for the 6 clusters of nations in Biodiversity and Habitat trend and the Average GDP per capita growth rate in the win-win (upper right), win-loss (bottom right), loss-win (upper left) and loss-loss (bottom left) categories.

Ecosystem Vitality: Agriculture trend, Growth and HDI 2000

Fig 2.5 shows the trends of nations in their association between Agriculture and the average GDP per capita over the decade. The win-win category which is the upper right quadrant contains nations that score well on both indicators. Clusters 1, 2, 5 and 6 have nations in a win-win situation (Table 2.5, Figure 2.5). Cluster 5 has 32 nations in a win-win situation with the most improved Agriculture trend consisting of nations with mainly very high (53.1%) and a few high (18.8%), medium (15.6%), low (12.5%) HDI nations like Finland (FIN), Thailand (THA), Romania (ROU) and Egypt (EGY). This finding is consistent with the EKC theory. However, Clusters 1 and 2 have a total of 126 nations in a win-win situation too but not as high agriculture improvements as Cluster 5 and are mainly low, medium and high HDI nations some of which include Central Asian, East Asian, Latin American and Caribbean countries. Cluster 2 dominates Cluster 1 in that it has higher economic growth while agriculture trend improvements are similar on average. Cluster 6 has 6 nations with a 0-win situation with the highest average GDP trend in this category indicating no change in their Agriculture trend are mainly medium HDI nations. This shows again that economic growth can be achieved without causing a deterioration of the environment for developing nations. Cluster 3 is a loss-win trend for 15 nations with mainly low HDIs consistent with the EKC theory. Cluster 4 reveals a 0-loss trend for 16 nations with decline in their economies and no change in their Agriculture trend and consists mainly of low HDI nations and a few medium and very high HDI nations. Seen from a perspective of positive economic growth and clusters with mainly no change in agriculture sector improvements, cluster 6 is best while the worse cluster is 4.

Table 2.5: The mean and p-values for Agriculture trend and the Average GDP per capita growth rate for the 6 clusters of nations in the different categories. The HDI 2000 shows the rank of the nations in percentage for each cluster.

Variables	Cluster 1	2	3	4	5	6
	Win-Win	Win-Win	Loss-Win	0-Loss	Win-Win	0-Win
EV-AG mean	3.56	1.11	-28.46	0.95	30.79	-0.63
p-values	0.001	0.026	<0.001	0.333	<0.001	0.363
Av growth mean	4.73	1.57	3.76	-1.61	2.21	10.32
p-values	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
HDI 2000 (%)						
Very high	6.4	20.3	0.0	25.0	53.1	16.7
High	25.5	21.5	13.3	25.0	18.8	0.0
Medium	31.9	34.2	26.7	6.3	15.6	66.7
Low	36.2	24.1	60.0	43.8	12.5	16.7
Count	47	79	15	16	32	6

In this category, the nations with high and very high HDIs have a very high win-win compared to nations with low to medium HDIs which also had a good win-win.

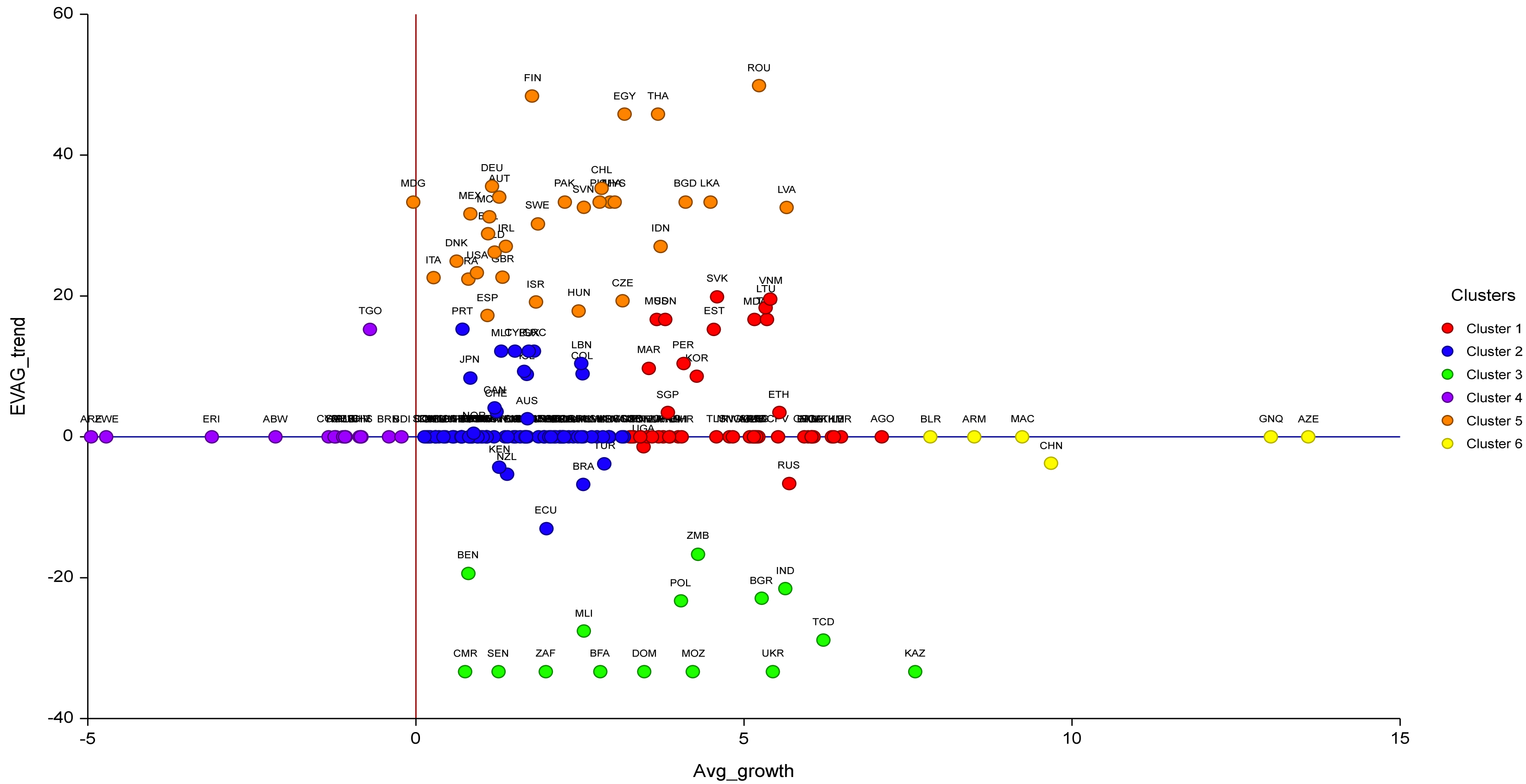

Figure 2.5: The distribution for the 6 clusters of nations in Agriculture trend and the Average GDP per capita growth rate in the win-win (upper right), win-loss (bottom right), loss-win (upper left) and loss-loss (bottom left) categories.

Ecosystem Vitality: Forestry trend, Growth and HDI 2000

In this category, due to its set up in the pilot trend index, the lowest performance benchmark is -50 while the highest target is 0 so nations above -50 approaching 0 are nations that are not doing as bad since they are closer to the target which is 0. This skew the computation in this category, hence the negative means (Table 2.6, Figure 2.6). Given the lowest performance benchmark as -50, all nations were below 0 for the Forestry category, all clusters are in a loss-win situation (Table 2.6) with some nations in the Loss-Loss segment. Clusters 5 and 2 contains nations in a loss-win situation with the smallest loss in Forestry trend. Cluster 5 has 37 nations with mainly medium (43.2%) HDI and a few high (29.7%), low (21.6%) and very high (5.4%) HDI nations which consists of some South and Central Asian countries. Cluster 2 has 68 nations with mainly very high (36.8%), high (25%), medium (22.1%) and a few low (16.7%) HDI nations which contains mainly European countries. Finally, cluster 5 dominates cluster 2 in that it has faster growing economies but a similar forest loss on average with cluster 2 whose economy is slower. Clusters 4 does not have significant economic growth rate ($p = 0.67$) as many nations in that cluster fall in the loss-loss area. Cluster 4 is performing worse than cluster 2 in terms of forest trend loss. Cluster 3 have a total of 56 nations in a loss-loss and has higher forest losses than those of clusters 5 and 2, they are mainly medium and low HDI nations. Cluster 6 has 23 nations with the highest loss-loss with mostly low and medium HDIs.

Table 2.6: The mean and p-values for Forestry trend and the Average GDP per capita growth rate for the 6 clusters of nations in the different categories. The HDI 2000 shows the rank of the nations in percentage for each cluster.

Variables	Cluster 1	2	3	4	5	6
	Loss-Win	Loss-Win	Loss-Win	Loss-Win	Loss-Win	Loss-Win
EV-Forests mean	-5.50	-3.88	-22.71	-15.38	-4.75	-33.75
p-values	0.296	<0.001	<0.001	<0.001	<0.001	<0.001
Av growth mean	12.10	1.61	4.53	0.14	5.03	1.58
p-values	0.010	<0.001	<0.001	0.670	<0.001	<0.001
HDI 2000 (%)						
Very high	0.0	36.8	0.0	26.7	5.4	4.3
High	0.0	25.0	15.4	13.3	29.7	13.0
Medium	66.7	22.1	38.5	16.7	43.2	30.4
Low	33.3	16.2	46.2	43.3	21.6	52.2
Count	3	68	26	30	37	23

In this category, based on the highest performance score as 0, high to very high HDI nations have a lower loss-loss trend while low to medium HDIs show a higher loss-loss trend. Nations that have no change in trend forest loss can be considered as a win and those are in cluster 5 and 2.

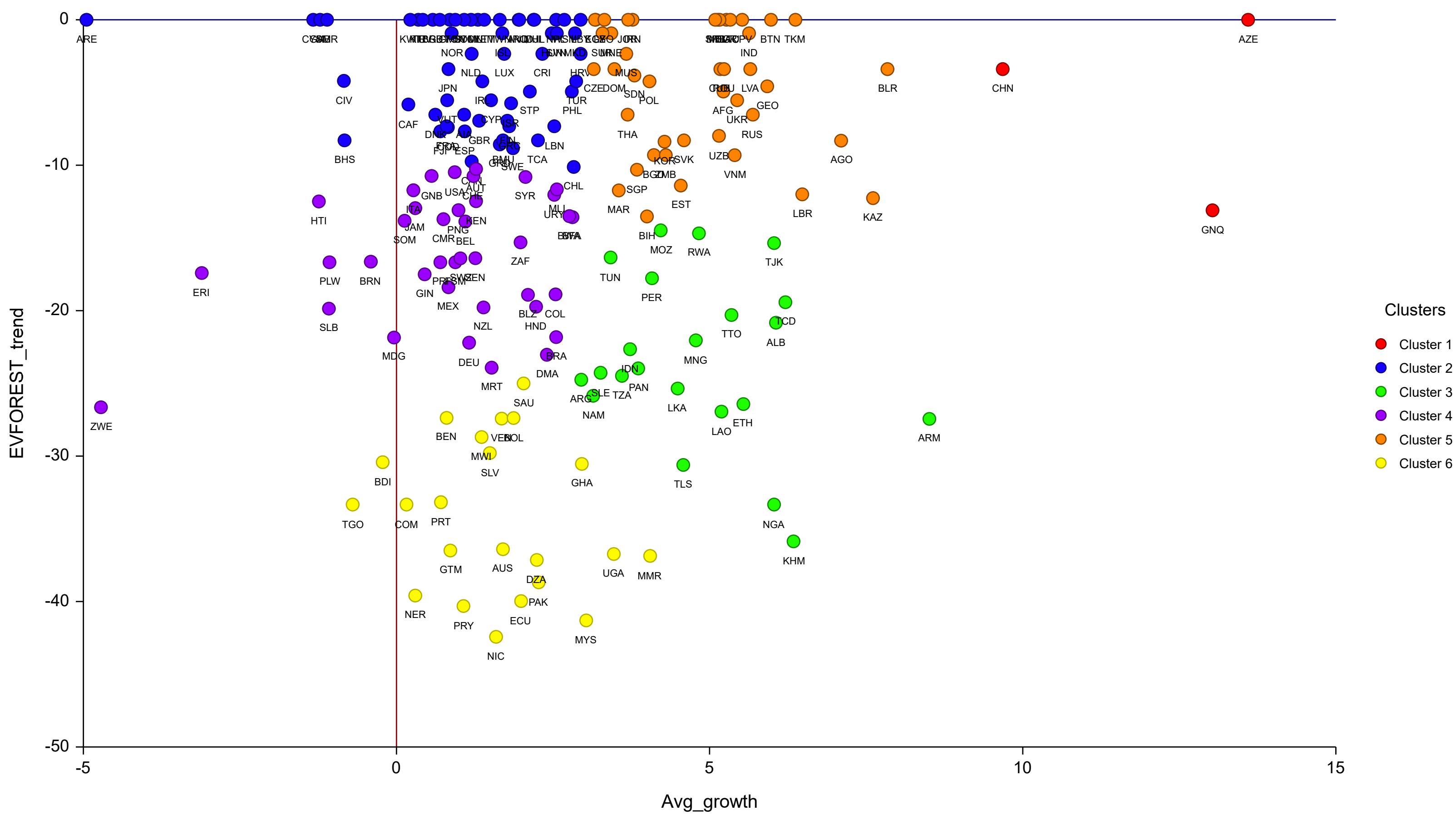

Figure 2.6: The distribution for the 6 clusters of nations in Forestry trend and the Average GDP per capita growth rate in the win-win (upper right), win-loss (bottom right), loss-win (upper left) and loss-loss (bottom left) categories.

Ecosystem Vitality: Fishery trend, Growth and HDI 2000

Fig 2.7 shows the trends of nations in their association between Fishery and the Average GDP per capita over the decade. Cluster 2 is a win-win trend with the highest Fishery trend (Table 2.7) and a high average growth rate (3%). It has a total of 23 nations spread across high (43.5%), medium (34.8%) and a few very high (13%) and low (8.7%) HDIs and are mostly Eastern European countries. Clusters 3, 5 and 6 have nations in a loss-win category with cluster 5 being the worst Fishery trend. Cluster 3 has 51 nations with mostly very high HDIs which is not what EKC theory would predict. Cluster 5 has 34 nations with mostly low HDIs and consistent with EKC theory. Cluster 6 has 32 nations with mostly medium HDIs and consistent with EKC theory given that most of these nations are developing with very high economic growth rate. Clusters 3, 5 and 6 have a total of 107 nations in a loss-win and is greater than the total nations in the win-win situation, they consist of some South Asian, Middle Eastern, European and Sub-Saharan African countries showing mostly consistency with the EKC theory. Cluster 4 has 10 nations is a win-loss situation with mainly low HDIs.

Table 2.7: The mean and p-values for Fishery trend and the Average GDP per capita growth rate for the 6 clusters of nations in the different categories. The HDI 2000 shows the rank of the nations in percentage for each cluster.

	Cluster					
Variables	1	2	3	4	5	6
	Win-Win	Win-Win	Loss-Win	Win-Loss	Loss-Win	Loss-Win
EH-Fisheries mean	8.78	18.68	-1.79	1.74	-23.28	-4.69
p-values	0.103	<0.001	0.028	0.573	<0.001	0.002
Av growth mean	9.76	3.04	1.16	-1.73	1.92	4.56
p-values	0.004	<0.001	<0.001	0.003	<0.001	<0.001
HDI 2000 (%)						
Very high	25.0	13.0	43.1	20.0	14.7	9.4
High	0.0	43.5	17.6	30.0	20.6	25.0
Medium	25.0	34.8	21.6	0.0	26.5	43.8
Low	50.0	8.7	17.6	50.0	38.2	21.9
Count	4	23	51	10	34	32

In this category, only few nations are in the win-win are mainly nations with high and medium HDIs. Nations with very high HDIs did not have a really good trend in the Fishery trend.

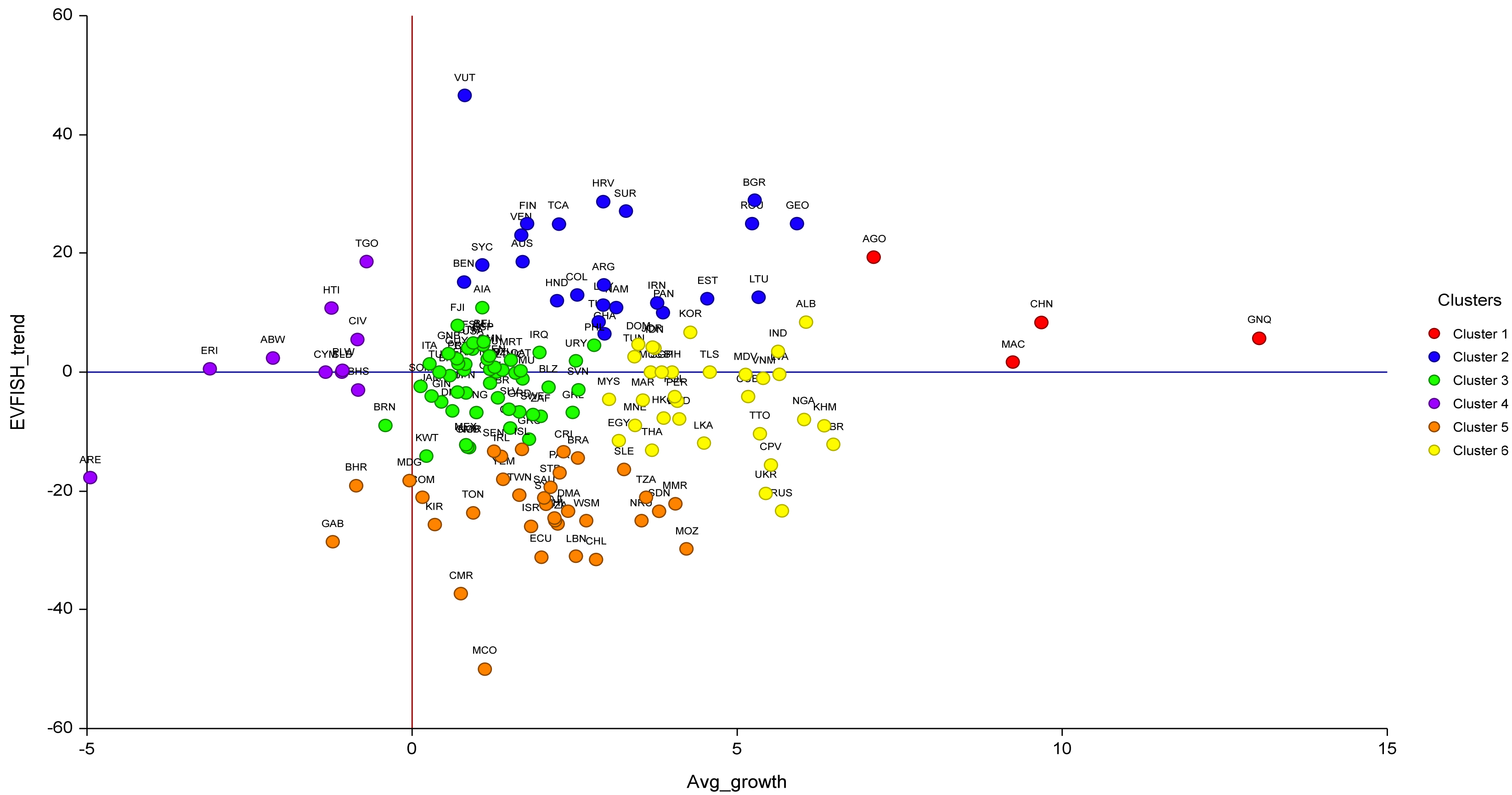

Figure 2.7: The distribution for the 6 clusters of nations in Fishery trend and the Average GDP per capita growth rate in the win-win (upper right), win-loss (bottom right), loss-win (upper left) and loss-loss (bottom left) categories.

Ecosystem Vitality: Change in Water Quantity trend, Growth and HDI 2000

In this category (Figure 2.8), also due to its construction in the pilot trend index, its lowest performance benchmark is -50 while its target score is 0 so nations on the 0 score are nations that have achieved the target and have a good performance. This also skews the computation in this category, hence the negative means (Table 2.8). Given the lowest performance benchmark as -50, all nations were below 0 for the Water Quantity category, are in a Loss-win situation (Table 2.8). Cluster 2 has 27 nations in a loss-win situation with the lowest Water Quantity loss trend (Figure 2.8), it consists of mainly low (40.7%), medium (33.3%) and a few high (11.1%) and very high (14.8%) HDI nations consisting of most Sub-Saharan African countries. The type of Cluster 2 nations is not consistent with the EKC theory. Clusters 1 and 3 are also in a loss-win situation but not as low as cluster 2 in water quantity loss (Table 2.8). Cluster 1 is a loss-win also with high Water Quantity loss and very little economic growth and has 48 nations with mostly very high and low HDIs. Cluster 3 with similar loss to cluster 1 but much higher economic growth has 44 nations with mostly low and high HDIs. These nations include some Southeastern European, Sub-Saharan African and Caribbean countries. Clusters 4 and 5 have a total of 60 nations with the worst Water Quantity trend with mainly medium and low HDI nations and a few high and very high HDI nations consisting of some European and Central Asian countries. Cluster 5 has a faster economic growth than cluster 4. Cluster 6 has the highest economic growth and in the middle of the pack in terms of water quantity loss.

Table 2.8: The mean and p-values for Change in water quantity trend and the Average GDP per capita growth rate for the 6 clusters of nations in the different categories. The HDI 2000 shows the rank of the nations in percentage for each cluster.

	Cluster					
Variables	1	2	3	4	5	6
	Loss-Win	Loss-Win	Loss-Win	Loss-Win	Loss-Win	Loss-Win
EV-Water mean	-30.89	-11.68	-28.54	-43.80	-40.85	-24.98
p-values	<0.001	<0.001	<0.001	<0.001	<0.001	0.467
Av growth mean	0.64	1.23	4.05	2.22	5.83	13.32
p-values	0.007	<0.001	<0.001	<0.001	<0.001	0.014
HDI 2000 (%)						
Very high	39.6	14.8	4.5	27.0	4.3	0.0
High	6.3	11.1	34.1	35.1	13.0	0.0
Medium	14.6	33.3	22.7	27.0	60.9	50.0
Low	39.6	40.7	38.6	10.8	21.7	50.0
Count	48	27	44	37	23	2

In this category, few nations with low and medium HDIs have a lower loss-win than nations with high and very high HDIs which were also in a loss-win.

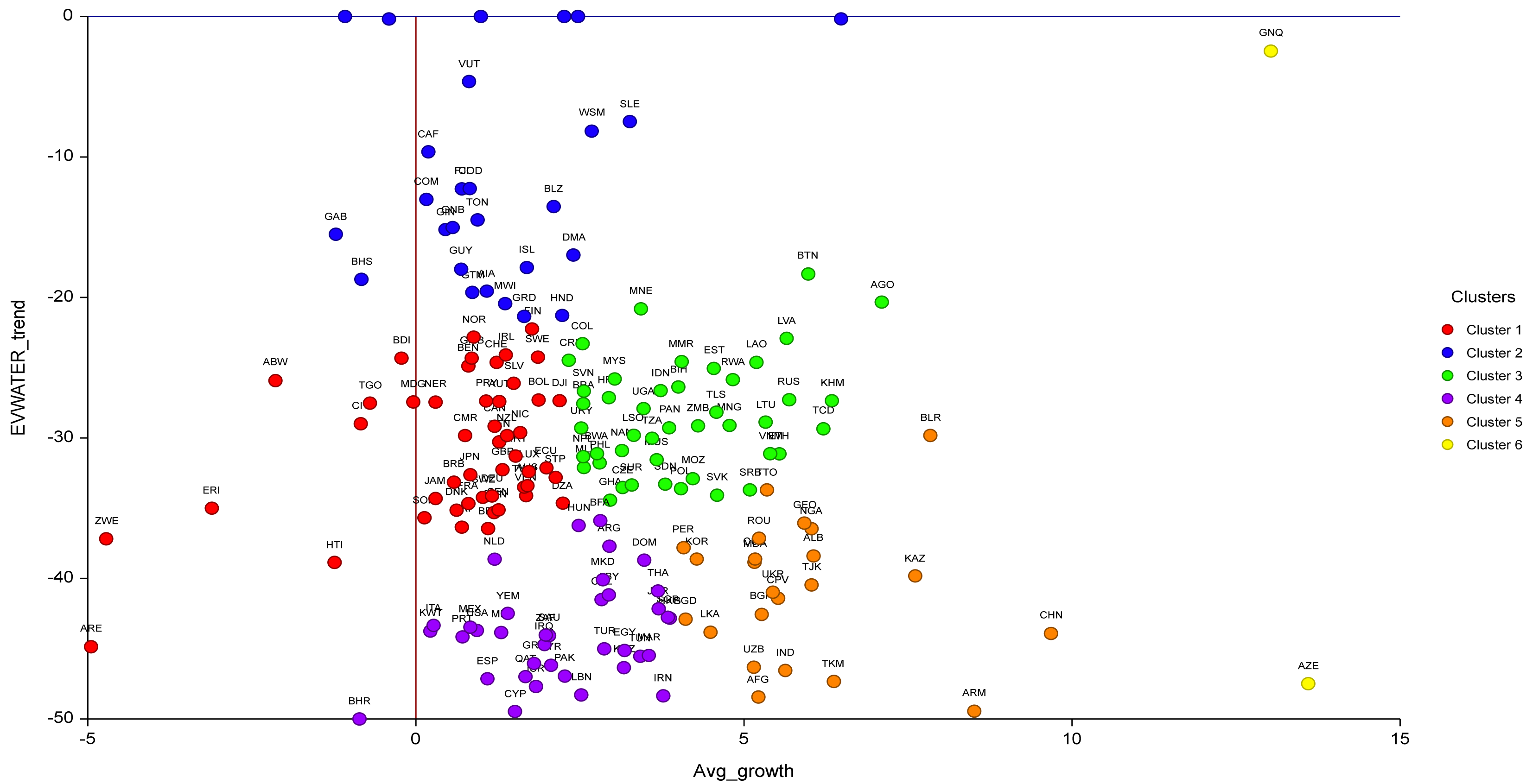

Figure 2.8: The distribution for the 6 clusters of nations in Change in water quantity trend (effects on ecosystem) and the Average GDP per capita growth rate in the win-win (upper right), win-loss (bottom right), loss-win (upper left) and loss-loss (bottom left) categories.

Ecosystem Vitality: Climate Change trend, Growth and HDI 2000

Fig 2.9 shows the trends of nations in their association between Climate Change and the Average GDP per capita over the decade. Cluster 1, 3 and 4 consists of nations with a win-win trend (Table 2.9). Cluster 4 has 21 nations in the win-win category with the highest Climate Change trend which are mostly very high (71.4%) and a few high (14.3%), medium (9.5%) and low (4.8%) HDI nations like Canada (CAD), USA, Singapore (SGP). Clusters 1 and 3 also have nations in a win-win situation but not as high as cluster 4 in terms of climate change trend improvement. Cluster 1 has high climate change trend and high economic growth. It consists of 22 nations with mainly high and medium HDIs some Southeastern Europe and Central Asian countries. Cluster 3 has 38 nations with mainly medium and very high HDIs and consists of some European and Latin American countries. Clusters 2 and 5 have a total of 49 nations in the loss-win category which are mostly medium, low and high HDI nations consisting of some Middle Eastern and South Asian countries. Cluster 6 has 3 nations in a win-loss situation which are United Arab Emirates (ARE), Zimbabwe (ZWE) and Eritrea (ERI).

Table 2.9: The mean and p-values for Climate change trend and the Average GDP per capita growth rate for the 6 clusters of nations in the different categories. The HDI 2000 shows the rank of the nations in percentage for each cluster.

	Cluster					
Variables	1	2	3	4	5	6
	Win-Win	Loss-Win	Win-Win	Win-Win	Loss-Win	Win-Loss
EV-CC mean	13.40	-22.10	5.77	28.76	-11.76	8.95
p-values	<0.001	<0.001	<0.001	<0.001	<0.001	0.233
Av growth mean	6.01	1.71	1.58	1.91	4.72	-4.26
p-values	<0.001	<0.001	<0.001	<0.001	<0.001	0.018
HDI 2000 (%)						
Very high	0.0	12.0	31.6	71.4	8.3	0.0
High	27.3	28.0	18.4	14.3	29.2	33.3
Medium	45.5	36.0	31.6	9.5	37.5	0.0
Low	27.3	24.0	18.4	4.8	25.0	66.7
Count	22	25	38	21	24	3

In this category, most nations with very high HDIs achieved a higher win-win which is in accordance with the EKC predictions, but we also find that some very high HDI nations were in a loss-win situation either performing very well in their climate change or really bad in their climate change trend even while their economies improve. Some nations with low to high HDIs also fell in a win-win category.

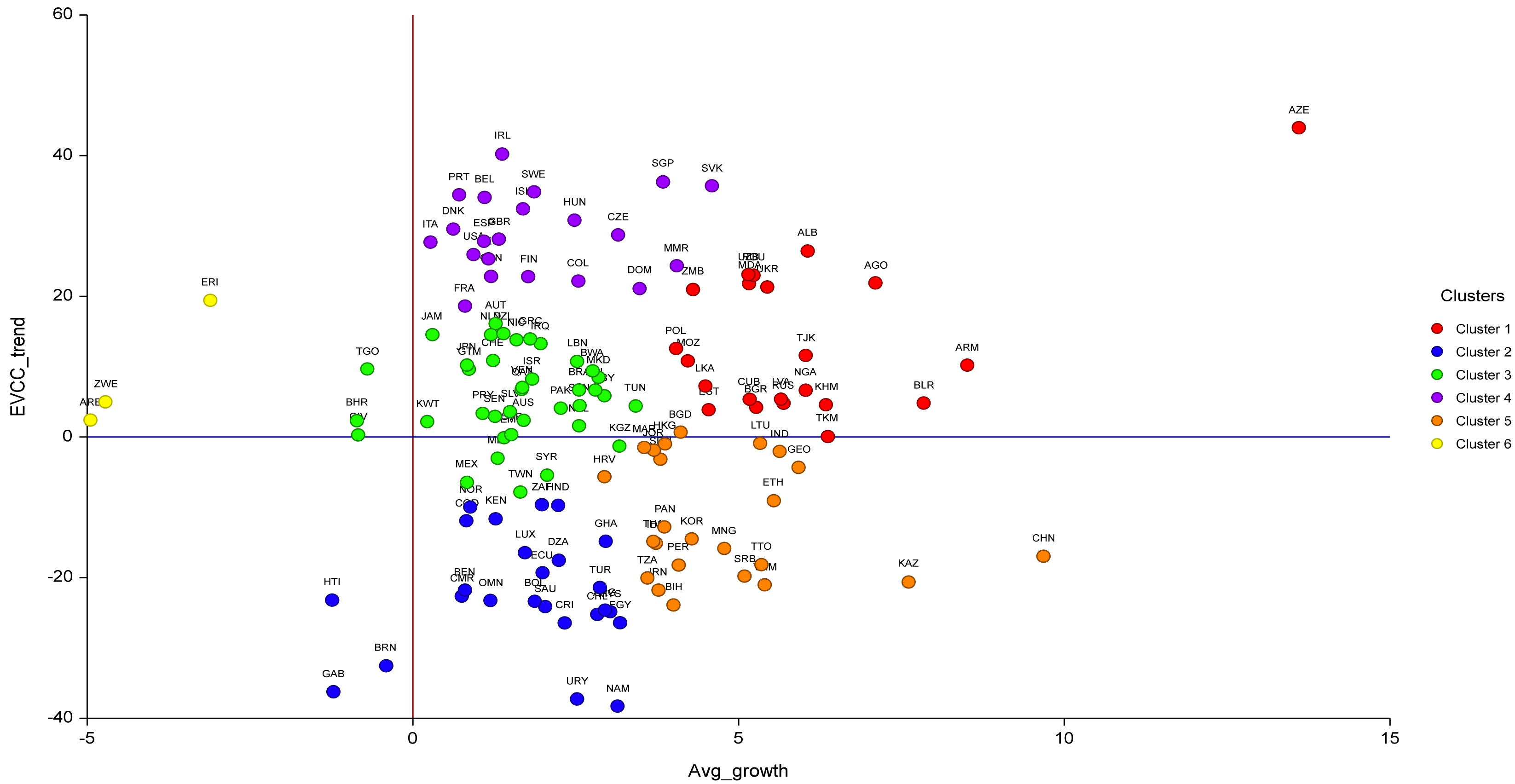

Figure 2.9: The distribution for the 6 clusters of nations in Climate Change trend and the Average GDP per capita growth rate in the win-win (upper right), win-loss (bottom right), loss-win (upper left) and loss-loss (bottom left) categories.

Ecosystem Vitality: Air Pollution trend, Growth and HDI 2000

Fig 2.10 shows the trends of nations in their association between Air Pollution and the Average GDP per capita over the decade. Cluster 2, 3 and 4 consists of nations with a win-win trend (Table 2.10). Cluster 4 has 21 nations in a win-win situation with the highest Air Pollution trend relatively spread between the very high (28.6%), high (28.6%), medium (19.1%) and low (23.8%) HDI nations like Hungary (HUN), Nigeria (NGA), Slovenia (SLV) and Latvia (LVA). Clusters 2 and 3 also have nations in the win-win situation but not as high as cluster 4 (Table 2.10). Cluster 2 had 54 nations in a win-win with mostly very high and a few high and medium HDI nations consisting of mostly European and some Middle Eastern countries. Cluster 2 has 54 nations in a win-win with mostly very high and high HDI nations and also very few low HDI nations which consists of some European, Latin American and Caribbean countries. Cluster 3 has 27 nations in a win-win with mostly medium and high HDI nations and only few low HDI nations which consists of some Middle Eastern and Central Asian countries. Clusters 1 and 6 has a total of 25 nations in a loss-win situation with mostly medium HDI nations and only a few very high, high and low HDI nations consisting of some Sub-Saharan African and Central Asian countries. Cluster 5 has 6 nations in a win-loss category with mostly low HDI and very few high HDI nations.

Table 2.10: The mean and p-values for Air pollution trend and the Average GDP per capita growth rate for the 6 clusters of nations in the different categories. The HDI 2000 shows the rank of the nations in percentage for each cluster.

	Cluster					
Variables	1	2	3	4	5	6
	Loss-Win	Win-Win	Win-Win	Win-Win	Win-Loss	Loss-Win
EV-Air mean	-9.51	11.53	5.37	39.92	12.28	-6.57
p-values	<0.001	<0.001	<0.001	<0.001	0.010	0.734
Av growth mean	3.01	1.77	5.29	2.82	-2.60	10.60
p-values	<0.001	<0.001	<0.001	<0.001	0.022	0.020
HDI 2000 (%)						
Very high	18.2	40.7	0.0	28.6	0.0	0.0
High	18.2	20.4	33.3	28.6	33.3	0.0
Medium	45.5	24.1	40.7	19.0	0.0	100.0
Low	18.2	14.8	25.9	23.8	66.7	0.0
Count	22	54	27	21	6	3

This category shows only few nations spread across the very high, high, medium and low HDIs in a very high win-win.

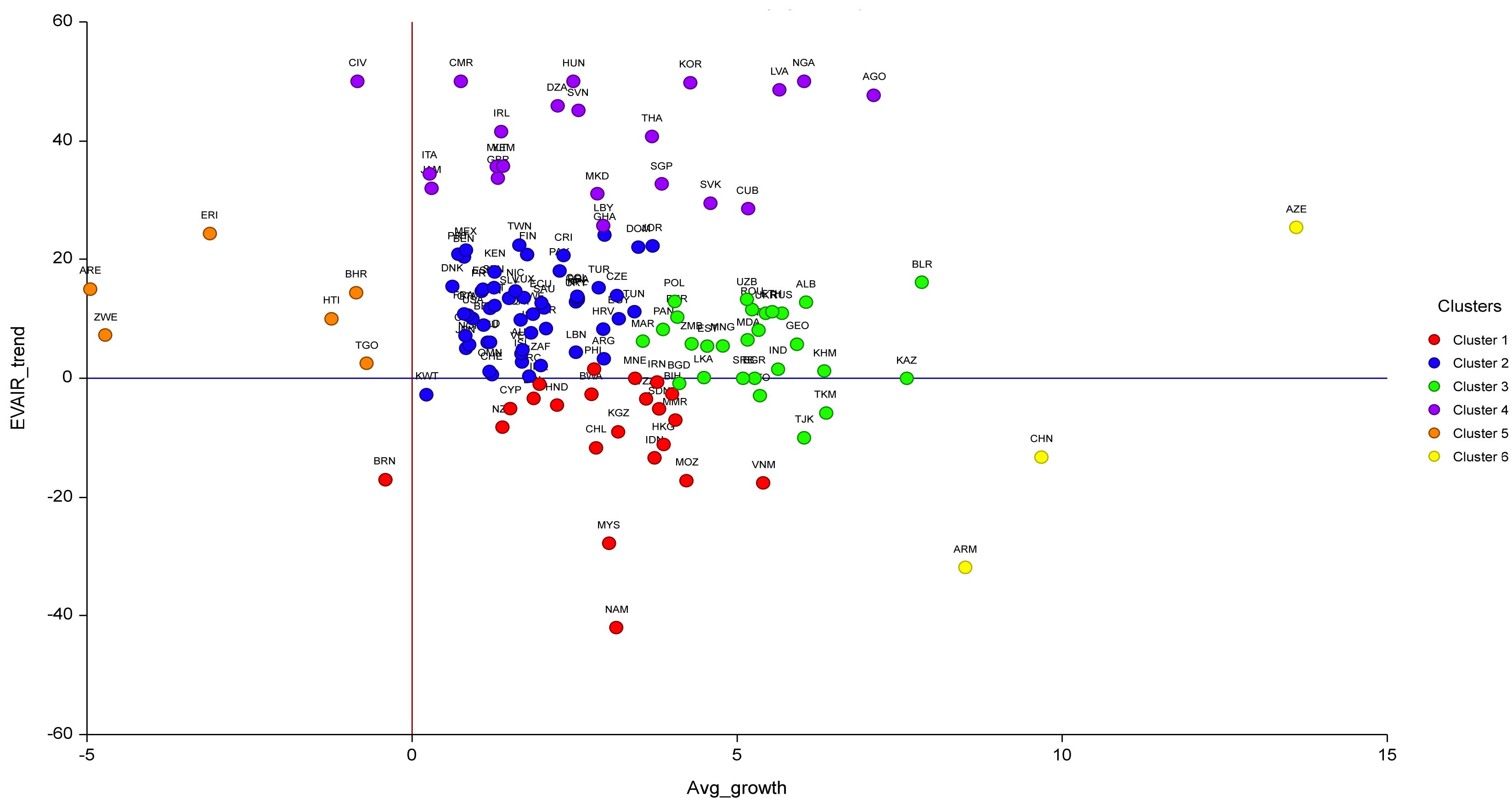

Figure 2.10: The distribution for the 6 clusters of nations in Air pollution trend (effects on ecosystem) and the Average GDP per capita growth rate in the win-win (upper right), win-loss (bottom right), loss-win (upper left) and loss-loss (bottom left) categories.

Discussion

How nations responded and regrouped in the different categories of win-win, win-loss, loss-win and a loss-loss situation varied across all the indicators in the Environmental Health and Ecosystem Vitality policy objectives. The win-win results for nations is consistent with the findings in Hsu, (2013) which also found that an improving environmental performance trend varied by the issue, country and region. A higher number of nations fell into a win-win trend for Child Mortality, Water Quality (human health effects), and Air Pollution (ecosystem effects). Forestry and Water (ecosystem effects) were found mostly in the loss-win area which is a serious concern and policy can be directed towards moving out of the environmental loss to a win without potentially hurting the economy.

Environmental Health

In the environmental health category which evaluates impacts on human health, the nations which had a high increasing trend in the win-win for the policy category of Child mortality, Water quality and Air quality consists more of nations with low and medium HDIs. Although some nations with high and very high HDIs were still in the win-win category, they do not show as much increasing trend as the low and medium HDI nations.

The most improved Child Mortality trend were 29 nations in a win-win with mostly low and medium HDIs consisting of Middle-eastern and North-African countries like Bangladesh (BGD), Rwanda (RWA), Mongolia (MNG) etc. These nations which are not high-income nations progressed significantly in this category which suggests that their progress may not be a function of only income. Some of the nations in the win-win may have reached diminishing returns and their economy doesn't grow as fast as developing nations and their child mortality is very low to start and hence improvements are only marginal.

The most improved Air Pollution trend had 34 nations which made the most progress in a win-win and had mostly high, medium and low HDI nations like Mexico (MEX), Malaysia (MYS), Slovak Republic (SVK), Zambia (ZMB) and Cameroon (CMR). Dinda (2004) documents evidence that mostly local air pollutants support the EKC model. Since local urban air quality indicators such as SO_2, SPM, CO, NOx directly affects human health, the inverted U shape EKC model holds. Pollutants that directly affect our human health have turning points that are very low and thus most nations, developing and developed, can achieve simultaneously win-win with the former growing faster. According to Dinda (2004), the estimated turning point for most pollutants is in the range of US$3000–10,000 (at a constant price, 1985 US dollar) and most developing nations are within that range. However, the evidence on pollutants that have little impact on our health (e.g., $C0_2$) evidence of EKC is not supported potentially because the turning point has not yet been reached. The highest improved Water Pollution trend had 23 nations with mostly medium HDIs like Ecuador (ECU), Uruguay (URY), Egypt (EGY) etc.

These results for the Environmental health indicators are similar to some previous studies like Stern (2004, 2017) that finds little support for the existence of an EKC which suggests that beyond a certain income threshold, only wealthier countries can impact their environmental issues positively (Grossman and Krueger, 1995). We see low and middle-income nations taking the lead for the highest improving trends in Environmental Health category. This is also probably due to a low turning point as well as social and political factors. Improvements in child mortality starting from a low turning point of income per capita makes sense since child's health is a priority for parents and governments. B O'Hare et al. (2013) conducted a meta-analysis of numerous studies for developing nations on the association between income and child mortality and found that income is the most important determinant of child mortality with no turning point. They concluded that if the GDP per capita (PPP adjusted) increases by 10%, the infant mortality will decrease to 45 per 1000 live births from 50 per 1000 (i.e., a 10% reduction in infant mortality).

However, consistent with the findings in Emerson et al. (2012), for developed nations which have top EPI rankings and very high HDIs over the years, the EPI and Average GDP trend results may not be particularly meaningful because many of these longtime leaders have limited room for improvement. Nations like USA, Canada (CAD), Australia (AUS), Slovenia (SVN) Iceland (ISL), etc. which have very high EPI ranking each year will have difficulties achieving large gains in trends. This finding is also peripheral to the macroeconomic growth convergence literature which suggests that developing economies' per capita incomes will tend to grow at faster rates than developed economies, which will result in all economies converging in terms of per capita income. Nevertheless, some very developed nations like South Korea (KOR), France (FRA), United Kingdom (GBR) still had high win-win trends in the Environmental Health indicators reflecting improved performance over the decade.

Ecosystem Vitality

In the Ecosystem vitality category which examines effects on the ecosystem, the performances of nations varied significantly for each policy categories. However, nations with very high HDIs mostly had a high win-win in categories of Air pollution, Climate change and Agriculture.

Although there were more nations in a win-win, the highest Agriculture trend consisting of 32 nations were mainly very high HDI nations like Finland (FIN), Germany (DEU), Slovenia (SVN) taking the lead. A few medium and high HDI nations like Egypt (EGY), Romania (ROU) and Thailand (THA) also scored high in Agriculture. The gains in their trends for these nations is largely due to their improvements in agricultural subsidies (Emerson et al., 2012). Performance in the Fishery category seem to be weakest in gaining a win-win situation which is similar to the results found in Hsu et al. (2013). The highest Fishery trend had only 23 nations with a win-win which were nations with mostly high and medium HDIs and only a few very high and low HDI nations. Nations like Estonia (EST), Lithuania (LTU), Croatia (HRV), Vanuatu (VUT) taking the lead in Fishery due to their improvements in coastal fishing shelf pressure (Emerson et al., 2012). Over 50% of the total nations in Fisheries were in a loss-win category from very high to low HDI nations like Kuwait (KUW), Monaco (MCO), Russia (RUS), Egypt (EGY) etc. and mostly had performance declines related to over-fishing. Some low HDI nations also had difficulties monitoring and controlling the fishing within their exclusive economic zone (EEZs) while some countries under-report their fish catches (Emerson et al., 2012).

Climate Change category had relatively higher number of nations in a win-win than in a loss-win, the highest Climate Change trend had 21 nations mostly very high HDI nations like Canada (CAD), USA, Singapore (SGP) taking the lead. CO_2 emissions correspond strongly to GDP but according to the International Energy Agency (IEA) (2011), CO_2 emissions grew faster than real GDP in 2010 which highlighted the need to be aware of emissions data to make judgments on current policies and future action plans. The results for Climate Change is consistent with previous studies like Jessberger (2011). A few high, medium and low HDI nations like Angola (AGO), Albania (ALB), Turkmenistan (TKM), Tajikistan (TJK) were also in the same win-win category as the very high HDI nations. However, many developed nations of very high HDIs are also found in the lowest Climate Change loss-win category like Taiwan (TWN), Luxembourg (LUX), South Korea (KOR), Norway (NOR). The findings for Climate Change are quite opposite to the results for Emerson et al. (2012) which found that developing countries in South Asia and Sub-Saharan Africa perform better in Climate Change than more developed countries in the Middle East, North Africa and North American regions. The high win-win trend for Climate Change may also be due to the level of good governance in the developed countries which have the ability to enforce environmental regulations.

The highest Air Pollution trend had 21 nations in a win-win with more of the very high and high HDI nations like Hungary (HUN), Slovenia (SVN), South Korea (KOR), Singapore (SGP), Latvia (LVA) etc. taking the lead. A few medium and low HDI nations like Nigeria (NGA), Angola (AGO), Cameroon (CMR), Algeria (DZA) also in a high win-win as the very high HDI nations. This suggests that while income plays a significant role in improving a nation's performance, there may be other factors which can also help to explain some differences in the countries' performances. The issues of renewable electricity generation, for which some countries have poor scores have been known to be tied to challenges with policy processes and choices. It is also important to point out that though these results present a win-win situation for some nations in the Climate Change and Air pollution policy categories, but on a global scale, notably climate change, has declined (Emerson et al., 2012).

Change Indicators: Water and Forestry

The Trend EPI used available historical data to measure performance changes from 2000 to 2010 but in cases of Water (ecosystem effects) and Forestry, no time series was available because the indicators themselves are change variables (e.g. Forest Loss, Forest Growing Stock, Forest Cover and Change in Water Quantity). Their trend scores range from -50 to 0 (the target is 0% change) and could be used directly to determine the rate of improvement or decline for each indicator (Emerson et al., 2012). The lowest Water Quantity loss trend with 27 nations in a loss-win situation had mainly low and medium HDI nations like Malawi (MWI), Guinea-Bissau (GNB), Guatemala (GTM) taking the lead. These low HDI nations had a reduced Water Quantity loss as a result of reduced pressures of water abstraction on aquatic ecosystems which most very high HDI nations struggle with (Vorosmarty et al., 2010). The Forestry category had 105 nations with the smallest loss in Forestry trend with mainly medium and very high HDI nations but also had several high and low HDI nations which was not quite expected for a declining trend in Forestry given the increasing levels of deforestation. However, as a result of differences in data collection methodology, there were significant variations in data quality between countries. For example, some countries were allowed to choose what they consider to be a minimum tree size for inclusion in the growing stock measure while some countries simply lack the resources to conduct regular forest surveys. The measure used to represent the change in growing stock for Forest categories covered one five-year period to the next (2000-2005, 2005- 2010) and considers the target to be zero change (Emerson et al., 2012).

This indicates that nations in the loss-win trend with the smallest Forestry loss trend did not necessarily improve but rather did not decline any further and while countries that had improving trends were not rewarded, those that are losing forest cover are penalized. The lack of long-term monitoring systems to regularly assess the condition of forests was also one of the major barriers to establishing sustainable forest practices and available data (Hsu et al., 2013).

Biodiversity and Habitat

In the case of Biodiversity and Habitat, there was a lack of accurate country-level data on species abundance and little consistent information on the management of habitats and the sustainable use of species (Emerson et al., 2012). In the 2012 EPI, the targets include measures of protected area coverage by terrestrial biome (17% weighted average of biomes protected), area of coastline (10% of country's terrestrial seas and EEZ protected) and a measure of the protection of highly endangered species (100% of critical habitats protected). Countries are not rewarded for protecting beyond these targets so that higher levels of protection cannot be used to offset lower levels of protection, so, a positive BH trend for this category only reflects the degree to which a country achieves these targets within its borders (Emerson et al., 2012).

In recent decades, natural habitats have witnessed considerable declines in biodiversity and many species are at risk of extinction. Costanza et al. (2014) also found an estimated loss of world eco-services due to land use change at $4.3–20.2 trillion/yr. from 1997 to 2011. Rockström et al. (2009) also used planetary boundaries framework to shows a loss in genetic biodiversity which surpassed the threshold level of a safe operating space for humanity. Only a few very high HDI nations like France (FRA), Taiwan (TWA), Belgium (BEL) were in a high win-win situation in this category, however, most nations remained unchanged in their BH trend.

Concluding Remarks

In conclusion, the win-win trends reveal improvements for many countries on indicators evident in the Environmental Health objectives for decreasing Child Mortality and increasing Water Quality. In the Ecosystem Vitality objective however, there remains challenges with respect to categories like Climate Change, Fisheries, Forests, Water (ecosystem) and Air Pollution categories. Countries in the Middle East, Sub-Saharan Africa, North Africa performed very well in some indicators like the Environmental Health indicators while Countries from Europe, North America performed better in Climate Change and Agriculture similar to findings in Hsu et al. (2013).

The findings using cluster analysis also sheds more light on the behavioral patterns of nations for a broader range of environmental indicators given their various GDP growth rates which is not seen in the EKC theory. Nations in the win-win category for indicators like Child Mortality, Water (human health), Water (ecosystem), Air Pollution (ecosystem) had developing nations with higher improving trends and are similar to findings in Dasgupta et al. (2002). The EKC which proposes that income growth, over a certain level reduces environmental degradation can suggest that economic growth is good for the environment. However, majority of studies have raised criticisms of the EKC theory in respect to analytical weaknesses and econometric misspecifications like heteroskedasticity, simultaneity, omitted variables bias and cointegration issues (Stern, 2004; Millimet et al., 2003; Sobhee, 2004). Other studies have also achieved mixed outcomes when considering the EKC for several environmental indicators and pollutions levels and local pollutants (Shafik, 1994; Mckitrick and Wood, 2017; Taylor and Brock, 2010). Some studies agree with the EKC theory (Gallego et al., 2014; Mavragani et al., 2016) that economic growth will lead to an improved environment for developed nations, however, we find that it also applies to developing nations or could also be opposite.

Applying cluster analytical technique for this study while bearing in mind, past theories, hypotheses and research of the variables used to identify win-win situations gives a graphical representation of the role of income in impacting several environmental indicators. This segmentation of nations into relative groups called clusters has displayed the behavioural patterns of nations' environmental performance in response to their GDP growth rates. This reveals that a very targeted policy and attitude approach for indicator-by-indicator basis should be adopted to make an improving environment compatible to the economic growth of that nation.

The results especially for the win-win categories using cluster analysis also warrants closer investigation into the underlying factors that may have led to a higher win-win even within the win-win groups. It lays the foundation for the next chapter which looks at some socio-economic variables like non-income HDI, and governance indicators like change in government effectiveness and political stability and the investment spending as a fraction of the size of the economy. They will be considered as factors that likely impact the likelihood of high performance (win-win) nations for environmental performance and economic growth simultaneously. The high performance will consider setting thresholds for the win-win categories in both the average GDP and environmental indicators to see particular nations that have progressed significantly and determine a possible cause and effect.

CHAPTER 3: DETERMINANTS OF HIGH PERFORMANCE NATIONS IN ENVIRONMENTAL AND ECONOMIC PERFORMANCE USING LOGISTIC ANALYSIS.

Introduction

In the past, majority of studies have established a clear connection between the progress in environmental performances of nations with their respective GDP per capita, a well-known theory being the Environmental Kuznets Curve. The EKC posits that countries follow a U-shaped path in which environmental degradation initially worsens with economic development, beyond a certain income threshold, richer countries can reduce such degradations some of which could be through cleaner technologies and changed citizen behaviour (Grossman and Krueger, 1995). While many studies have used the EKC approach to explain the relationship, Shafik (1994) took into account other determinants of environmental quality. He considered factors such as the impact of rising industrialization and urbanization at middle-income levels and the growing importance of services in high-income economies. He argued that income per capita served to measure directly the relationship between economic growth and environmental quality and measures indirectly the endogenous characteristics of growth. However, (Stern, 2017) proposes that proximate variables such as scale of production, composition effect, technique effect and changes in input mix are a more realistic view of the effect of economic growth and technological changes on environmental quality. He pointed out that when diagnostic statistics and specification tests are considered, and appropriate techniques are used, the EKC does not exist. These proximate variables were also used in a study conducted by Mckitrick and Wood (2017) and their results revealed no scale effect for CO after controlling for changes in composition and technique, no composition effect for SO_2 but composition effects for CO and NO_2 existed.

Other researchers have linked progress in environmental performance with improved Human Development Index (HDI) and human capital accumulation as necessary factors nations must develop to prevent environmental degradation (Constantini and Salvatore, 2008; Mukherjee and Chakraborty, 2010). Hsu et al. (2013) also examined the progress in the Millennium Development Goal 7 (MDG7) by associating the progress in the MDG7 with the non-income HDI, GDP per capita and governance indicators likewise. Other approaches like the 2012 EPI employs science-based methodologies to set targets that is applied to all nations to determine their improvement or decline in the policy targets for environmental performance (Emerson et al., 2012). The EPI uses a transparent approach and has a consistent framework which has been used by policymakers and the public to see how close or farther away efforts are made to ensure improved environmental health and ecosystem health. Moran et al. (2007) uses a different approach to determine sustainable development in nations. Sustainable development according to Moran et al. (2007) was defined as advancing human well-being, within the constraint of ecological limits of the biosphere. Their study employed UN Human Development Index (HDI) as an indicator of development and the Ecological Footprint as an indicator of human demand on the biosphere. They also set the threshold to be an HDI of no less than 0.8 (HDI ≥ 0.8) and a per capita Ecological Footprint (EF) less than the globally available biocapacity per person (Footprint to biocapacity ratio ≤ 1.0) as minimum requirements for sustainable development that is globally replicable. Their findings also showed that despite growing global adoption of sustainable development as a major policy goal, only one of the 93 countries surveyed met both of these minimum requirements in 2003. They also found that some lower-income countries achieved higher levels of development without a corresponding increase in per capita demand on ecosystem resources. The trend for high-income countries on the other hand had improvements to their HDI which came with a disproportionately larger increase in Ecological Footprint, showing a movement away from sustainability.

The approach Moran et al. (2007) employed in determining if a nation is making progress towards sustainability using specific measurements can also be applied to determine the progress of nations in environmental and economic performance which has not been looked into broadly. While a precise definition of sustainability may be elusive according to Carter (2001), it is still possible and sensible to define measurable bottom-line conditions for economic development and environmental performance.

The goal of this chapter is to determine the underlying factors that bring about a high-performance outcome simultaneously for the association between economic and environmental performance for the period of 2000 – 2010 by setting thresholds for both factors to determine a high win-win situation. This study uses the GDP per capita growth rate as the indicator for economic performance with a threshold set at 2% (i.e., average GDP growth rate > 2% represents high growth rate) to identify those nations with a faster growing rate in the economy relative to those that are not. In economic theory, the GDP growth rate which is an important indicator of economic wealth gives insight into the general direction and magnitude of growth of the economy which can be positive or negative. Developed nations which are most highly industrialized countries for example USA, Canada, Japan, Australia have a long-term GDP growth rate per capita around 2%. Fast-growing economies experience rates of 6-10% (e.g. China over the last 30-40 years grew at over 6% per year on a per capita basis) which is not likely to be sustainable over the long term. The 2012 pilot trend EPI which was compiled to allow countries to examine the improvement or decline in the environmental policy targets from 2000 to 2010 is used as the indicator for environmental performance. The threshold for high performance in the environmental policy categories used in this study will be determined separately for each policy category based on their trend scores which is set differently by Yale University. A nation with a high win-win is the nation that falls within these thresholds for a positive economic and environmental performance trend.

This study explores the factors that influence the likelihood of achieving high performances in both areas simultaneously. The initial GDP per capita and initial non-income HDI (i.e., education and health) are used as control variables possibly associated with the likelihood of such high-performance nations that meets the thresholds in both areas. Explanatory factors include the change in government effectiveness and political stability which are mostly governance indicators over the decade to likely impact the likelihood of high performance nations in both areas simultaneously relative to other nations that are not. Also, the investment spending as a fraction of the size of the economy which is considered one of the engines of economic growth will be considered. These indicators are selected to not only reflect changes in standard of living, but also to show if these changes are compatible with their current environmental conditions.

Methods

This study employs logistic regression which is a statistical technique used to analyse any dataset in which there are one or more independent variables that determine an outcome which in this case is a high performance for average GDP per capita growth rate and the 2012 EPI pilot trend policy categories.

Model Specification

The model specification for this study for the outcome of a high-performance in average GDP per capita growth and the 2012 EPI pilot trend policy categories is as follows:

$$ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 lnGDP_{2000} + \beta_2 HDI_{2000} + \beta_3 \frac{I}{GDP} + \beta_4 \Delta GE + \beta_5 \Delta PS + \beta_6 \Delta H + \varepsilon$$

where p is the probability of presence of the characteristic of interest in this case, likelihood of a high-performance in both areas of economy and environment for any given nation. The logit transformation is defined as the logged odds:

$$odds = \frac{p}{1-p} = \frac{probability\ of\ presence\ of\ a\ high\ performance\ case}{probability\ of\ absence\ of\ a\ high\ performance\ case} = e^{\beta_0+\beta_1 X_1+\beta_2 X_2+\beta_3 X_3+\cdots+\beta_k X_k+\varepsilon}$$

The likelihood of a high performance depends on thresholds and are used to generate larger win-win outcomes for both indicators. Throughout all the environmental indicators being examined, the threshold for a win in average GDP per capita growth is set to be greater than 2 percent (2%). The dependent variable is the log of the likelihood of a high win-win p relative to all other cases. This threshold is imposed because most developed nations like Canada, many northern European nations, the United States have a long-term growth rate of this magnitude. As for the threshold for each environmental policy, recall that the 2012 pilot trend EPI which was conducted by Yale university have different trend scores for each category based on data availability, expertise judgement and standards. Low performances and high-performance benchmarks vary for some of the categories, so the threshold for each category is also defined differently. A high performance (high win-win) covers a win for average GDP per capita growth rate greater than 2% and the win for the environmental indicator as would be defined per category.

The logistic technique is employed in this study to find the best fitting model to describe the relationship between the dependent variable and a set of independent variables. Estimation in logistic regression chooses parameters that maximize the likelihood of observing the sample values unlike in ordinary regression that chooses parameters that minimize the sum of squared errors. The statistical software used to conduct the logistic regression analysis is the Econometric Views 10 (EViews10) software developed by IHS Markit (1994).

Variables

The parameters used covers the period of 2000 to 2010. GDP Per capita at Purchasing Power Parity (PPP) in constant 2005 international dollars from the World Bank database was used as my indicator for economic performance. It is measured as the average growth rate of GDP per capita over the decade. The average investment share in GDP over the same period obtained from the UN Statistics Division is also employed in this study as an indicator that measures the share of investment in total production for any nation. The rate of investment reflects the infusion of requisite capital to support the development process in any given nation. The HDI is a summary measure of human development that assesses the average achievements in a country in three dimensions of human development: health, education, and income (Sustainable & We, 2012). Because income is a component of the HDI and we also considered the initial GDP per capita in year 2000 as a control variable, the non-income HDI in 2000 (UNDP, 2012) is used separately to control for the initial state of social development of the nations.

Government effectiveness was selected from the Worldwide Governance Indicators database because of prior literature that has established the link between governance and environmental regulation (Hsu et al., 2013). It reflects the perceptions of the quality of public services, the quality of the civil service and how independent they are from political pressures. It also reflects the quality of policy formulation and implementation, and how credible the government's commitment to such policies are (WGI, 2012). This variable reflects the change in public perceptions from 2000 to 2010. A positive change indicates perception of improvement in government effectiveness. Political stability was also selected from the Worldwide Governance Indicators database. There is a very close link between economic growth and political stability (WGI, 2012). It measures perceptions of the tendencies of political instability and violence which may be political in nature. Another indicator used is the Public expenditure on health by the Organization for Economic Co-operation and Development (OECD**)** which refers to expenditure on health care incurred by public funds which constitutes of state, regional and local government bodies and social security schemes.

The environmental policy categories represent core areas of environmental policy concern for which measurable indicators can be assessed. The method employs a multi-step process to produce indicators on a consistent scale to allow for comparison across sectors (Hsu et al., 2013). The policy indicators are based on a proximity-to-target methodology. For the purposes of evaluating the trends in the different country's performances, the ten policy categories from the 2012 EPI and Trend EPI are used in this study. The Environmental Health objective measures the impacts on human health in three policy categories of Air, Water and Human Health (Hsu, 2016). The Ecosystem Vitality measures the impacts on the ecosystem and natural resources in seven policy categories of Air, Water, Fisheries, Forests, Climate Change and Energy, Biodiversity and Habitat, and Agriculture. We have a total of 10 policy categories, 3 from Environmental Health and 7 from Ecosystem Vitality (Figure 1.2). All data on 2012 Environmental Performance trend index for the 10 policy categories on environmental health and ecosystem vitality were collected electronically from Yale web portal (www.epi.yale.edu). All data on GDP per capita for a range of 170 – 230 nations were electronically retrieved from Gap minder Compiled by Mattias Lindgren for the period of 2000 – 2010 which was used to compute the growth rate.

Two types of independent variables where used to estimate the likelihood of a high performance for nations in average GDP per capita growth and the 2012 EPI pilot trend policy categories. First, the 2000 values of GDP in natural log ($lnGDP_{2000}$) and the non-income HDI (HDI_{2000}) are to control for the initial state of the nation. If $\beta_1 < 0$ then it shows that the win-win outcome is more likely to occur if the nation is of low income per capita initially than rich nations which may be due to diminishing returns for rich nations. Similar, if $\beta_2 < 0$ then win-win is more likely to occur with nations that have a low initial social development relative to nations that have a high initial score in social development as measured by health and education outcomes. However, in this case it could possibly be the case that $\beta_2 > 0$ which would indicate a high state of initial social development increases the likelihood of a win-win outcome.

Once the initial state of the economy is controlled for, the economic and policy variables will determine the likelihood of a high-performance event relative to the absence of a high-performance. These remaining variables are the average investment as a percent of GDP over the 2000-2010 period; the change from 2000 to 2010 in perceptions of government effectiveness; the change in perceptions of political stability and in some occasions health change also is considered. A positive change in government effectiveness or political stability shows a perception of improvement and an increased likelihood of a high-performance. A higher investment as a percent of GDP should increase the likelihood of a high-performance also.

Thresholds for Trends in Environmental Indicators

The environmental health indicators focus on impacts on human health (Figure 3.1). With the trend scores in child mortality for low and high performances ranging from -50 to 50, nations above 0 (no change) were the nations with improvements in their child mortality rates by reducing the number of death between the ages 1-5 over the decade. The threshold is set to be greater than a trend score of 10 (Child Mortality > 10) because the EPI had a record of over 100 nations with a positive trend score above 0 (Figure 3.1). This threshold will capture those nations with a higher improving trend that is well above 0 or minimum improvements. The trend scores in water quality category also ranges from -50 to 50, the threshold is set to be greater than a trend score of 10 (Water Quality > 10) as it will reveal those nations with a good improving trend that is above 0 (no change) (Figure 3.1). The trend scores in air quality is also from -50 to 50, the threshold was set to be greater than a trend score of 0 (Air Quality > 0) as air quality trends has been shown from numerous studies to perform badly over the decade with only few nations with an improving trend (Emerson et al., 2012), hence the low threshold (Figure 3.1).

The ecosystem vitality indicators focus on impacts on the environment (Figure 3.2). The trend scores in Biodiversity and Habitat (BH) ranges from -50 to 50, the threshold was set to be greater than a trend score of 0 (BH > 0) because this category had no nation with a negative trend score which was due to the nature of the criteria of improvement and how it was set (Figure 3.2). Trend scores for Agriculture category spans -50 to 50 also with 0 representing no change, the threshold was set to be greater than a trend score of 0 (Agriculture > 0) as there were only few nations with an improving trend that was above zero (Figure 3.2). Trend scores for the forestry category was set at a range of -50 to 0 because it is a change variable and 0 was the highest trend score to be achieved (0% change as target) (Figure 3.2). The threshold for forestry was set to be greater than -10 (Forestry> -10) as these nations showed a less loss trend towards the target. The trend scores for fisheries category ranges from -50 to 50. The threshold was set to be greater than 0 (Fisheries > 0) as only few nations had an improving trend that was above zero (Figure 3.2). Change in Water Quantity trend scores ranges from -50 to 0 and is also a change variable with 0 as the highest target for reducing Water Quantity use. The threshold was set to be greater than -25 (Water Quantity use > -25) because many nations had a significant deteriorating trend, however this threshold will reveal those nations with a lower loss trend (Figure 3.2). The trend scores in climate change category ranges from -50 to 50, the threshold as set to be greater than 0 (Climate Change > 0) as those are the nations with an improving trend that is above 0 which is no change (Figure 3.2). The trend scores for Air Pollution category also ranges from -50 to 50, the threshold was set to be greater than 0 (Air Pollution > 0) as those are the nations with an improving trend that is above 0 which is no change (Figure 3.2).

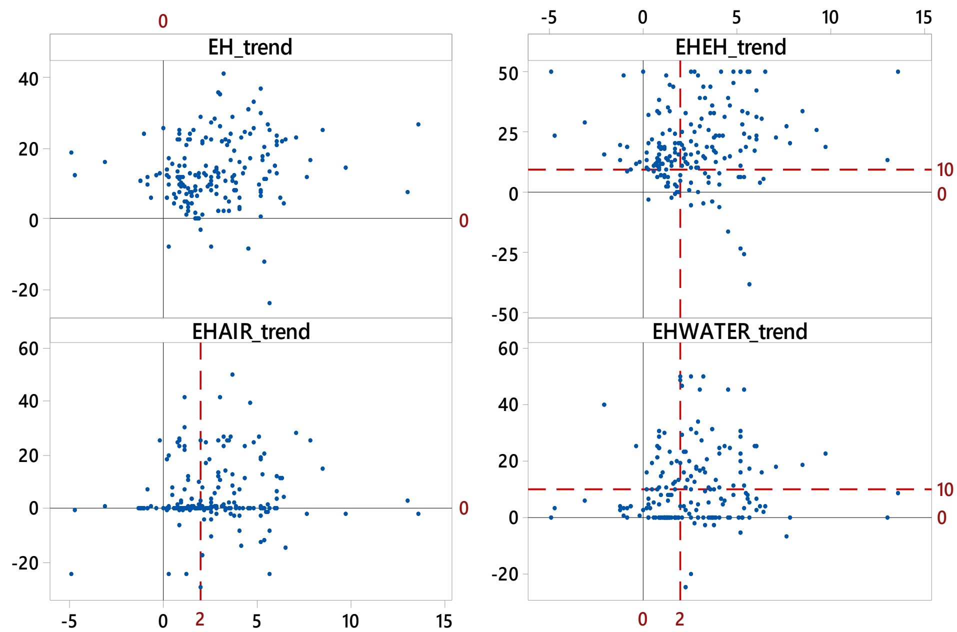

Figure 3.1: Thresholds for a high-performance win-win for the Environmental Health categories and Average GDP per capita growth rate. EHEH_trend is the Child Mortality trend set at 10, EHAIR_trend is Air Pollution trend set at 0, EHWATER_trend is Water Pollution trend set at 10 and EH_trend is the general Human health trend set at 0. The Average GDP growth rate is set at 2 for all the indicators.

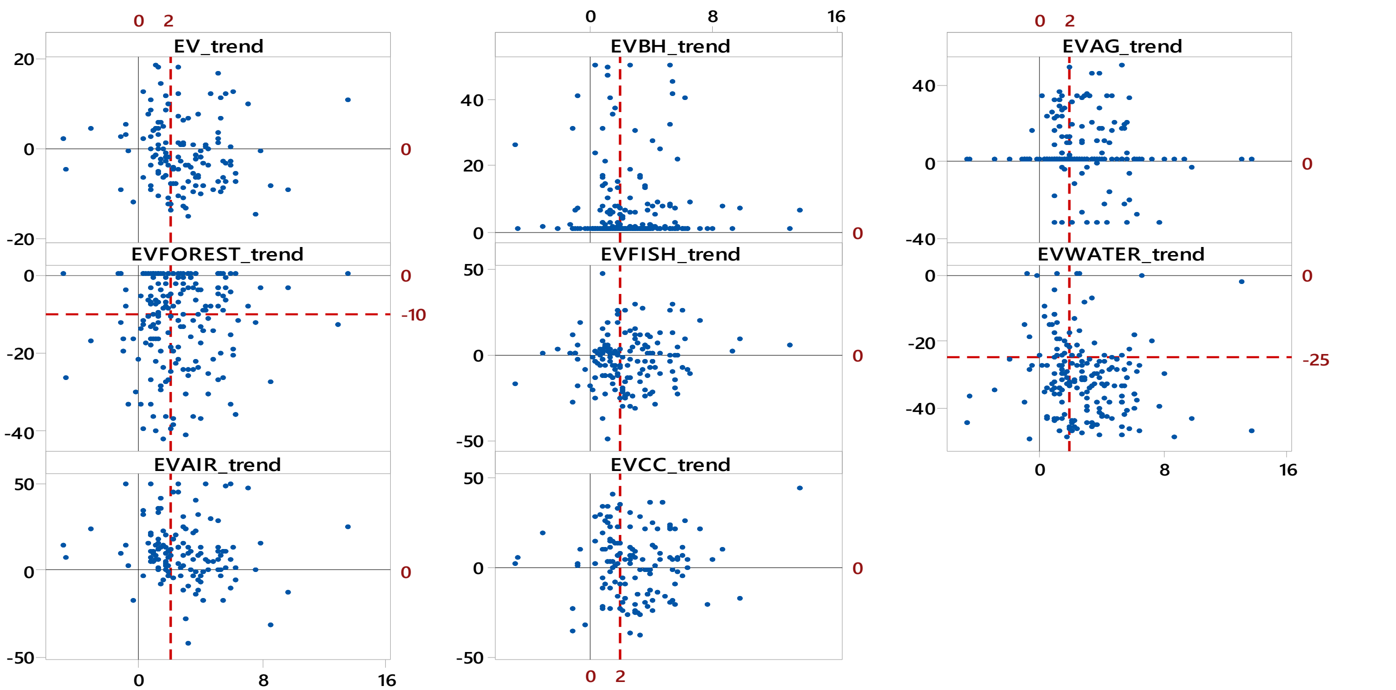

Figure 3.2: Thresholds of a high-performance win-win for the Ecosystem Vitality categories and Average GDP per capita growth. The first column consists of a general Ecosystem Vitality trend (EV_trend) set at 0, Forestry trend (EVFOREST_trend) set at -10, Air Pollution trend (EVAIR_trend) set at 0. The second column consists of Biodiversity and Habitat trend (EVBH_trend) set at 0, Fisheries trend (EVFISH_trend) set at 0, Climate Change trend (EVCC_trend) set at 0. The third column consists of Agriculture trend (EVAG_trend) set at 0 and Water Quantity use trend (EVWATER_trend) set at -25. The threshold for Average GDP per capita growth is set at 2 for all the indicators.

Results

High win-win in economic growth and environmental health

Results of factors influencing the likelihood of a high win-win relative to no win-win is presented below:

Table 3.1: The coefficients followed by odds ratio and p-values (in parentheses) for the determinants of a likelihood of a high win-win for the environmental health indicators and Average GDP per capita using logistic regression. Coefficients with statistically significant p-values are bolded. The environmental health indicators are Child Mortality (EH-EH), Water Quality (EH-Water) and Air Pollution (EH-Air).

	EH-EH	EH-Water	EH-Air
Constant term	2.341	3.922	0.788
	(0.194)	(0.036)	(0.614)
$\ln GDP_{2000}$	**-0.753**, 0.471	**-1.173**, 0.309	-0.303, 0.739
	(0.021)	(0.002)	(0.283)
HDI_{2000}	0.004, 1.004	**0.066**, 1.068	0.008, 1.008
	(0.869)	(0.016)	(0.696)
Inv/GDP	**0.160**, 1.174	**0.051**, 1.052	0.027, 1.027
	(0.000)	(0.081)	(0.291)
GE change	1.058, 2.881	-0.328, 0.720	0.130, 1.139
	(0.149)	(0.653)	(0.844)
PS change	**0.822**, 2.275	-0.124, 0.883	**0.670**, 1.954
	(0.029)	(0.743)	(0.054)
Health change	0.061, 1.063	0.056, 1.058	0.018, 1.018
	(0.284)	(0.321)	(0.737)
Observations without win-win	84	106	100
Observations with win-win	65	41	50
McFadden R-Square	0.250	0.097	0.051
S.E. of regression	0.422	0.431	0.466
LR statistics	56.82	16.86	9.82
Thresholds	GDP>2, EH>10	GDP>2, WATER>10	GDP>2, AIR>0

Child Mortality

The win-win category in child mortality had a total of 65 out of 149 that met the threshold for a high win-win in GDP per capita growth rate and health improvement (Table 3.1). There were only 8 high-income nations out of the 69 that met the threshold of a high-win-win which includes Panama, Slovak Republic, Slovenia, Singapore, Saudi Arabia, South

Korea, Hong Kong China, Latvia and Argentina. The majority of nations were the low and middle-income nations consisting mainly of Central Asian, Sub-Saharan African, Latin American, Caribbean and Middle-Eastern nations like Afghanistan, Angola, Nigeria, Columbia. This is a statistically significant amount of improvement in both areas and especially for low and middle-income countries which is supported by the theory of economic growth that a faster growth rate is seen mostly for developing economies as opposed to developed economies. The initial GDP ($p < 0.05$), Average investment as a % of GDP ($p < 0.001$) and Political Stability change ($p < 0.05$) were the statistically significant variables impacting the high win-win trend. A statistically significant initial GDP but with a negative coefficient is most likely due to convergence hypothesis. The odds ratio for this variable implies that initial GDP is not a strong factor for win-win because it is 0.471 times less likely going to increase a win-win relative to no win-win. This may be due to developed nations reached high levels of both standard of living and low child mortality. Furthermore, the initial social development indicator is not statistically significant. Hence, a win-win in this case is more dependent on the initial standard of living of a nation as measured by GDP per capita in 2000 than the initial level of education and health score in the HDI. However, after controlling for the initial state of the socioeconomic situation of the nations, we find that the average investment as a percent of GDP shows that it increases the odds of being in a win-win 1.174 times more than the odds of not obtaining a win-win for child mortality and economic growth. Similarly, political stability change is a strong indicator for improvement in child mortality and economic performance by increasing the chances of a win-win 2.275 times more that the odds of having no win-win. The remaining variables such as initial non-income HDI and government effectiveness were not statistically significant in this category.

Water (human health effects)

The win-win trend for water quality had 41 out of 147 nations meeting the threshold for a high win-win for GDP and water quality (Table 3.1). There were only 5 high-income nations out of the 41 in a high win-win which includes Uruguay, Panama, Trinidad and Tobago, South Korea and Hungary. The majority were low and middle-income nations similar to the nations in the Child Mortality but mostly Latin American, Caribbean and Middle-Eastern nations like Afghanistan, Cuba, Egypt and Brazil. This also shows a statistically significant improving trend in both areas especially for low and middle-income countries which is also consistent with the theory of economic growth as it relates to a faster growing rate for developing economies. Initial GDP ($p < 0.005$), Average investment ($p < 0.05$) and initial HDI ($p < 0.1$) were the statistically significant variables impacting a high win-win trend. The odds ratio for this category shows that the level of impact by the Initial GDP is 0.309 times less likely to result in a high win-win which indicates it is not a strong indicator for this category which supports the EKC theory for an initial low level of income. Average investment has a positive impact of 1.052 times towards achieving a high win-win for water quality. The initial HDI also promotes a high win-win in water quality by 1.068 times. The change in perceptions of government effectiveness and political stability were not statistically significant in this case to affect the likelihood of a high win-win.

Air pollution (human health effects)

In this category, we have 50 out of 150 in the win-win that met the threshold for GDP and air quality (Table 3.1). A total of 8 high-income nations out of the 50 were in a high win-win which were Trinidad and Tobago, Poland, Panama, Hungary, Croatia, Slovak Republic, South Korea and Argentina. Majority of the nations in this category were low and middle-income nations with same regions as Child Mortality and Water like Syria, Sudan, Chad, Egypt, Pakistan, Costa Rica and Cuba. Political stability change ($p < 0.05$) was the only statistically significant variable impacting the win-win for air quality. Political stability change had an odds ratio of 1.954 which implies that it positively impacts a high win-win for air quality. All the other variables such as initial GDP, initial non-income HDI, average investment % of GDP, change in perceptions of government effectiveness and health expenditure change were not statistically significant in this category.

In summary, in the environmental category, child mortality had the highest number of nations (65) in a high win-win while water had the least number of nations (41). The explanatory power of the independent variables to determine a high win-win is strongest for child mortality improvements and economic growth, followed by water but only a single factor, change in political stability, was statistically significant to explain a high win-win in for air quality improvements and economic growth (See Appendix E for the logistic results from Eviews).

High win-win in economic growth and ecosystem vitality

Results of factors influencing the likelihood of a high win-win relative to no win-win is presented below:

Table 3.2: The coefficients followed by odds ratio and p-values (in parentheses) for the determinants of a likelihood of a high win-win for the ecosystem vitality indicators and Average GDP per capita using logistic regression. Coefficients with statistically significant p-values are bolded. The ecosystem vitality indicators are Biodiversity and Habitat (EV-BH), Agriculture (EV-AG), Forestry (EV-FOREST), Fishery (EV_FISH), Water Quantity use (EV-WATER), Climate Change (EV-CC) and Air Pollution (EV-AIR).

	LAND			WATER		AIR	
	EV-BH	EV-AG	EV-FOREST	EV-FISH	EV-WATER	EV-CC	EV-AIR
Constant term	4.532	-0.913	-0.399	-1.171	-6.468	5.847	4.417
	(0.014)	0.642	0.848	0.704	0.032	0.133	0.046
$\ln GDP_{2000}$	**-1.453**, 0.234	**-0.575**, 0.563	**-1.189**, 0.305	-0.422, 0.656	-0.397, 0.672	**-1.196**, 0.302	**-0.730**, 0.482
	(0.000)	(0.097)	(0.003)	(0.363)	(0.406)	(0.013)	(0.024)
EV_2000	-0.002, 0.998	0.009, 1.009	**0.064**, 1.066	**-0.052**, 0.949	**0.061**, 1.063	-0.016, 0.984	**-0.021**, 0.979
	(0.791)	(0.282)	(0.000)	(0.036)	(0.000)	(0.310)	(0.082)
HDI_{2000}	**0.098**, 1.103	**0.051**, 1.052	0.044, 1.045	0.025, 1.025	0.023, 1.023	**0.059**, 1.061	0.032, 1.033
	(0.000)	(0.064)	(0.116)	(0.499)	(0.553)	(0.097)	(0.218)
GE change	0.869, 2.385	**1.642**, 5.166	1.121, 3.068	0.698, 2.010	-0.826, 0.438	-0.644, 0.525	**1.555**, 4.735
	(0.229)	(0.033)	(0.195)	(0.515)	(0.526)	(0.532)	(0.045)
PS change	**0.708**, 2.030	-0.421, 0.656	0.202, 1.224	**1.319**, 3.740	**1.772**, 5.883	**1.667**, 5.296	0.194, 1.214
	(0.069)	(0.314)	(0.681)	(0.034)	(0.009)	(0.004)	(0.629)
Inv/GDP	**0.062**, 1.064	0.031, 1.031	**0.087**, 1.091	**0.150**, 1.162	**0.116**, 1.123	0.035, 1.036	0.016, 1.016
	(0.029)	(0.340)	(0.009)	(0.004)	(0.061)	(0.433)	(0.642)
Cases of no win-win	99	122	110	92	139	88	74
Cases with win-win	52	29	38	26	11	34	47
Adjusted R-Square	0.182	0.074	0.298	0.237	0.353	0.187	0.107
S.E. of regression	0.430	0.390	0.364	0.367	0.227	0.405	0.468
LR statistics	35.471	10.925	50.222	29.535	27.744	27.023	17.329
Thresholds	GDP>2 BH=>0	GDP>2 AG>0	GDP>2 FOR>-10	GDP>2 FISH>0	GDP>2 WAT>-25	GDP>2 CC>0	GDP>2 AIR>0

Biodiversity and Habitat

A total of 52 out of 151 nations met the threshold of a high win-win for GDP growth and BH trend (Table 3.2). There was a total of 13 high-income nations out of the 52 in a high win-win like Singapore, South Korea, Slovenia, Croatia, Uruguay, Panama, Greenland etc while the majority were low and middle-income nations like Malaysia, Brazil, Cuba and Costa Rica. The outcome for this indicator varied across nations but a high win-win was dominant for low and middle-income nations. The initial GDP ($p < 0.001$), initial HDI ($p < 0.001$) Political Stability change ($p < 0.1$) and average investment ($p < 0.005$) were the statistically significant variables impacting the high win-win trend for biodiversity and habitat and the economy. The odds ratio for these variables suggest that Initial GDP was 0.234 times less likely contributing to the odds of being in a high win-win for both areas. Here again it shows that nations with a low initial income are more likely to achieve a high win-win relative to high-income nations. Contrary to the environmental health where non-income HDI was found to be statistically significant, the initial non-income HDI in this case increases the likelihood of achieving a win-win 1.103 times relative to having no win-win. Political stability change is also seen to have a strong positive impact being 2.030 times indicates a large positive increase in the odds for a win-win. Similarly, the average investment as a percent of GDP has a positive impact on the odds ratio as well. Initial BH score and change in government effectiveness was not found to be statistically significant in influencing the likelihood of a high win-win outcome.

Agriculture

A total of 29 out of 151 nations met the threshold for being in a high win-win for GDP and agriculture (Table 3.2). There were only 6 high-income nations out of the 29 in a high win-win which includes Slovak Republic, Slovenia, South Korea, Singapore, Latvia and Hungary while the rest were mostly middle-income and low-income nations from North African and Latin American regions. The initial GDP ($p < 0.1$), initial HDI ($p < 0.1$) and government effectiveness change ($p < 0.05$) were the statistically significant variables impacting the high win-win trend. The odds of Initial GDP imply that an initial high GDP for agriculture is 0.563 times less likely contributing to the odds of being in a win-win relative to no win-win. Here again low-income nations are more likely to achieve a win-win than developed nations. The initial HDI impacts a win-win for agriculture 1.052 times more than a no win-win outcome. Nations with a high HDI are more likely to have a win-win relative to nations that have a low HDI score. Similarly, government effectiveness change is a strong positive indicator for a win-win as it fosters a win-win 5.166 times more that the odds of having no win-win. Initial agriculture score, change in political stability and investment as a % of GDP were not statistically significant in explaining a high win-win outcome.

Forestry

A total of 38 out of 148 nations met the threshold for a high win-win for GDP and forestry (Table 3.2). There were only 7 high-income nations in this category consisting of Latvia, Lithuania, Slovak Republic, Slovenia, Poland and South Korea which have some nations in common with those in agriculture. The rest of the nations with a high win-win were middle and low-income nations including Azerbaijan, Egypt, Bhutan, Bulgaria and Cape Verde. The initial GDP ($p < 0.005$), initial forestry level ($p < 0.001$) and average investment ($p < 0.05$) were the statistically significant variables impacting the high win-win trend. Initial GDP is 0.305 times less likely contributing to the odds of being in a high win-win. Low-income nations are more likely to have a high win-win outcome. The initial forestry level of any given nation also is a positive indicator as it increases the chances of a high win-win by 1.052 times. This indicates that nations that have a good forest level initially will want to further protect their forests while having economic growth relative to nations that their forest levels initially do not score high. Similarly, average investment also positively contributes to a win-win 1.091 times more that the odds of not. Changes in government effectiveness and political stability were not found to be statistically significant. Initial non-income HDI has a positive impact but marginal ($p = 0.11$).

Fisheries

A total of 26 out of 118 nations met the threshold for win-win for GDP and fisheries (Table 3.2). There was a total of only 7 high-income nations in this category which includes Uruguay, Turks and Cacao Islands, South Korea, Estonia, Panama, Croatia and Lithuania while the majority were low and middle-income nations like India, Indonesia, Tunisia and Namibia. The initial fishery level ($p < 0.1$), political stability change ($p < 0.1$) and average investment ($p < 0.01$) were the statistically significant variables impacting the high win-win trend. The result showed that a high initial fishery score leads to a lower likelihood of a win-win relative to a low initial fishery score. This factor contributes to the odds of being in a high win-win by 0.949 times. Political stability change also positively affects the fisheries category by an increase in the chances of a win-win by 3.740 times. Similarly, average investment contributes to a win-win 1.162 times in this category. The remaining variables such as initial GDP per capita, initial HDI and government effectiveness were not statistically significant in this category.

Water (ecosystem effects)

A total of only 11 out of 150 nations met the threshold for a high win-win for GDP and water quantity (Table 3.2). There were only 3 high-income nations in this high win-win which were Greenland, Turks and Cacao Island and Latvia while the majority were low and middle-income nations like Bhutan, Belize, Sierra Leone, Myanmar and Angola. The initial water quantity level ($p < 0.001$), political stability change ($p < 0.01$) and average investment ($p < 0.1$) were the statistically significant variables impacting the high win-win trend. A high initial water score contributes positively to the odds of being in a high win-win 1.063 times in this category relative to a low initial water score. Political stability change is also a strong indicator for a high win-win by increasing the chances by 5.883 times. Similarly, average investment also contributes to a high win-win 1.123 times. The remaining variables such as initial GDP per capita, initial HDI and government effectiveness were not statistically significant in this category.

Climate Change

A total of 34 out of 122 nations met the threshold for a high win-win for GDP and climate change (Table 3.2). There was a total of 7 high-income nations which include Estonia, Latvia, Slovak Republic, Slovenia, Singapore, Poland and Hungary while the majority were low and middle-income nations like Ethiopia, Ghana, Libya, Morocco, Nepal and Nigeria. The initial GDP ($p < 0.1$), initial HDI ($p < 0.1$) and political stability change ($p < 0.01$) were the statistically significant variables impacting the high win-win trend for climate change. The odds ratio of these variables shows that an initial high GDP is 0.302 times less likely contributing to the odds of being in a win-win which indicates a weak indicator. The initial HDI being 1.061 indicates a strong indicator for a high win-win by increasing the odds 1.061 times. Political stability shows some strong win-win odds as it contributes to a high win-win 5.296 times for climate change. The remaining variables such as government effectiveness and average investment were not statistically significant in this category.

Air Pollution (ecosystem effects)

A total of 47 out of 121 nations met the threshold for a high win-win for GDP and air quality (Table 3.2) which is a higher number of nations compared to climate change. There was a total of 14 high-income nations similar to climate change and also includes Saudi Arabia, Uruguay, Argentina and South Korea, the rest which are majority were the low and middle-income nations like Cuba, Ghana, Peru, Russia and Ukraine in a high win-win. The initial GDP ($p < 0.1$), initial air quality level ($p < 0.1$) and government effectiveness change ($p < 0.1$) were the statistically significant variables impacting the high win-win trend for air quality. The odds ratio for these variables shows that Initial GDP is a weak high win-win indicator because it is 0.482 times less likely contributing to the odds of being in a win-win. The initial air quality improves the chances of win-win to occur by 0.979 times. Government effectiveness change shows a strong win-win indicator by increasing the odds of a win-win 4.735 times more that the odds of having no win-win in this category. The remaining variables such as initial HDI, political stability and average investment were not statistically significant in this category.

In conclusion, the high win-win for ecosystem vitality had only a few nations consistent throughout the indicators that met the thresholds. However, low and middle-income nations were dominant in the high-performance win-win trends. But, we see an overall lesser number of nations within the thresholds with the highest being 52 high in-win nations in biodiversity and habitat and the lowest as 11 high win-win for Water out of over 150 nations surveyed. The explanatory power of the independent variables to determine a high win-win is varied across all the indicators for ecosystem vitality (See Appendix E for the logistic results from Eviews).

Comparison with a single high win situation for environmental indicators

In order to further distinguish the importance of a win-win situation for these two factors, a comparison with a win in one factor, in this case, the environmental categories alone, is presented below to highlight the differences.

Table 3.3: The coefficients and p-values for the determinants of a likelihood of a single win for environmental health ecosystem vitality indicators using logistic regression. Coefficients with statistically significant p-values are bolded.

	Environmental Health			Ecosystem Vitality						
	EH	Water	Air	BH	Ag	Forest	Fish	Air	CC	Water
Constant term	2.353 (0.257)	-3.428 (0.006)	0.038 (0.971)	-1.864 (0.097)	-2.499 (0.088)	-8.307 (0.000)	-0.130 (0.929)	0.269 (0.873)	-1.470 (0.327)	-0.541 (0.496)
Initial Env_{2000}	-0.037 (0.149)	**-0.065** (0.000)	**-0.021** (0.028)	-0.002 (0.720)	0.003 (0.753)	**0.114** (0.000)	**-0.054** (0.001)	0.006 (0.649)	-0.010 (0.373)	
HDI_{2000}	0.015 (0.758)	**0.091** (0.000)	0.023 (0.192)	**0.040** (0.015)	0.024 (0.252)	-0.001 (0.965)	0.024 (0.246)	0.011 (0.622)	**0.035** (0.042)	-0.012 (0.336)
FGE change	-0.122 (0.724)	0.070 (0.841)	-0.380 (0.197)	0.110 (0.708)	**1.178** (0.001)	**-0.704** (0.071)	**-0.608** (0.072)	0.244 (0.478)	**-1.741** (0.025)	-1.110 (0.136)
PS change	-0.086 (0.841)	-0.490 (0.134)	0.259 (0.403)	0.316 (0.292)	-0.580 (0.149)	**-0.903** (0.062)	0.019 (0.957)	-0.628 (0.136)	**0.753** (0.067)	**0.796** (0.037)
Health change	0.019 (0.781)	**0.115** (0.033)	-0.031 (0.536)							
Observations without a win	39	93	73	60	100	80	72	28	50	120
Observations with a win	114	60	80	97	57	74	52	93	72	34
Adjusted R-Square	0.122	0.168	0.070	0.084	0.272	0.510	0.092	0.473	0.834	0.046
S.E. of regression	0.409	0.443	0.485	0.466	0.400	0.330	0.474	0.421	0.475	0.410
LR statistics	21.272	34.477	15.010	17.560	55.890	108.92	15.598	6.196	13.8111	7.552

There are more nations in a high win situation that met the threshold for all the environmental indicators without considering a win for economic growth alongside as opposed to a high win-win which had fewer nations (Table 3.3). When considering progress for a single environmental indicator, its initial level of environmental performance determines how farther a nation will improve over the year. A nation with an initial high environmental performance level may have lesser room for further improvements. In the categories of child mortality, water pollution (human health), forestry and fisheries, the initial environmental level is statistically significant ($p<0.005$) all of which also have a negative coefficient except for forestry which has a positive coefficient. This implies that a nation with an initial high level in child mortality, water pollution, forestry and fisheries is likely to have a high win at a slower rate than a nation with an initial low level which will progress at a faster rate.

In the case of forestry, a nation with an initial high forestry level in terms of forest loss and forest covers will likely perform better than a nation with an already deteriorating forest cover or high forest loss. Also, the impact of governance indicators are not strong indicators of a high win in the environmental cases as opposed to a consideration of a win-win situation which considers economic growth. This shows the interrelationship between the economic and environmental elements such that the performance of one factor, in this case, economic growth, cannot be totally isolated from the resulting impact it has on the other, which are the environmental categories.

Comparison with a single high win situation for high economic performance

Also, in considering a win in just the GDP over the decade, we show results for a win in GDP to assess the factors that lead to a win in progress of GDP alone to see how it differs from a win-win situation.

Table 3.4: The coefficients and p-values for the determinants of a likelihood of a single win for environmental health ecosystem vitality indicators simple linear regression. Coefficients with statistically significant p-values are bolded for Average GDP (Av GDP) and the probability of obtaining a win for GDP growth (Prob).

	Av GDP	Prob(GDP>2)
Constant term	4.990	3.706
	(0.008)	(0.040)
$\ln GDP_{2000}$	-1.165	-1.133
	(0.000)	(0.001)
HDI_{2000}	0.060	0.050
	(0.012)	(0.053)
FGE change	0.184	1.524
	(0.000)	(0.033)
PS change	1.385	1.180
	(0.023)	(0.003)
Health change	1.100	0.152
	(0.005)	(0.000)
Observations without a win		91
Observations with a win		105
Adjusted R-Square	0.452	0.265
S.E. of regression	1.868	0.420
LR statistics		55.180

There was a general high win trend most nations (105) in their economic performance over the years that met the threshold (Table 3.4). The initial GDP level, HDI level, governance indicators were all statistically significant ($p<0.05$) in impacting a win for GDP. The initial level of GDP also reveals that a nation with a high level of GDP is likely to increase at a lesser rate than a nation with initial low level of GDP which also leads to convergence. Economic growth is very much reflective of the progress of its governance, economy, human development index (HDI), human health, environmental and social factors, hence the statistical significance of all the explanatory variables in positively impacting the economic growth over the decade.

In conclusion, we see the examination of a high win-win situation for nations in their economic growth and environmental indicators to be very relevant in revealing how the progress in the association of these two factors varies from one environmental indicator to another. It also reveals how a high GDP growth rate is favorable low and middle-income nations and only a few high-income nations.

Discussion

The results presented reveal some significant relationships and trends for a high win-win when thresholds are set for GDP per capita growth rate and the 2012 EPI pilot trend policy categories. The first of the relationships that is clearly seen to favour a high win-win is the link between the growth rate of GDP and the environmental performance being achieved by mostly middle and low-income nations. These findings are consistent with the theory of economic growth for a faster growth rate for emerging economies but finds little support for the existence of an EKC which should favour high-income nations. However, numerous studies suggest that nations follow a development path that solely relates to income and environment inevitably. Consistent with the findings of Hsu et al. (2013) there were few wealthy countries for example Slovak Republic, Slovenia, South Korea, Singapore and Latvia who were in a high win-win situation for most of the policy categories for human health and ecosystem which still highlights the role of income. But, generally, the trends for high win-win suggests that income growth alone is not enough to explain the differences in environmental performance between countries as can be seen in the indicators of air (human health), fisheries and water (ecosystem).

The link between the non-income HDI and environmental performance trend for the high win-win cases were also found (Constantini and Salvatore, 2008; Mukherjee and Chakraborty, 2010; Hsu et al., 2013; Melnick et al., 2005). As opposed to using HDI as an explanatory variable which includes income as a component of its indicator, this study uses the non-income HDI which makes for a stronger factor that impacts a high win-win for nations between social development and environmental performance trend (Hsu et al., 2013). However, some indicators like child mortality, air quality (human health), air pollution(ecosystem), forests, fisheries and water quantity (ecosystem) were shown to not have been impacted by their initial non-income HDIs as they were statistically not significant.

Another underlying factor considered as a possible explanation for differences in outcomes for high win-win which has also been widely examined in previous studies is governance indicators. Sachs and McArthur (2005) in an analysis of the progress toward MDGs attributes poor performance toward achieving MDG goals to poor governance. This study however observes mostly no statistical significance of the change in government effectiveness to increase the likelihood of a high win-win for indicators like child mortality, air quality (human health), water pollution (human health), biodiversity and habitat, forests, fisheries, water quantity (ecosystem) and climate change. It seems to be significant for only two indicators which are agriculture and air pollution (ecosystem). Change in political stability, on the other hand is documented in this study to have increased the chances of a high win-win in child mortality, air quality (human health), biodiversity and habitat, fisheries, water quantity (ecosystem) and climate change. This suggests that for mostly low and middle-income nations, the progress towards a more politically stable economy increases the government's ability to enforce environmental regulations for these indicators which may lead to higher win-win cases (Lopez and Mitra, 2000; Damania et al., 2003). However, while Kaufmann et al. (1999) affirms that "governance matters'' and as the author of the World Governance Indicator (WGI) database, has employed several techniques like validation by correlation and impact, to authenticate the indicators. There have been criticisms of governance indicators from the WGI which say that they are based on expert perceptions and they are inherently subjective. Authors like Razafindrakoto and Roubaud (2010) and Morse (2006) question whether these indirect validation techniques guarantee a definite link between subjective governance indicators and real levels of corruption control in a country. They suggest more appropriate levels of analysis to include the sub-national and local levels, so interactions can be further identified, and relationships refined.

While income growth rate, social development as non-income HDI, and governance can help to explain some differences in individual countries' performance, the average investment share in GDP over the same period is another factor that measures the share of investment in total production for any nation. The rate of investment reflects the infusion of requisite capital to support the development process in any given nation (UNSD, 2010). This factor increased the chances of a high win-win for many middle and low-income nations for indicators like child mortality, water quality (human health), biodiversity and habitat, forests, fisheries and water quantity (ecosystem) and for only a few high-income nations. A positive average investment impacts the chances of a high win-win by accelerating the pace of development through infused requisite capital which is reflected in the processes and patterns of economic activities of low and middle-income countries. This factor also enhances a high win-win by increasing their partnership in the global economy (UNSD, 2000).

The findings obtained from this study is similar to Gallego et al. (2014), Hsu et al. (2013) and Mavragani et al. (2016) that point out that socioeconomic factors, such as economic wealth and education, as well as institutional factors represented by the style of public administration are determining factors of environmental performance in the countries analysed but in the case of my study a high win-win situation. This study also found that in regard to the two groups of variables in the EPI, in environmental health, the disparity in the ratio of high-income to low and middle-income nations for a high win-win is wider as seen in child mortality (8/69), water pollution (5/41) and air quality (8/50). Whereas variables related to ecosystem vitality, the gap was not as broad as seen in biodiversity and habitat (13/52), agriculture (6/29), forest (7/28), Water (3/11) climate change (7/34) and air pollution (14/47). This shows that some high-income nations like Singapore, Slovenia, Latvia and Uruguay still performed very well over the decade despite the thresholds, their outcomes can also be attributed to their level of income growth and the positive impacts it has had on their environmental degradation which is consistent with the EKC theory.

Society has shown increased interest in environmental issues on the microeconomic level where stakeholders are increasingly concerned with the environmental performance of firms and use it to make decisions about their investments. On the macroeconomic level however, it focuses on the environmental performance of countries and their ability to produce environmental public goods (Gallego et al., 2014). Citizens have become increasingly aware of their right to a high-quality environment, which has led to each country being accountable to its citizens for the environmental policies it puts into practice thereby fostering the pursuit for a high win-win situation in economy and environment simultaneously.

CHAPTER 4: CONCLUSION AND IMPLICATIONS FOR FUTURE STUDIES

This study set out to investigate the trends in the performances of over 200 nations for the 2012 trend EPI environmental policy categories associated with their average GDP per capita growth rate simultaneously. The aim was to discover clusters of nations within a win-win trend relative to those which were not as well as those nations which had very high performances in both areas and the underlying factors which influenced the likelihood of such performances. To achieve this goal, the k-means clustering technique was used to identify homogenous groups of nations within the win-win category for nations in their economic and environmental performance trends. This approach gave a broader perspective in form of a graphical representation of several clusters of nations each representing a unique trend to the association of economic and environmental performances. This approach was in contrast to previous works that use only one type of variable, either economic or institutional, or present only a theoretical perspective. This study provided a graphic representation that differentiates between countries' environmental and economic performance in relation to environmental health, on the one hand, and to ecosystem vitality on the other as seen in chapter 2. The second goal was to identify the underlying factors that may have led to a win-win for some nations and especially a high win-win situation for both variables. To identify these factors, the countries and variables (average GDP growth rate and environmental indicators) were contextualized by setting thresholds for both variables as minimum requirements for a high win-win. A logit model was used to verify which economic and institutional variables had an impact on a high win-win situation. This study reveals socioeconomic factors, such as GDP and non-income HDI level, as well as institutional factors represented by change in political stability and government effectiveness were some of the determining factors of a high win-win situation which are consistent with findings in Gallego et al. (2014), Hsu et al. (2013) and Mavragani et al. (2016). This provided an explanation in form of factors that increase the likelihood of a high win-win situation for nations in relation to environmental health and ecosystem vitality and their respective average GDP growth rate.

This paper has demonstrated one way in which the 2012 pilot trend EPI and the average GDP growth are useful in measuring progress of nations that have achieved a high performance in global environmental policy goals and a high performance in its economic growth simultaneously by incorporating thresholds. The goal of the 2012 Trend EPI was to draw the attention of decision-makers to the environmental issues in their countries on which they both lag and perform well (Hsu et al., 2013), compared to other nations economically, geographically, as well as globally. An issue-by-issue examination of environmental goals alongside their GDP growth over a decade provides a more useful insight to detect issues of concern for policymakers at the country-level. This was achieved by identifying the leading countries and those lagging behind which in turn helps enable make sense of global trends toward achieving sustainability. This paper has revealed the environmental progress of low, middle and high-income nations by using a methodology of clustering and logistic analysis as the framework to assess which group of nations have improved significantly over the last decade in the 2012 EPI environmental policy targets as seen in chapter 2 and 3.

Economic development and good governance (mostly with the use of governance indicators) had been suggested to individually positively affect environmental performance (Mavragani et al., 2016). However, a positive average investment also played significant role in increasing the chances of a high win-win especially for low and middle-income countries by accelerating their pace of development through infused requisite capital which helped accelerate their processes and patterns of economic activities. The results showed an interesting trend for countries whereby some environmental issues like child mortality and water pollution (human health) had win-win situations across high-income, middle-income and low-income countries. In categories like climate change and agriculture, high-income countries dominated the win-win category which is consistent with the EKC predictions for the pathway nations follow on their relationship between economic growth and environmental quality.

This study contributes to the field of environmental economics and could be of interest to policy makers as it emphasizes the strong correlation between economic development in combination with good governance and environmental performance over a long period of time which consequently leads to sustainable development. By broadening the sample to include more years for a longitudinal study, this study has made an attempt to provide research-based approach to ensure environmental sustainability, which is one of the priorities of environmental authorities around the world (Gallego-Alvarez et al., 2014).

However, like other studies, this study has limitations that might be good starting points for future research. Firstly, though the variables used in this study are reliable and the statistical analysis follows a standard procedure, there could be one or more variables which could be incorporated in addition to economic growth. Other variables such as the control of corruption, population density, role of science and technology, the importance of market dynamics, the role of economic agents and the ideology of social movements that affect environmental performance that have not been considered in this study can be looked into. In addition, the fact that data for the pilot trend environmental policy categories were only available for the period of 2000 to 2010 restricts the generalization of the findings beyond the time frame, an updated analysis for recent years to this study, when more data is available, is necessary in the future.

The results obtained have real-world applications and can be useful for policy makers. The standout outcome is that income growth is not the only explanatory variable for understanding environmental performances and sustainability across countries. Institutional factors such as political stability (regime type: democratic regimes show higher levels of environmental performance than authoritarian regimes), government effectiveness, and other institutional factors must also be considered, since they can affect environmental performance indicators. Governments should also consider that being a wealthy country does not always lead to better environmental performance, especially considering the long term in the environmental health aspect apart from natural or ecological resources. In the case of environmental health, over a long period of time it can be affirmed that there is convergence for both low-income and wealthy countries such that all nations tend towards a win-win situation. However, in the case of natural or ecological resources, it varies greatly from one environmental issue to the other even over a period of time; there is no relation in some cases at all, it is negative for some and of minimal impact for others. This may be due to the fact that although wealthy countries may be able to invest money in order to improve their environment, they also tend to increase environmental issues due to their high level of consumption (Gallego-Alvarez et al., 2014).

Evident from some of our results however, is that income growth and effective governance leads to better environmental performance as few high-income nations still achieved a high-performance trend. Also stated by Gallego-Alvarez et al. (2014), an effective, innovative and adaptable governance is a necessary condition for nations geared towards sustainability. Some governance policies may include integrating environmental policies and enhancing social capital when introducing legislations and regulations, in order to achieve higher levels of environmental performance.

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Appendices

Appendix A: Indicator frameworks and EPI exploration

Transforming Raw Indicators

The first step involves conducting some standard normalizations for transforming raw values, GDP, or another denominator to make data comparable across countries. The second step involves applying statistical transformations to the data by which to better differentiate performance amongst countries. Logarithmic transformations are applied to address the skewness of the underlying datasets. The transformed data are then used to calculate performance indicators using a proximity-to-target methodology, which reflects how close a country is to an identified policy target (Hsu et al., 2013). The target, or high-performance benchmark, is defined by international or national policy goals, established scientific thresholds, or expert judgment.

Proximity-to-Target Score Methodology

The proximity-to-target score ($PT_{S,i,t}$) of each nation for each time period the methodology is shown in

The formula for $PT_{S,i,t}$ used was as follows:

$$PT_{S,i,t} = \frac{L_P - T_P - (I_{i,t} - T_P)}{L_P - T_P} * 100$$

Where L_P is the poor performance benchmark, T_P is the top performance benchmark or the target and $I_{i,t}$ is the indicator of nation i at time t = 2000 – 2010 all variables transformed as explained previously. The proximity to target shows how far the indicator score is from the poor performance benchmark as a fraction of the distance between poor and top performances. If it is not far from the target, then the $PT_{S,i,t}$ will be closer to zero and if it is close to the target it will be closer to 100.

Trend Score Methodology

For each indicator, a simple linear regression model of the annual proximity-to-target scores is used to determine a rate of improvement or decline for each indicator. The slope of the trend line determines the scale. 0 slope reflects “no change”, a positive slope reflects improvement and a negative slope indicates decline.

This is done for every nation and for every indicator. Then these slopes for each indicator are ranked from "best improvement" receiving a score of 50 and defined by the 95% percentile of the slopes, 0 slope reflecting "no change" again and -50 is for the "worst trend decline". Forest Loss, Forest Growing Stock, Forest Cover, and Change in Water Quantity have trend scores that range from -50 to 0 as they are change indicators.

Final Aggregation Methodology

The indicator scores are then aggregated (averaged) according to assigned weightings to produce scores within each policy category (Hsu et al., 2013). Differential weighting of the indicators as percentages of a policy category is determined through expert judgments based on considerations of data quality, relevance of the indicator to measure a particular issue. The 2012 pilot Trend Index scores and ranks countries based on improvement or decline from 2000 to 2010.

Exploratory patterns of some indicators

This chapter aims to explore the already existing trends of some nations for some indicators in the policy categories of the EPI in order to capture existing patterns that can also contribute to the win-win or win-loss categories.

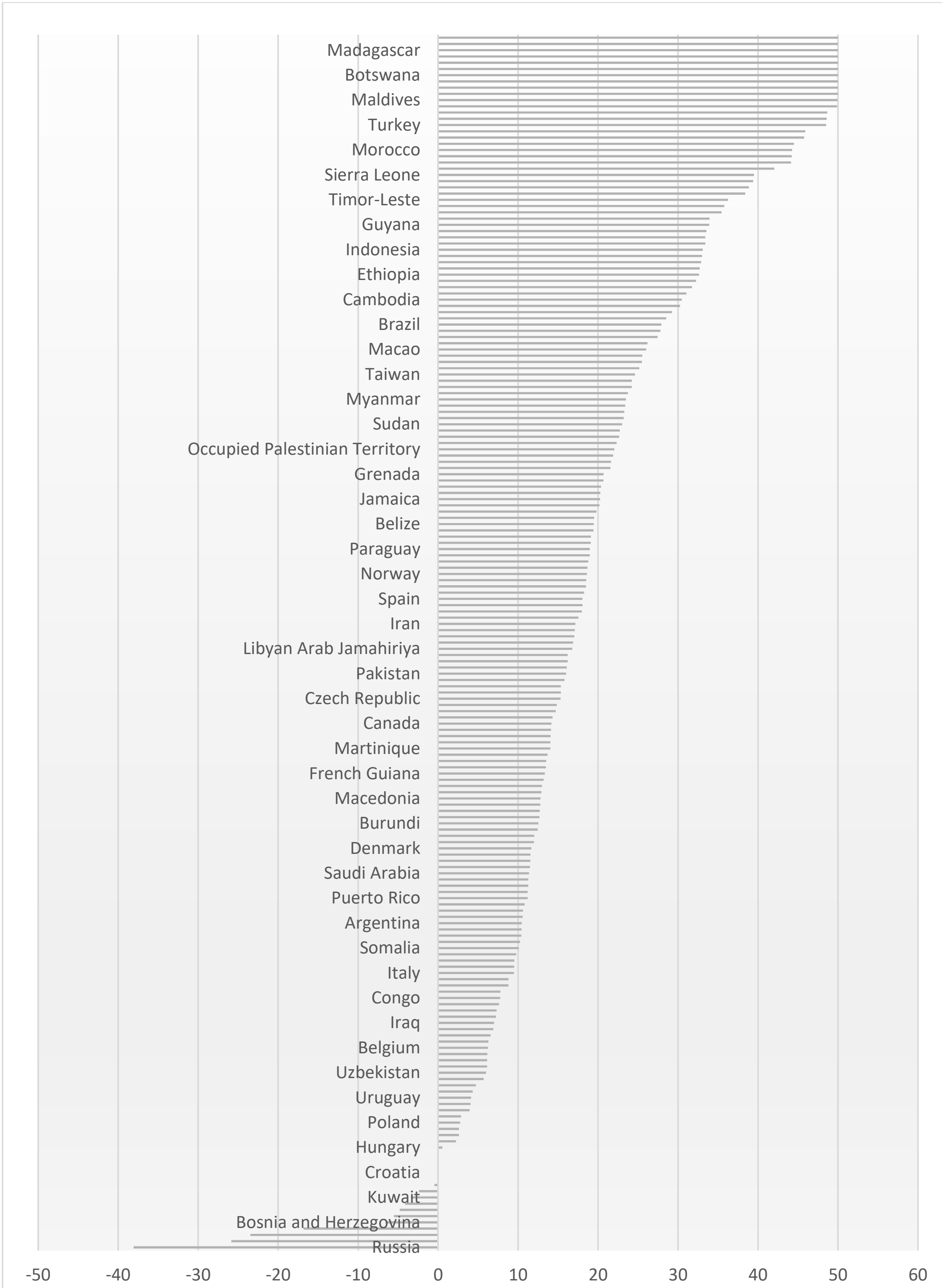
Application to Environmental burden of disease policy category

Child mortality is the only indicator in this policy category and it is defined as the probability of dying between a child's first and fifths birthdays per 1000 children aged 1year old. Many environmental and socioeconomic factors influence child mortality for ages 1 – 4 years old. The target and low performance benchmark for this indicator is shown in the table below:

EPI framework for Child Mortality (CHMORT) Indicator

Indicators	**Target**	**Low performance benchmark**	**Statistical transformation**	**Transformed targets**	**Transformed low performance benchmark**
Child mortality	0.0007 probability of dying between age 1 and 5	0.113	natural logarithm	-6.91	-2.18

Child mortality slopes of the trends of the proximity to target of 195 nations is shown in the figure below. The table below also shows nations with both increasing and a decreasing trend in CHMORT towards achieving this indicator target or still at the low performance benchmark.



Trend scores for a selected number of nations in CHMORT Indicator

Most improved trends	Trend score	Most decline trends	Trend Score
United Arab Emirates	50	Russia	-38.07
Azerbaijan	50	Lithuania	-25.85
Bangladesh	50	Cuba	-23.46
Botswana	50	Estonia	-16.83
Laos	50	Bosnia and Herzegovina	-6.56
Liberia	50	Slovenia	-5.52
Latvia	50	Kyrgyzstan	-4.79
Madagascar	50	Mauritius	-4.12
Nepal	50	Kuwait	-3.4
Rwanda	50	El Salvador	-2.39

Trend scores for a selected number of nations in CHMORT Indicator

From the above table, a declining trend were mostly nations that are underdeveloped, while the nations that show no change or little are the developed nations. Nations that show major a major increasing trend in child mortality are nations from the former Soviet Union and Cuba. For most developed nations, CHMORT is usually not caused by environmental factors but by factors such as accidents or congenital diseases.

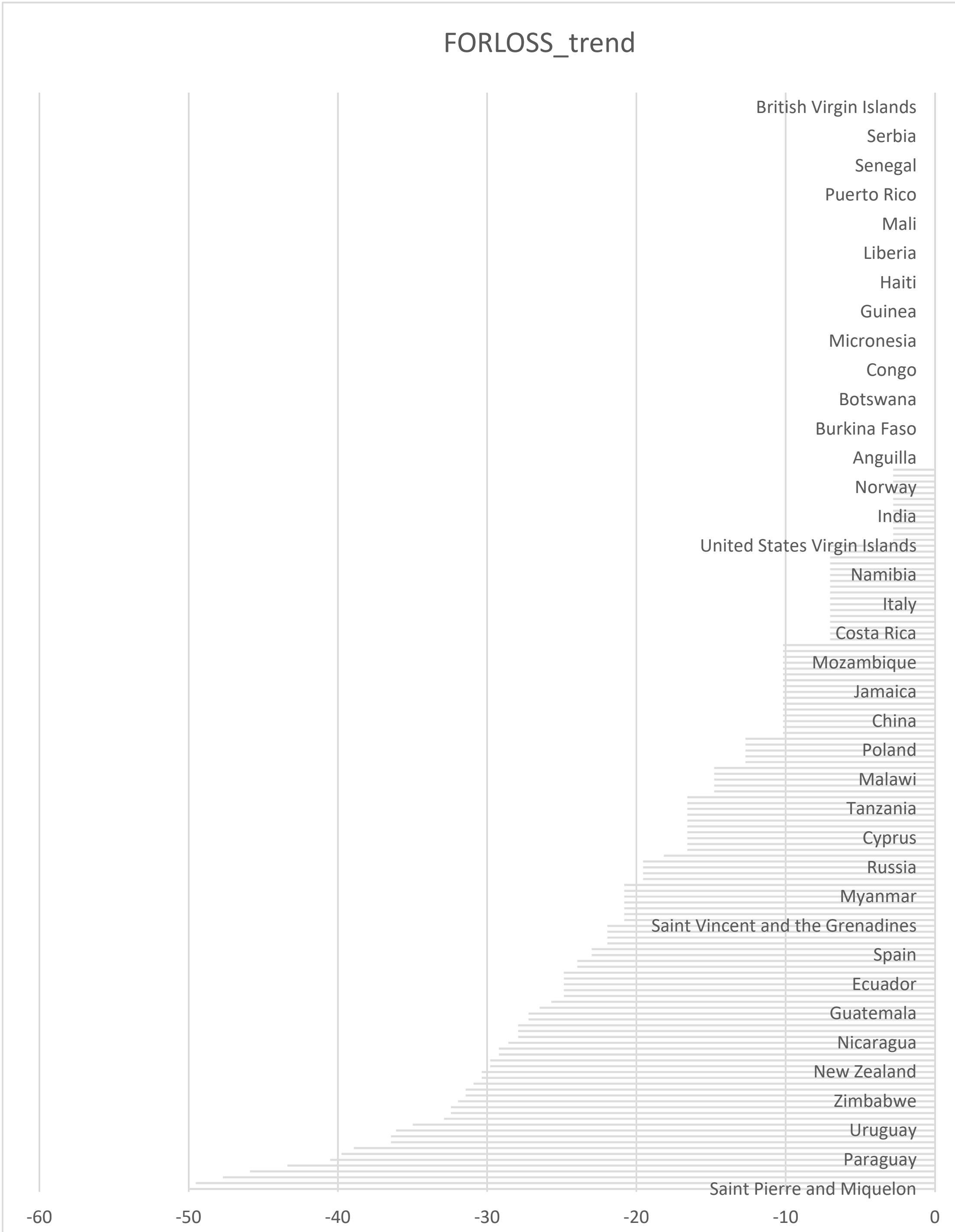
Application to Forests policy category

Forests are cover almost 30% of the Earth's terrestrial surface and are a major source of biomass, food products, wood, pulp, medicine etc. Forest loss (FORLOSS) indicator is used as a demonstration from this policy category. Forest Loss measures the loss of forest area owing to deforestation from either human or natural causes. The targets and low performance benchmark is shown below:

Indicators	Target	Low performance benchmark	Statistical transformation	Transformed targets	Transformed low performance benchmark
Forest loss	0.015 % loss	7 % loss	natural logarithm	-8.81	-2.66

EPI framework for Forest Loss (FORLOSS) Indicator

The slopes of the trends of the proximity to target of 188 nations for FORLOSS indicator is shown below. The table below also show nations with both an improving and declining trend in FORLOSS towards achieving this indicator target or still at the low performance benchmark.


FORLOSS_trend
British Virgin Islands
Serbia
Senegal
Puerto Rico
Mali
Liberia
Haiti
Guinea
Micronesia
Congo
Botswana
Burkina Faso
Anguilla
Norway
India
United States Virgin Islands
Namibia
Italy
Costa Rica
Mozambique
Jamaica
China
Poland
Malawi
Tanzania
Cyprus
Russia
Myanmar
Saint Vincent and the Grenadines
Spain
Ecuador
Guatemala
Nicaragua
New Zealand
Zimbabwe
Uruguay
Paraguay
Saint Pierre and Miquelon
-60
-50
-40
-30
-20
-10
0

Rank	Country	Forest Loss	Rank	Country	Forest Loss
1	Saint Pierre and Miquelon	-50.0	13	Tajikistan	-32.9
2	Portugal	-49.5	14	Syria	-32.4
3	Swaziland	-47.7	15	Trinidad and Tobago	-32.4
4	South Africa	-45.9	16	Zimbabwe	-31.9
5	Malaysia	-43.4	17	Indonesia	-31.4
6	Paraguay	-40.5	18	United States of America	-31.4
7	Australia	-39.8	19	Singapore	-30.9
8	Cambodia	-38.9	20	Chile	-30.4
9	Argentina	-36.4	21	New Zealand	-30.4
10	Montserrat	-36.4	22	Bolivia	-29.8
11	Uruguay	-36.1	23	Saint Lucia	-29.8
12	Brazil	-35.0	24	Canada	-29.2

Trend scores for a selected number of nations in FORLOSS Indicator

124 nations show a declining trend away from the target with most of them being advanced nations, 64 nations show no change in their FORLOSS over the years. Deforestation rates are mostly higher in Southeast Asia, South America and Africa even though recent evidence suggests they may be delining (Emerson, 2012).

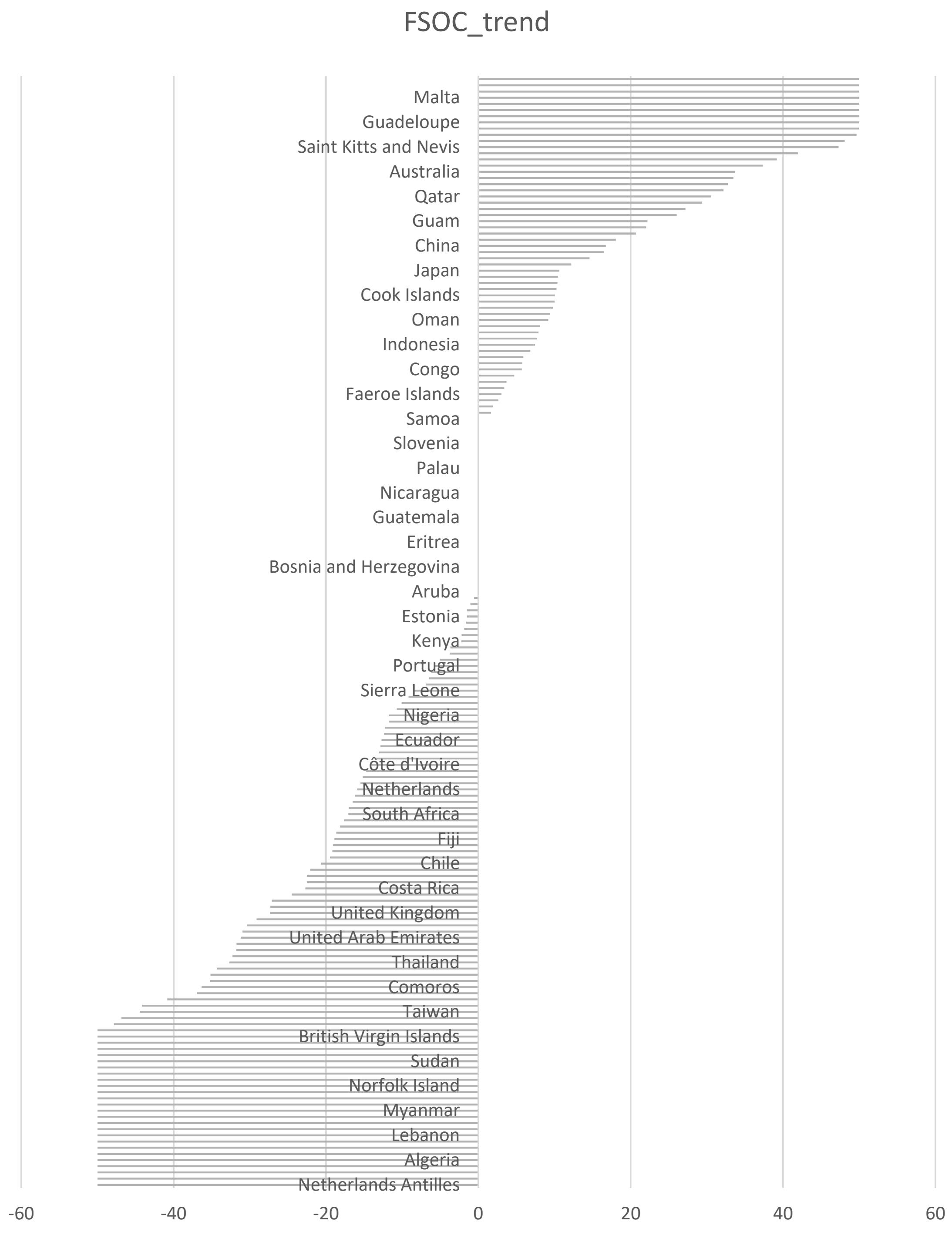
Application to Fisheries policy category

Fishing and aquaculture are mainly the activities that have a direct impact on the marine ecosystem. Overfishing of species can be detrimental to marine biodiversity and ecosystem stability. Fish Stocks Overexploited or Collapsed (FSOC) indicator is used as a demonstration from this category. FSOC measures the fraction of species that are fished in each country's EEZ that are exploited or collapsed. The target and low performance benchmark for this indicator is shown below:

Indicators	**Target**	**Low performance benchmark**	**Statistical transformation**	**Transformed targets**	**Transformed low performance benchmark**
Fishing stocks overexploited*	0 species overexploited or collapsed within EEZ	1	natural logarithm	-2.64	0.07

EPI framework for Fish Stocks overexploited (FSOC) Indicator

The slopes of the trends of the proximity to target of 180 nations for the fishing stocks overexploited are shown below in the figure below. The table below also shows nations with an increasing or decreasing trend in Fish stocks overexploitation towards achieving this indicator target or still at the low performance benchmark.



Trend scores for a selected number of nations in FSOC Indicator

Countries with the most improvement	Trend scores
Antigua and Barbuda	50
Guadeloupe	50
French Guiana	50
Croatia	50
Haiti	50
Malta	50
Suriname	50
Turks and Caicos Islands	50
Vanuatu	50

Trend scores for a selected number of nations in FSOC Indicator

96 nations were shown to have an increasing trend in FSOC which was further away from the target, 29 nations show no change, and 55 nations were found to have a decreasing trend in overexploitation towards the target. The best improved nations are mostly in the Caribbean Sea and Northeast South America as seen in the table above. Fisheries are an important aspect of most developing economies with half of global fish exports by value attributed to developing countries (Emerson, 2012). The demand for fresh seafood continues to rise with population growth and increasing affluence in developing countries hence the increasing trend in FSOC.

Application to Agriculture policy category

Agricultural demands have enormous impacts on global ecosystems due to practices that are heavily dependent on natural resources such as soil, water, and climate. Pesticide regulation of persistent organic pollutants (POPs), endocrine disruptors, or carcinogens indicator is used as a demonstration in this category. This indicator examines the legislative status of countries according to Stockholm Convention on persistent organic pollutants. It rates the degree to which these countries have kept those objectives by limiting the use of certain toxic chemicals. Pesticides are a significant source of pollution in the environment affecting both human and ecosystem health. The target and low performance benchmark for this indicator is shown below in the table below:

Indicators	Target	Low performance benchmark	Statistical transformation	Transformed targets	Transformed low performance benchmark
Pesticide regulation	22 points	0	None		

EPI framework for Pesticide Regulation (POPS) Indicator

The slopes of the trends of the proximity to target of 231 nations for POPs indicator is shown below in the figure below. The table below also shows nations with a trend in improvement or decline in POPs towards achieving this indicator target or still at the low performance benchmark.

Trend scores for a selected number of nations in POPs Indicator

Rank	Most improved	Trend score	Rank	Most improved	Trend score
1	Belgium	50.0	11	Thailand	50.0
2	Chile	50.0	12	Trinidad and Tobago	50.0
3	Finland	50.0	13	Zambia	50.0
4	Indonesia	50.0	14	Germany	37.5
5	Saint Kitts and Nevis	50.0	15	Egypt	37.5
6	Moldova	50.0	16	Bulgaria	31.3
7	Mexico	50.0	17	Lebanon	31.3
8	Mauritius	50.0	18	Monaco	31.3
9	Romania	50.0	19	Peru	31.3
10	Sudan	50.0	20	Austria	29.2

Trend scores for a selected number of nations in POPs Indicator

31 nations showed an increasing trend in POPs with some meeting the target and other nations towards the target while 200 countries showed no change in their POPS.

Application to Biodiversity and habitat policy category

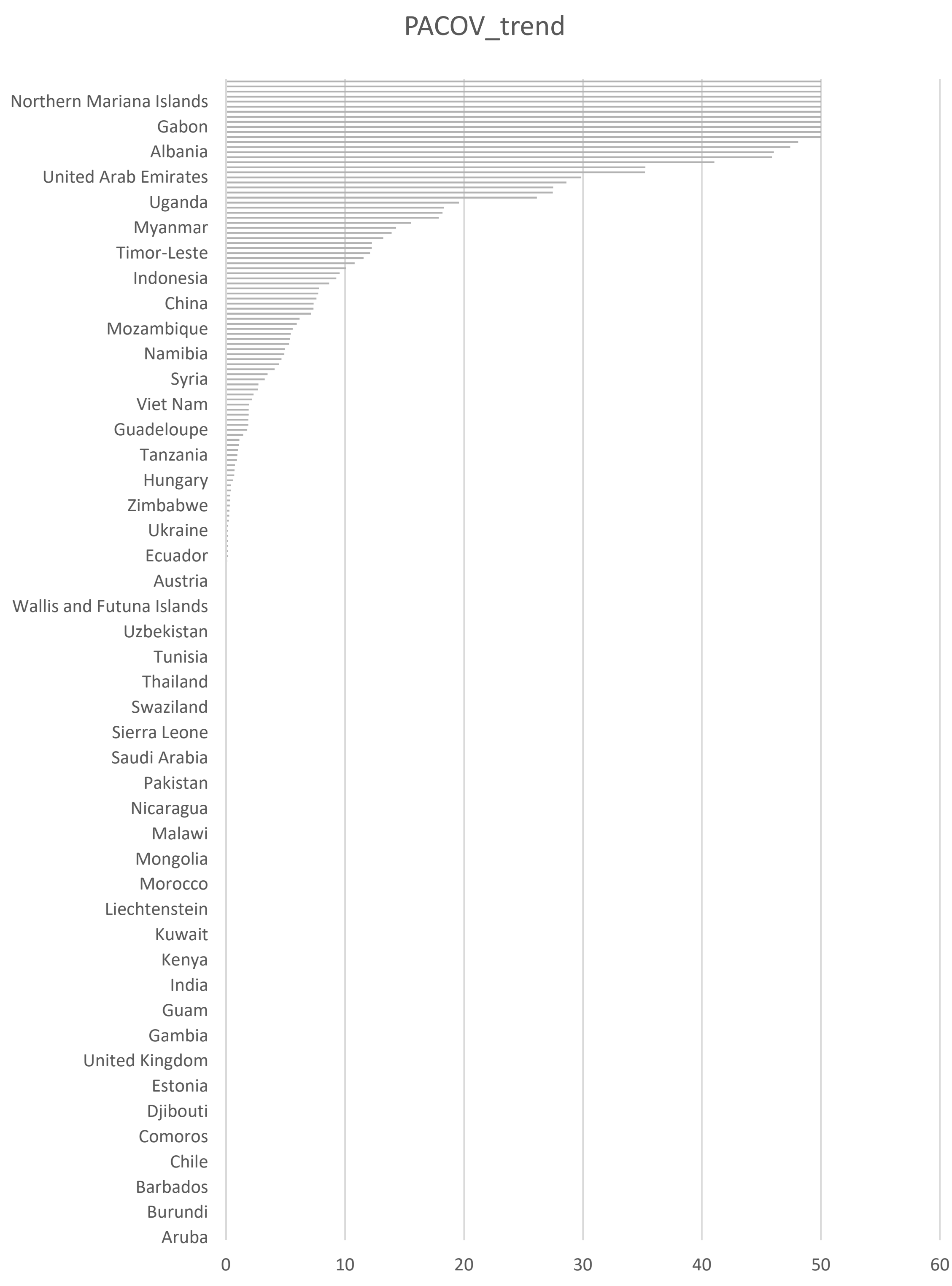
Human activities impacts the world's terrestrial, freshwater and marine ecosystem significantly throughout history and has intensified over the last 50 years (Emerson, 2012). Biome protection (PACOV) indicator is used as a demonstration from this category. PACOV measures the degree to which a country achieves the target of protecting at least 17% of each terrestrial biome within its borders and represents a weighted average of protection by biome (Emerson, 2012). The target and low performance benchmark for this indicator is shown in the table below:

-

Indicators	Target	Low performance benchmark	Statistical transformation	Transformed targets	Transformed low performance benchmark
Biome protection	17% weighted average of biomes protected	0	none		

EPI framework for Biome Protection (PACOV) Indicator

The slopes of the trends of the proximity to target of 230 nations for Biome Protection are shown in the Figure below. The table below also shows nations with an increasing trend in achieving the target of biome protection or still at the low performance benchmark.



Trend scores for a selected number of nations in PACOV Indicator

Countries with most improvement	Trend Score
Gabon	50
Greece	50
French Guiana	50
Iceland	50
Italy	50
Northern Mariana Islands	50
New Caledonia	50
Peru	50
Réunion	50
Slovenia	50

Trend scores for a selected number of nations in PACOV Indicator

129 nations show no change in their percentage of biomes under protected status over the years, while 101 nations show a progressive trend in their percentage of biomes under protected status with some nations meeting the target as seen above.

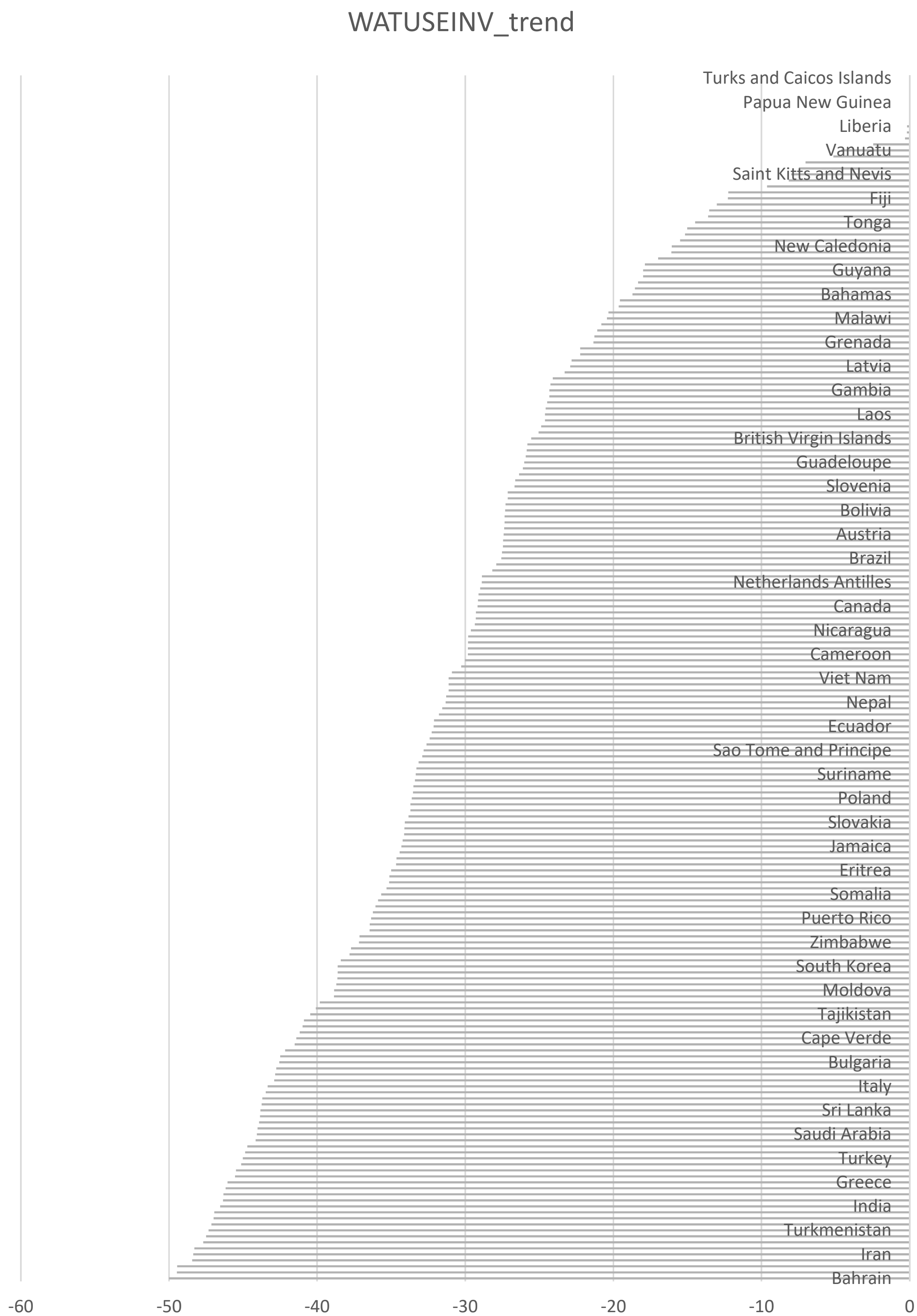
Application to Water policy category: (Effects on ecosystem)

Factors such as air pollution, climate change, economic development have grossly increased the pressures on global freshwater resources. Change in water quantity (WATUSE) is the only indictor in this category. It represents the area-weighted percent change in river flow from a pre-industrial natural state owing to water withdrawals and reservoirs. The target and low performance benchmark for this indicator is shown in the table below:

Indicators	Target	Low performance benchmark	Statistical transformation	Transformed targets	Transformed low performance benchmark
Change in water quantity	0% reduction	-44.38	inverse, natural logarithm	-7.41	3.79

EPI framework for Change in Water Quantity (WATUSE) Indicator

The slopes of the trends of the proximity to target of 201 nations for the Change in water quantity (natural river flows) owing to water withdrawals and reservoirs are shown in the figure below. The table below also shows nations with a decreasing trend in the change in annual water quantity 1towards achieving this indicator target or still at the low performance benchmark.



Trend scores for a selected number of nations in WATUSE Indicator

Countries with worst trends	Trend Score
Bahrain	-50.0
Cyprus	-49.5
Armenia	-49.5
Afghanistan	-48.4
Iran	-48.4
Lebanon	-48.3
Israel	-47.7
Azerbaijan	-47.5
Turkmenistan	-47.3
Spain	-47.1

Trend scores for a selected number of nations in WATUSE Indicator

193 nations show a decreasing trend in the change annual river quantity further away from the target while 8 nations show no change in their change in annual water quantity.

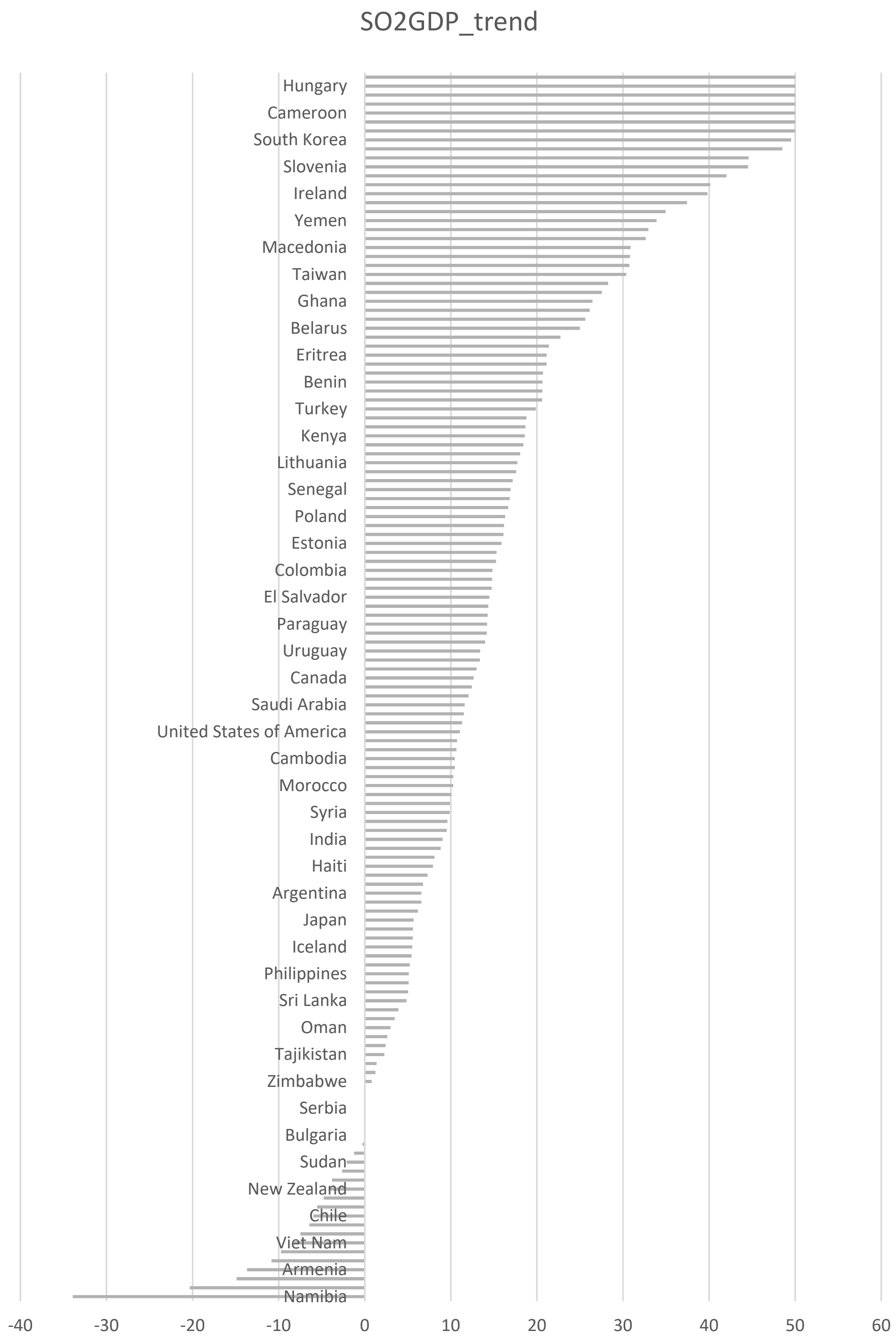
Application to Air pollution policy category (Effects on ecosystems)

Air pollution negatively impacts plant growth, contributes to acid rain which is detrimental to ecosystems. $S0_2$ emissions per GDP (SO2GDP) indicator is used as a demonstration from this category. It is the ratio of SO_2 emissions to GDP in 2005 constant international prices PPP. The target and low performance benchmark for this indicator is shown in the table below:

Indicators	Target	Low performance benchmark	Statistical transformation	Transformed targets	Transformed low performance benchmark
Sulfur dioxide emissions per GDP	0 grammes SO2 per US 2005 $s PPP	11.38625	natural logarithm	-2.59	2.44

EPI framework for Sulfur dioxide emissions (SO2GDP) Indicator

The slopes of the trends of the proximity to target of 137 nations for SO2GDP are shown below in the figure below. The table below also shows nations with a decreasing trend in Sulfur dioxide emissions and nations with an increasing trend in SO_2 emissions towards achieving this indicator target or still at the low performance benchmark.



Trend scores for a selected number of nations in SO2GDP Indicator

Countries with the most improved trends	Trend score	Countries with the most declining trends	Trend score
Algeria	44.6	Namibia	-33.9
Latvia	48.5	Malaysia	-20.3
South Korea	49.5	Brunei Darussalam	-14.9
Angola	50.0	Armenia	-13.7
Côte d'Ivoire	50.0	Mozambique	-10.8
Cameroon	50.0	Iraq	-9.7
Congo	50.0	Viet Nam	-8.2
Gabon	50.0	Indonesia	-7.5
Hungary	50.0	Myanmar	-6.4
Nigeria	50.0	Chile	-6.0

Trend scores for a selected number of nations in SO2GDP Indicator

18 nations showed a decreasing trend in SO2GDP emissions, 5 nations show no change over this period and 114 nations showed a positive trend in SO2GDP emissions with some nations meeting the target.

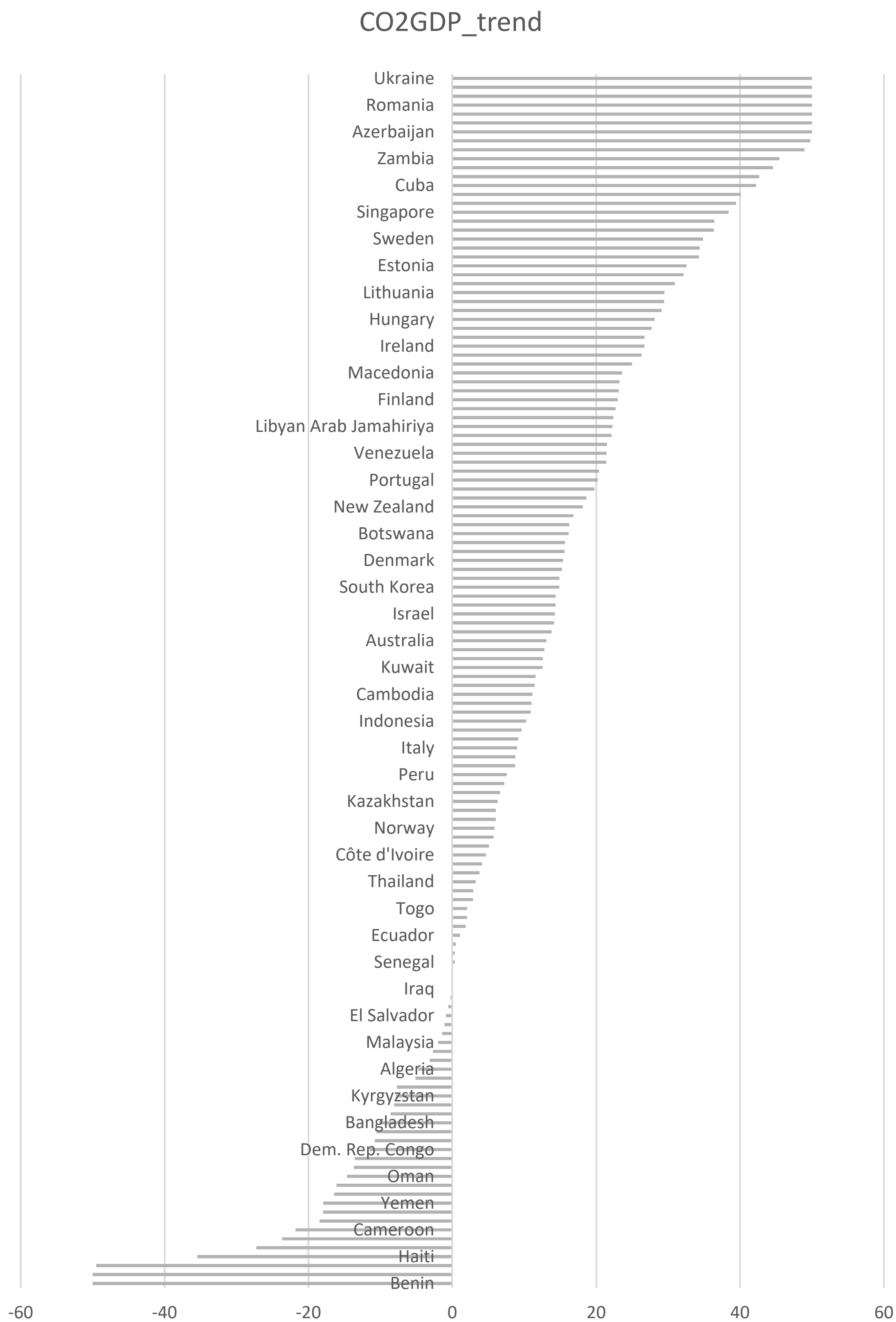
Application to Climate change policy category (CO_2 per GDP)

Impacts of climate change such as sea level rise, coastal flooding, droughts, desertification etc., are being felt globally. CO_2 emissions per GDP (CO2GDP) ratio was obtained using the Sectoral Approach CO_2 emissions and the GDP using purchasing power parities data from the IEA. The target and low performance benchmark for this indicator is shown in the table below. The target is an estimated value associated with 50% reduction in global GHG emissions by 2050, against 1990 levels.

Indicators	**Target**	**Low performance benchmark**	**Statistical transformation**	**Transformed targets**	**Transformed low performance benchmark**
CO2 per GDP	0.078 kg CO_2 eq.	1.533	natural logarithm	-2.04	0.46

EPI framework for $C0_2$ emissions per GDP (CO2GDP) Indicator

The slopes of the trends of the proximity to target of 136 nations for CO2GDP emissions are shown below in the figure below. The table below also shows nations with a decreasing trend in CO2GDP emissions and nations with an increasing trend in Carbon dioxide emissions towards achieving this indicator target or still at the low performance benchmark.



Trend scores for a selected number of nations in CO2GDP Indicator

Countries with most improvement	Trend Score	Countries with most improvement	Trend score
Benin	-50.0	Zambia	45.5
Congo	-50.0	Albania	49.0
Brunei Darussalam	-49.5	Nigeria	49.8
Haiti	-35.5	Azerbaijan	50.0
Tanzania	-27.2	Belarus	50.0
Viet Nam	-23.7	Moldova	50.0
Cameroon	-21.8	Romania	50.0
Bolivia	-18.5	Slovakia	50.0
Saudi Arabia	-18.8	Turkmenistan	50.0
Yemen	-17.9	Ukraine	50.0

Trend scores for a selected number of nations in CO2GDP Indicator

33 nations show a declining trend in CO2GDP emissions away from the target, 2 nations show no change over this period and 101 nations show a much positive trend in CO2GDP emissions.

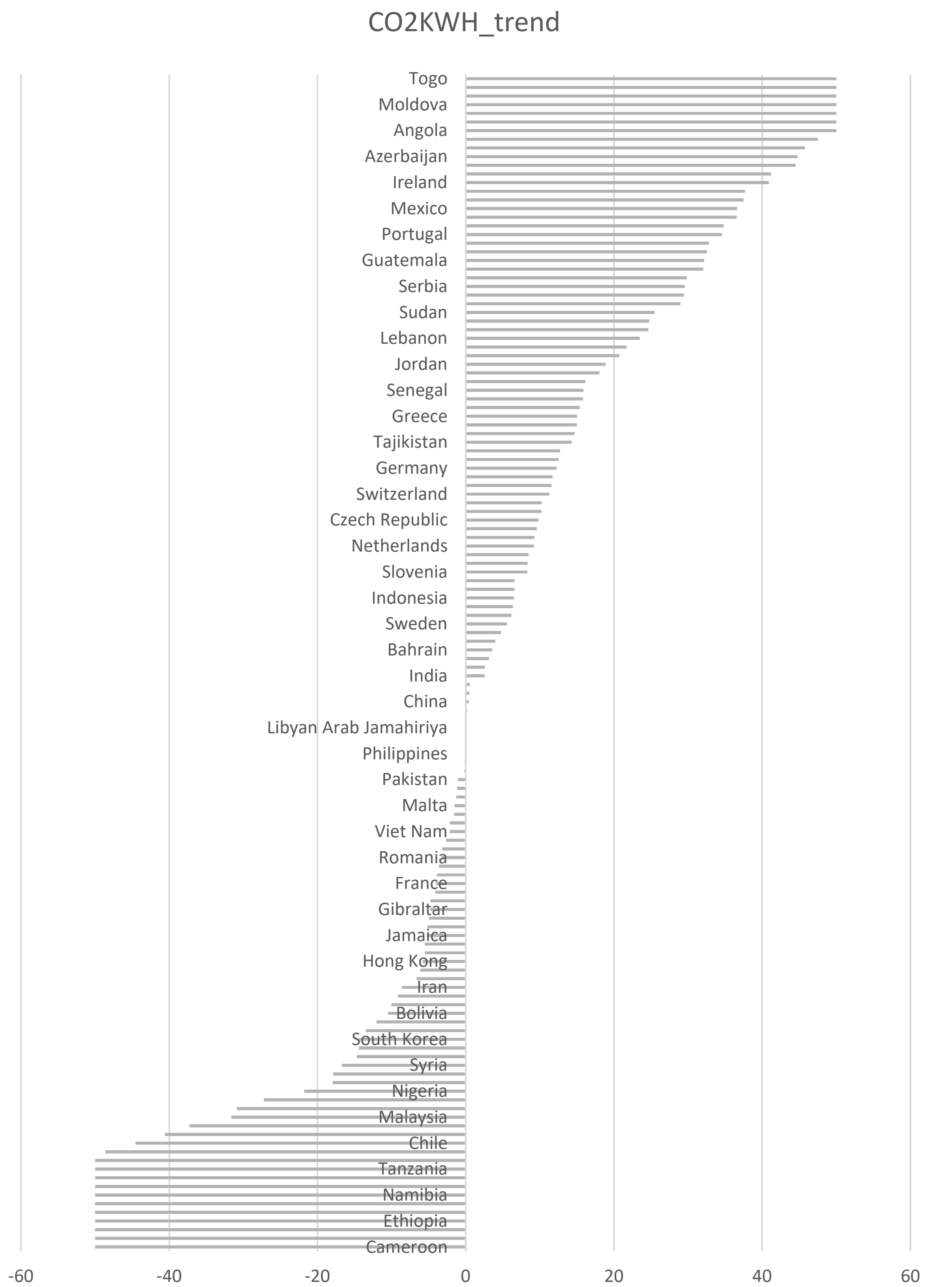
Application to Climate change policy category (CO2 per energy use)

This is CO_2 emissions per kilowatt hour (CO2KWH) that represents the ratio of CO_2 emissions to the electricity generated by thermal power plants, nuclear and hydro production and geothermal. The target and low performance benchmark for this indicator is shown below in the table below:

Indicators	Target	Low performance benchmark	Statistical transformation	Transformed targets	Transformed low performance benchmark
CO2 emissions per electricity generation	0 grammes CO2 per KWh	845.3289722	natural logarithm	-0.69	6.74

EPI framework for $C0_2$ emissions per kilowatt hour (CO2KWH) Indicator

The slopes of the trends of the proximity to target of 136 nations for the CO2KWH are shown below in the figure below. The table below also shows nations with a decreasing trend in emissions of CO2KWH and nations with an increasing trend in emissions of CO2KWH towards achieving this indicator target or still at the low performance benchmark.



Trend score for a selected number of nations in CO2KWH Indicator

Countries with decreasing trend in CO2/KWH emissions	Trend score	Countries with increasing trend in CO2/KWH Emissions	Trend score
Azerbaijan	44.8	Ghana	-50.0
Qatar	45.9	Luxembourg	-50.0
Singapore	47.5	Namibia	-50.0
Angola	50.0	Norway	-50.0
Albania	50.0	Peru	-50.0
Armenia	50.0	Tanzania	-50.0
Moldova	50.0	Uruguay	-50.0
Myanmar	50.0	Haiti	-48.6
Mozambique	50.0	Chile	-44.5
Togo	50.0	Dem. Rep. Congo	-40.6

Trend scores for a selected number of nations in CO2KWH Indicator

58 countries show an increasing trend in CO2KWH emissions with majority of these countries being in the emerging and developing countries categories. This is as a result of the expansion of their economies especially in the manufacturing, oil and gas sector etc. 4 countries show no change within this period. 74 nations show a decreasing trend in CO2KWH emissions with many of these nations coming from both developed and developing nations. Developed nations with initial high emissions are enforcing policy regulations and other strategies to curb the level of already high emissions.

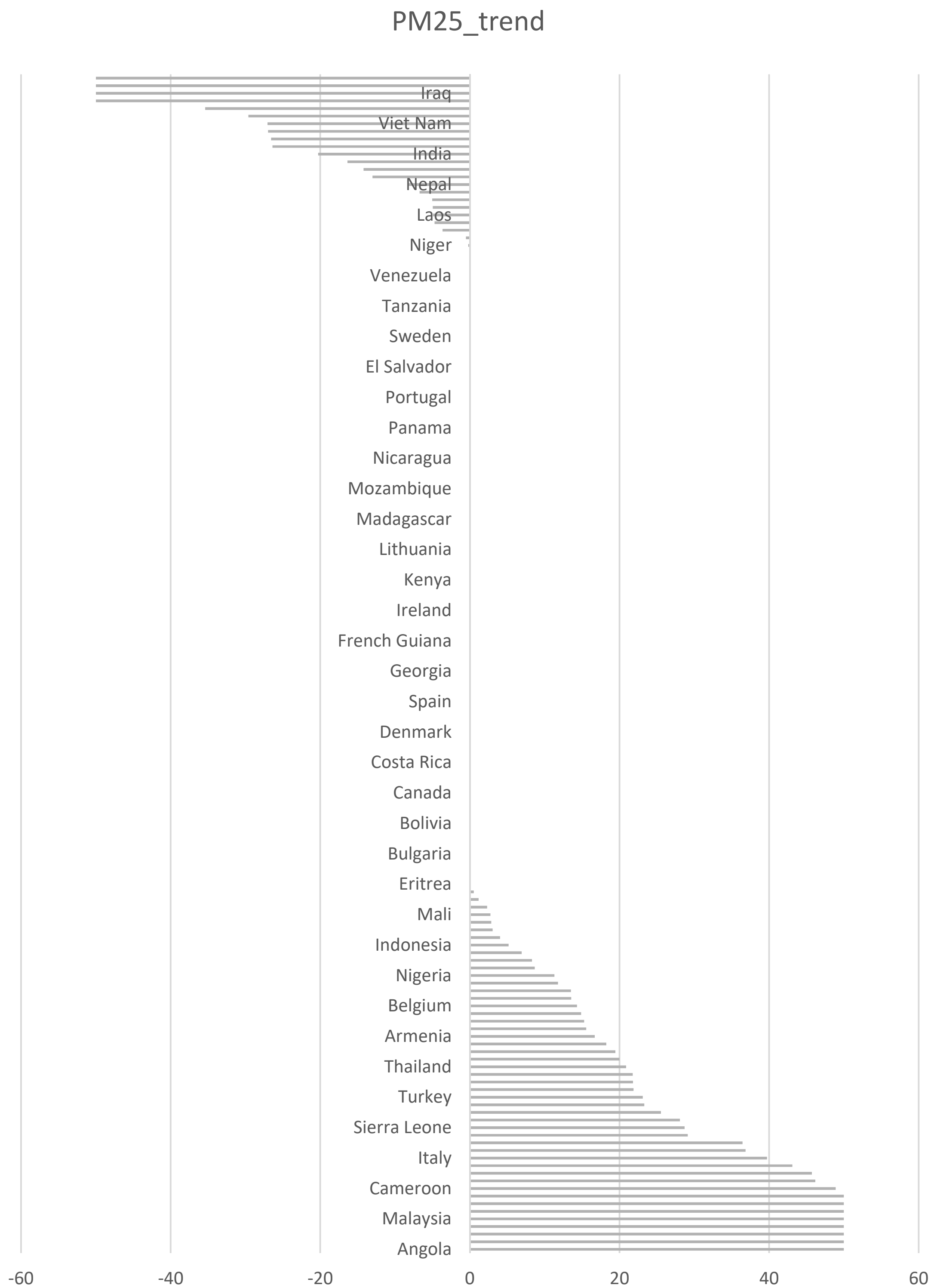
Application to Air pollution policy category (Effects on Human Health)

Air pollutions is a high leading environmental factor that causes infections which leads to high levels of premature death yearly (Emerson, 2012). Particulate matter (PM25) indicator which is an outdoor air pollution is used as a demonstration from this category. They are suspended particulates derived from a model by MODIS Aerosol Optical Depth (AOD) data. The target and low performance benchmark for this indicator is shown in the table below:

Indicator	**Target**	**Low performance benchmark**	**Statistical transformation**	**Transformed targets**	**Transformed low performance benchmark**
Particulate matter	10 ug/m3	48.7916	natural logarithm	2.34	3.89

EPI framework for Particulate Matter (PM25) Indicator

The slopes of the trends of the proximity to target of 155 nations for the Particulate Matter are shown below in the figure below. The table below also shows nations with a decreasing trend of $PM_{2.5}$ and nations with an increasing trend in $PM_{2.5}$ towards achieving this indicator target or still at the low performance benchmark.



Trend scores for a selected number of nations in PM25 Indicator

Countries with decreasing trend in $PM_{2.5}$ concentrations	Trend score	Countries with increasing trend in $PM_{2.5}$ concentrations	Trend score
Angola	50.0	Bangladesh	-26.4
Burundi	50.0	Iran	-26.6
France	50.0	Afghanistan	-27.0
Mexico	50.0	Viet Nam	-27.1
Malaysia	50.0	Liberia	-29.6
Rwanda	50.0	Saudi Arabia	-35.4
Serbia	50.0	United Arab Emirates	-50.0
Uganda	50.0	Iraq	-50.0
Cameroon	48.9	Kuwait	-50.0
Dem. Rep. Congo	46.2	Oman	-50.0

Trend scores for a selected number of nations in PM25 Indicator

While many nations have no change in the concentration of $PM_{2.5}$. Out of the 155 nations, 49 nations have improved their air quality as measured by $PM_{2.5}$ towards the target, 82 nations have no change in $PM_{2.5}$, while 24 nations air quality deteriorated which was closer to the low performance benchmark. From the above table 21, most middle-eastern countries such as Iran, Iraq, Saudi Arabia are shown to have increased trend in concentrations of $PM_{2.5}$ due to the the desert environment in this region which will always contain significant amounts of windblown dust, mostly during dust storms. Also, expansion of the oil and gas sector and industrialization are part of the contributors.

Appendix B: Definitions of indicators for EPI policy categories

INDOOR (Indoor air pollution); This indicator measures the use of solid fuels which are used in households.

PM25 (Particulate matter); These are suspended particulates derived from a model by MODIS Aerosol Optical Depth (AOD) data which causes acute lower respiratory infections and other diseases detrimental to human health.

WATSUP (Access to drinking water); This indicator measures the percentage of a country's population that has access to an improved source of drinking water.

ACSAT (Access to sanitation); It measures the percentage of a country's population that has access to an improved source of sanitation such as connection to a public sewer, connection to septic system, pour-flush latrine, simple pit latrine, ventilated improved pit latrine.

CHMORT (Child mortality); It is described as the probability of dying between a child's first and fifths birthdays per 1000 children aged 1. This was chosen because environmental factors influence child mortality for ages 1 – 4 years old.

SO2CAP (Sulfur dioxide emissions per capita); This is the ratio of SO_2 emissions to population.

SO2GDP (Sulfur dioxide emissions per GDP); This is the ratio of SO_2 emissions to GDP in 2005 constant international prices PPP.

WATUSE (Change in water quantity); This measures the area-weighted percent reduction of mean annual river flow from natural state owing to water withdrawals and reservoirs.

PACOV (Biome Protection); This measures the weighted percentage of biomes under protected status (weight is determined by relative size of biomes within a country).

MPAEEZ (Marine protection); This measures the percentage of each country's exclusive economic zone that is under protection by a marine protected area.

AZE (Critical habitat protection); This is described as the percentage of the total biodiversity and habitat area that is within protected area.

FORLOSS (Forest loss); This measures the loss of forest area owing to deforestation from either human or natural causes.

FORCOV (Forest cover change); This measures the change in forest cover area between time periods of 2005 to 2010.

FORGROW (Growing stock change); This measures the cubic meters of wood over bark of all living trees more than X cm (vary by country) in diameter at breast height.

TCEEZ (Coastal shelf fishing pressure); This measures the catch from trawling and dredging gears divided the EEZ area by country and year.

FSOC (Fish stock overexploited); This measures the fraction of species that are fished in each country's EEZ that are exploited or collapsed.

AGSUB (Agricultural subsidies); This indicator evaluates the magnitude of subsidies to assess the degree of environmental pressure they exert.

POPs (Pesticide regulation); This indicator examines the legislative status of countries on one of the landmark agreements on POPS usage, the Stockholm Convention, and rates the degree to which these countries have kept those objectives by limiting the use of certain toxic chemicals.

CO2CAP (CO2 emissions per capita); CO_2 emissions per capita ratio was obtained using the Sectoral Approach CO_2 emissions and population data from the IEA.

CO2GDP (CO2 emissions per GDP); CO_2 emissions per GDP ratio was obtained using the Sectoral Approach CO_2 emissions and the GDP using purchasing power parities data from the IEA.

CO2KWH (CO2 emissions per electricity generation); This is carbon dioxide emissions per kilowatt hour that represents the ratio of CO_2 emissions to the electricity generated by thermal power plants, nuclear and hydro production and geothermal.

RENEW (Renewable electricity); This measures the percentage of the total renewable electricity net generation in total electricity net generation.

Appendix C: Cluster Analysis

The primary methods of modern multivariate analysis include; Cluster analysis (CA), principal components analysis (PCA), and discriminant analysis (DA). These methods focus on characterizing group differences and assigning unknowns to one of the known groups (Kettenring, 2006).

PCA is used to reduce dimensionality and visualize data in a reduced number of dimensions corresponding to the leading PCs. PCA is sometimes used as a method to find clusters directly, bypassing any of the usual CA algorithms. There is no easy and rigorous way to quickly extract clusters from complex data, hence, hundreds of different algorithms have been proposed to achieve results where each has its own benefits and problems. There is need to be cautious at all phases: the form in which the data are analyzed, the choice of algorithm and any associated parameters, and the manner in which outputs are checked for validity (Kettenring, 2006). CA is used to assess the trend of academic research within a specific discipline (Abson et al, 2014, Kajikawa et al, 2014) on the assessment of sustainability and economic development of nations (Neri et al, 2017), on assessment of environmental issues such as impacts of carbon emissions (Lamb et al, 2014), analysis for cities and planning (Chévez et al, 2017). CA is also widely used commercially. An example is in market segmentation services which involves k-means clustering and also has been described in several publications.

CA is as a three-step process that involves preprocessing of the data, invoking algorithms to assist in identification of clusters, and assessing the results. CA applications involves certain practices that are observed to stand out as beneficial and some as dangerous. Good practice involves looking at the data in different forms, considering alternative metrics and distance functions, comparing the results from different clustering algorithms, and checking the stability and validity of findings (Kettenring, 2006). Understanding of the properties of all the methods and processes involved will produce better results. The process of CA can be further explained below;

- Autoscaling; Scales of the variables can have a huge impact on the outcome of a CA due to the different nature of the variables. It is required to auto scale each of them separately. This process can obscure clusters in the data and render them undetectable in the output of a clustering algorithm. Also, simple transformations of variables, such as taking logs can be very helpful for ameliorating scaling problems. Another consideration is differential weighting to intentionally overemphasize those which are more likely to help the CA (Kettenring, 2006).

- PCA an CA; The role of PCA for reducing dimensionality and the number of variables entering the CA is surrounded with a lot of confusion. Developing viable alternatives to PCA for reducing dimensionality in CA problems will prove very useful.
- Variable Clustering; This involves clustering variables instead of the objects or observations. Variable clustering should be done such that it is not thrown off if the observations themselves are clustered.
- DA and CA; DA and CA utilize extra information, such as group labels on some of the data or constraints designed to keep certain pairs of points in the same or different clusters (Kettenring, 2006).
- Tree Cutting; Another way of obtaining a partition of data into clusters is to perform a straight line cut of the dendrogram at an appropriate level and then to treat each separate branch as a cluster. Several software's are available to perform this.
- Very Large Problems; Sampling is often a sensible strategy when observations (n) is large, especially if it can be done repeatedly, so as not to miss small clusters completely. The results can be compared across samples and integrated as appropriate.
- Validation and Interpretation; The need for solid validation and careful interpretation of CA results is clear and has been recognized by many researchers. There are a variety of approaches that can be applied like simple graphical displays, sensitivity analyses in ensuring robust results. When using an iterative procedure, such as k-means CA, experimenting with different starting points is beneficial, this enables a probability Statement about the chance that the next restart will discover a previously unobserved local maximum, and the chance that it will be better than any one previously found.
- Circularity; Circularity is used here to refer to the risk of obtaining CA results that are more due to the vagaries of the process than to the strength of the cluster Structure in the data (Kettenring, 2006).

Great methods and supporting software are available to support applications. With such approaches, one can capitalize on the added structure to make a variety of inferences about the model such as the number of clusters present and their shapes. Some of the approaches to cluster analysis can be grouped into two categories known as hierarchical methods and the non-hierarchical methods described below;

Hierarchical methods; This consists of agglomerative methods and divisive methods.

- Agglomerative methods are a type of clustering whereby the subjects start in their own separate cluster and then the most similar clusters are then combined together. This is done repeatedly until all subjects are in one cluster and an optimum number of clusters is chosen in the end (Rosie, 2007). There are several methods to determine which clusters should be joined together at each stage. Some of them include nearest neighbour method, furthest neighbour method, average linkage method, centroid method, and wards method among many others. It is usually advisable to try two or three of the methods so that the results can be confirmed and be much more believable. The tool for determining the suitable number of clusters is called a dendrogram (Řezanková, 2014).

Divisive methods involve all subjects starting in the same cluster and the two farthest clusters are then separated. This is done repeatedly until all subjects are in a separate cluster.

Appendix D: HDI Classification in 2000 and Codes

Very high development	High Development	Medium Development	Low Development
Norway	United Arab Emirates	Dominica	Guatemala
Australia	Bahrain	Cuba	Tajikistan
Switzerland	Montenegro	Sri Lanka	Morocco
United States	Kuwait	Brazil	Equatorial Guinea
Netherlands	Poland	Kazakhstan	Swaziland
Sweden	Malta	Saint Lucia	Nigeria
Belgium	Antigua and Barbuda	Fiji	Sao Tome and Principe
New Zealand	Portugal	Belarus	India
Canada	Estonia	Jamaica	Congo
United Kingdom	Bahamas	Peru	Ghana
Liechtenstein	Argentina	Belize	Comoros
Denmark	Hungary	Tonga	Timor-Leste
Germany	Slovakia	St. Vincent/ Grenadines	Bangladesh
Ireland	Chile	Mauritius	Lao Republic
Finland	Lebanon	Ukraine	Madagascar
Japan	Lithuania	Georgia	Pakistan
Iceland	Barbados	Venezuela	Kenya
Luxembourg	Croatia	Ecuador	Nepal
Israel	Uruguay	Palestine, State of	Mauritania
France	Saudi Arabia	Iran	Yemen
Austria	Grenada	Turkmenistan	Lesotho
Italy	Saint Kitts and Nevis	Albania	Haiti
Spain	Palau	Dominican Republic	Solomon Islands
Hong Kong, China	FYROM	Tunisia	Cameroon
Slovenia	Libya	Colombia	South Sudan
Czech Republic	Latvia	Turkey	Zimbabwe
Singapore	Malaysia	Thailand	Myanmar
South Korea	Panama	Samoa	Togo
Brunei	Russian Federation	Algeria	Zambia
Andorra	Trinidad and Tobago	Armenia	Papua New Guinea
Qatar	Seychelles	Azerbaijan	Cambodia
Greece	Bulgaria	Gabon	Guinea-Bissau
Cyprus	Bosnia and Herzegovina	South Africa	Eritrea
	Serbia	Paraguay	Sudan

Very high development	High Development	Medium Development	Low Development
	Romania	Philippines	Uganda
	Costa Rica	El Salvador	Benin
	Jordan	Egypt	Côte d'Ivoire
	Oman	Bolivia	Angola
	Suriname	Iraq	Tanzania
	Mexico	Guyana	Malawi
		Indonesia	Liberia
		Micronesia	Gambia
		Moldova	Senegal
		Uzbekistan	Burkina Faso
		Kyrgyzstan	Djibouti
		China	Afghanistan
		Vanuatu	Rwanda
		Syrian	Congo
		Mongolia	Guinea
		Maldives	Central African Republic
		Kiribati	Sierra Leone
		Viet Nam	Chad
		Bhutan	Mozambique
		Nicaragua	Mali
		Cabo Verde	Ethiopia
		Botswana	Burundi
		Honduras	Niger
		Namibia	

Nations for the study	Acronyms	HDI 2000
Afghanistan	AFG	L
Albania	ALB	M
Algeria	DZA	M
Andorra	AND	VH
Angola	AGO	L
Antigua and Barbuda	AIA	H
Argentina	ARG	H
Armenia	ARM	M
Aruba	ABW	VH
Australia	AUS	VH
Austria	AUT	VH
Azerbaijan	AZE	M
Bahamas	BHS	H
Bahrain	BHR	H

Bangladesh	BGD	L
Barbados	BRB	H
Belarus	BLR	M
Belgium	BEL	VH
Belize	BLZ	M
Benin	BEN	L
Bermuda	BMU	VH
Bhutan	BTN	M
Bolivia	BOL	M
Bosnia and Herzegovina	BIH	H
Botswana	BWA	M
Brazil	BRA	M
Brunei	BRN	VH
Bulgaria	BGR	H
Burkina Faso	BFA	L
Burundi	BDI	L
Cambodia	KHM	L
Cameroon	CMR	L
Canada	CAN	VH
Cape Verde	CPV	M
Cayman Islands	CYM	VH
Central African Republic	CAF	L
Chad	TCD	L
Chile	CHL	H
China	CHN	M
Colombia	COL	M
Comoros	COM	L
Congo, Dem. Rep.	COD	L
Costa Rica	CRI	H
Cote d'Ivoire	CIV	L
Croatia	HRV	H
Cuba	CUB	M
Cyprus	CYP	VH
Czech Republic	CZE	VH

Denmark	DNK	VH
Djibouti	DJI	L
Dominica	DMA	M
Dominican Republic	DOM	M
Ecuador	ECU	M
Egypt	EGY	M
El Salvador	SLV	M
Equatorial Guinea	GNQ	L
Eritrea	ERI	L
Estonia	EST	H
Ethiopia	ETH	L
Fiji	FJI	M
Finland	FIN	VH
France	FRA	VH
Gabon	GAB	M
Gambia	GMB	L
Georgia	GEO	M
Germany	DEU	VH
Ghana	GHA	L
Greece	GRC	VH
Greenland	GRL	VH
Grenada	GRD	H
Guatemala	GTM	L
Guinea	GIN	L
Guinea-Bissau	GNB	L
Guyana	GUY	M
Haiti	HTI	L
Honduras	HND	M
Hong Kong, China	HKG	VH
Hungary	HUN	H
Iceland	ISL	VH
India	IND	L
Indonesia	IDN	M
Iran	IRN	M

Iraq	IRQ	M
Ireland	IRL	VH
Israel	ISR	VH
Italy	ITA	VH
Jamaica	JAM	M
Japan	JPN	VH
Jordan	JOR	H
Kazakhstan	KAZ	M
Kenya	KEN	L
Kiribati	KIR	M
Kuwait	KWT	H
Kyrgyz Republic	KGZ	M
Lao	LAO	L
Latvia	LVA	H
Lebanon	LBN	H
Lesotho	LSO	L
Liberia	LBR	L
Libya	LBY	H
Lithuania	LTU	H
Luxembourg	LUX	VH
Macao, China	MAC	VH
Macedonia, FYR	MKD	H
Madagascar	MDG	L
Malawi	MWI	L
Malaysia	MYS	H
Maldives	MDV	M
Mali	MLI	L
Malta	MLT	H
Marshall Islands	MHL	H
Mauritania	MRT	L
Mauritius	MUS	M
Mexico	MEX	H
Micronesia, Fed. Sts.	FSM	M
Moldova	MDA	M

Monaco	MCO	VH
Mongolia	MNG	M
Montenegro	MNE	H
Morocco	MAR	L
Mozambique	MOZ	L
Myanmar	MMR	L
Namibia	NAM	M
Nauru	NRU	H
Nepal	NPL	L
Netherlands	NLD	VH
New Zealand	NZL	VH
Nicaragua	NIC	M
Niger	NER	L
Nigeria	NGA	L
North Korea	PRK	VH
Norway	NOR	VH
Oman	OMN	H
Pakistan	PAK	L
Palau	PLW	H
Panama	PAN	H
Papua New Guinea	PNG	L
Paraguay	PRY	M
Peru	PER	M
Philippines	PHL	M
Poland	POL	H
Portugal	PRT	H
Puerto Rico	PRI	VH
Qatar	QAT	VH
Romania	ROU	H
Russia	RUS	H
Rwanda	RWA	L
Samoa	WSM	M
San Marino	SMR	VH
Sao Tome and Principe	STP	L

Saudi Arabia	SAU	H
Senegal	SEN	L
Serbia	SRB	H
Seychelles	SYC	H
Sierra Leone	SLE	L
Singapore	SGP	VH
Slovak Republic	SVK	H
Slovenia	SVN	VH
Solomon Islands	SLB	L
Somalia	SOM	L
South Africa	ZAF	M
South Korea	KOR	VH
Spain	ESP	VH
Sri Lanka	LKA	M
Sudan	SDN	L
Suriname	SUR	H
Swaziland	SWZ	L
Sweden	SWE	VH
Switzerland	CHE	VH
Syria	SYR	M
Taiwan	TWN	VH
Tajikistan	TJK	L
Tanzania	TZA	L
Thailand	THA	M
Timor-Leste	TLS	L
Togo	TGO	L
Tonga	TON	M
Trinidad and Tobago	TTO	H
Tunisia	TUN	M
Turkey	TUR	M
Turkmenistan	TKM	M
Turks and Caicos Islands	TCA	VH
Tuvalu	TUV	M
Uganda	UGA	L

Ukraine	UKR	M
United Arab Emirates	ARE	H
United Kingdom	GBR	VH
United States	USA	VH
Uruguay	URY	H
Uzbekistan	UZB	M
Vanuatu	VUT	M
Venezuela	VEN	M
Vietnam	VNM	M
Yemen	YEM	L
Zambia	ZMB	L
Zimbabwe	ZWE	L

Appendix E: Logistic results

Eviews

Dependent Variable: PROB_1 childmortality
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 04/17/18 Time: 12:57
Sample: 1 196
Included observations: 149
Convergence achieved after 4 iterations
Coefficient covariance computed using observed Hessian
GLM adjusted covariance (variance factor =0.988453669828)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.340819	1.802563	1.298606	0.1941
LNGDP	-0.753160	0.325281	-2.315410	0.0206
HDI_2000	0.004087	0.024771	0.164993	0.8689
AV_INV	0.160248	0.038123	4.203474	0.0000
FGE_CHANGE	1.058351	0.732913	1.444033	0.1487
PS_CHANGE	0.822252	0.377028	2.180878	0.0292
HEALTH_CH	0.061322	0.057206	1.071940	0.2837

McFadden R-squared	0.248979	Mean dependent var	0.436242
S.D. dependent var	0.497591	S.E. of regression	0.422438
Akaike info criterion	1.122850	Sum squared resid	25.34049
Schwarz criterion	1.263975	Log likelihood	-76.65234
Hannan-Quinn criter.	1.180187	Deviance	153.3047
Restr. deviance	204.1284	Restr. log likelihood	-102.0642
LR statistic	50.82376	Avg. log likelihood	-0.514445
Prob(LR statistic)	0.000000		

Obs with Dep=0	84	Total obs	149
Obs with Dep=1	65		

Dependent Variable: PROB_1 air(human health)
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 04/17/18 Time: 13:00
Sample: 1 196
Included observations: 150
Convergence achieved after 4 iterations
Coefficient covariance computed using observed Hessian
GLM adjusted covariance (variance factor =1.00572933837)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.787797	1.559912	0.505027	0.6135
LNGDP	-0.303108	0.282462	-1.073093	0.2832
HDI_2000	0.008498	0.021720	0.391246	0.6956
AV_INV	0.027166	0.025701	1.057034	0.2905
FGE_CHANGE	0.130019	0.659414	0.197173	0.8437
PS_CHANGE	0.670090	0.347106	1.930507	0.0535
HEALTH_CH	0.017611	0.052394	0.336127	0.7368

McFadden R-squared	0.051425	Mean dependent var	0.333333
S.D. dependent var	0.472984	S.E. of regression	0.466497
Akaike info criterion	1.300896	Sum squared resid	31.11952
Schwarz criterion	1.441392	Log likelihood	-90.56721
Hannan-Quinn criter.	1.357975	Deviance	181.1344
Restr. deviance	190.9543	Restr. log likelihood	-95.47713
LR statistic	9.819835	Avg. log likelihood	-0.603781
Prob(LR statistic)	0.132447		

Obs with Dep=0	100	Total obs	150
Obs with Dep=1	50		

Dependent Variable: PROB_1/ water(human health)
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 04/17/18 Time: 13:02
Sample: 1 196
Included observations: 147
Convergence achieved after 4 iterations
Coefficient covariance computed using observed Hessian
GLM adjusted covariance (variance factor =1.04038755889)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.921657	1.874373	2.092250	0.0364
LNGDP	-1.173327	0.369151	-3.178445	0.0015
HDI_2000	0.065647	0.027183	2.415008	0.0157
AV_INV	0.050768	0.029132	1.742662	0.0814
FGE_CHANGE	-0.328025	0.728477	-0.450288	0.6525
PS_CHANGE	-0.124211	0.379448	-0.327346	0.7434
HEALTH_CH	0.055830	0.056257	0.992416	0.3210

McFadden R-squared	0.096865	Mean dependent var	0.278912
S.D. dependent var	0.449997	S.E. of regression	0.430587
Akaike info criterion	1.164410	Sum squared resid	25.95674
Schwarz criterion	1.306812	Log likelihood	-78.58415
Hannan-Quinn criter.	1.222270	Deviance	157.1683
Restr. deviance	174.0252	Restr. log likelihood	-87.01259
LR statistic	16.85688	Avg. log likelihood	-0.534586
Prob(LR statistic)	0.009824		

Obs with Dep=0	106	Total obs	147
Obs with Dep=1	41		

Dependent Variable:

PROB EV –BH GDP > 2, EV => 0

Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)

Date: 04/18/18 Time: 13:02

Sample: 1 196

Included observations: 151

Convergence achieved after 4 iterations

Coefficient covariance computed using observed Hessian

GLM adjusted covariance (variance factor =0.977306368645)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.531828	1.840797	2.461883	0.0138
LN_GDP	-1.452538	0.366990	-3.957977	0.0001
EVBH_2000	-0.001954	0.007389	-0.264475	0.7914
HDI_2000	0.098468	0.027433	3.589385	0.0003
FGE_CHANGE	0.869390	0.722834	1.202753	0.2291
PS_CHANGE	0.707928	0.389059	1.819589	0.0688
AV_INV	0.062258	0.028554	2.180380	0.0292

McFadden R-squared	0.182410	Mean dependent var	0.344371
S.D. dependent var	0.476744	S.E. of regression	0.430141
Akaike info criterion	1.145595	Sum squared resid	26.64301
Schwarz criterion	1.285469	Log likelihood	-79.49240
Hannan-Quinn criter.	1.202419	Deviance	158.9848
Restr. deviance	194.4554	Restr. log likelihood	-97.22772
LR statistic	35.47064	Avg. log likelihood	-0.526440
Prob(LR statistic)	0.000003		

Obs with Dep=0	99	Total obs	151
Obs with Dep=1	52		

Dependent Variable: PROB

EV-AG GDP > 2, EV > 0

Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)

Date: 04/18/18 Time: 13:05

Sample: 1 196

Included observations: 151

Convergence achieved after 5 iterations

Coefficient covariance computed using observed Hessian

GLM adjusted covariance (variance factor =0.956023681118)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.913061	1.960877	-0.465639	0.6415
LNGDP	-0.574984	0.345914	-1.662217	0.0965
EVAG_2000	0.009060	0.008426	1.075166	0.2823
HDI_2000	0.050926	0.027508	1.851307	0.0641
FGE_CHANGE	1.642096	0.768074	2.137939	0.0325
PS_CHANGE	-0.420510	0.417978	-1.006058	0.3144
AV_INV	0.031287	0.032765	0.954890	0.3396

McFadden R-squared	0.073953	Mean dependent var	0.192053
S.D. dependent var	0.395225	S.E. of regression	0.390366
Akaike info criterion	0.998734	Sum squared resid	21.94357
Schwarz criterion	1.138608	Log likelihood	-68.40444
Hannan-Quinn criter.	1.055558	Deviance	136.8089
Restr. deviance	147.7342	Restr. log likelihood	-73.86711
LR statistic	10.92533	Avg. log likelihood	-0.453010
Prob(LR statistic)	0.090712		

Obs with Dep=0	122	Total obs	151
Obs with Dep=1	29		

Dependent Variable: PROB
EV-FORESTS GDP > 2, EV > -10
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 04/18/18 Time: 13:18
Sample: 1 196
Included observations: 148
Convergence achieved after 6 iterations
Coefficient covariance computed using observed Hessian
GLM adjusted covariance (variance factor =1.02081117144)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.399116	2.085267	-0.191398	0.8482
LNGDP	-1.188948	0.397057	-2.994400	0.0027
EVFOREST_2000	0.064288	0.015155	4.242128	0.0000
HDI_2000	0.044396	0.028271	1.570376	0.1163
FGE_CHANGE	1.121019	0.865370	1.295422	0.1952
PS_CHANGE	0.201529	0.489639	0.411587	0.6806
AV_INV	0.087209	0.033593	2.596038	0.0094

McFadden R-squared	0.297855	Mean dependent var	0.256757
S.D. dependent var	0.438327	S.E. of regression	0.364384
Akaike info criterion	0.894531	Sum squared resid	18.72138
Schwarz criterion	1.036291	Log likelihood	-59.19527
Hannan-Quinn criter.	0.952128	Deviance	118.3905
Restr. deviance	168.6126	Restr. log likelihood	-84.30630
LR statistic	50.22206	Avg. log likelihood	-0.399968
Prob(LR statistic)	0.000000		

Obs with Dep=0	110	Total obs	148
Obs with Dep=1	38		

Dependent Variable: PROB

EV_FISH

Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)

Date: 04/18/18 Time: 13:21

Sample (adjusted): 2 194

Included observations: 118 after adjustments

Convergence achieved after 5 iterations

Coefficient covariance computed using observed Hessian

GLM adjusted covariance (variance factor =1.0800807778)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-1.170811	3.080845	-0.380029	0.7039
LN_GDP	-0.422360	0.464483	-0.909311	0.3632
EVFISH_2000	-0.052511	0.025096	-2.092380	0.0364
HDI_2000	0.024691	0.036500	0.676478	0.4987
FGE_CHANGE	0.698047	1.072088	0.651110	0.5150
PS_CHANGE	1.318861	0.621928	2.120601	0.0340
AV_INV	0.150027	0.052745	2.844380	0.0044

McFadden R-squared	0.237322	Mean dependent var	0.220339
S.D. dependent var	0.416243	S.E. of regression	0.367036
Akaike info criterion	0.923020	Sum squared resid	14.95338
Schwarz criterion	1.087383	Log likelihood	-47.45821
Hannan-Quinn criter.	0.989757	Deviance	94.91641
Restr. deviance	124.4515	Restr. log likelihood	-62.22573
LR statistic	29.53504	Avg. log likelihood	-0.402188
Prob(LR statistic)	0.000048		

Obs with Dep=0	92	Total obs	118
Obs with Dep=1	26		

Dependent Variable: PROB

EV-WATER

Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)

Date: 04/18/18 Time: 13:23

Sample: 1 196

Included observations: 150

Convergence achieved after 8 iterations

Coefficient covariance computed using observed Hessian

GLM adjusted covariance (variance factor =0.574778886279)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-6.467667	3.018477	-2.142692	0.0321
LN_GDP	-0.397214	0.478357	-0.830371	0.4063
EVWATER_2000	0.060461	0.015416	3.921972	0.0001
HDI_2000	0.023228	0.039105	0.593992	0.5525
FGE_CHANGE	-0.825834	1.301628	-0.634463	0.5258
PS_CHANGE	1.771936	0.681703	2.599278	0.0093
AV_INV	0.115888	0.061837	1.874089	0.0609

McFadden R-squared	0.352738	Mean dependent var	0.073333
S.D. dependent var	0.261556	S.E. of regression	0.227248
Akaike info criterion	0.432728	Sum squared resid	7.384738
Schwarz criterion	0.573224	Log likelihood	-25.45461
Hannan-Quinn criter.	0.489807	Deviance	50.90922
Restr. deviance	78.65314	Restr. log likelihood	-39.32657
LR statistic	27.74392	Avg. log likelihood	-0.169697
Prob(LR statistic)	0.000105		

Obs with Dep=0	139	Total obs	150
Obs with Dep=1	11		

Dependent Variable: PROB
EV-CC
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)
Date: 04/18/18 Time: 13:26
Sample (adjusted): 2 196
Included observations: 122 after adjustments
Convergence achieved after 5 iterations
Coefficient covariance computed using observed Hessian
GLM adjusted covariance (variance factor =1.19748332424)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	5.847042	3.889508	1.503286	0.1328
LN_GDP	-1.195622	0.483680	-2.471925	0.0134
EVCLIMAT_2000	-0.016323	0.016068	-1.015872	0.3097
HDI_2000	0.058848	0.035448	1.660142	0.0969
FGE_CHANGE	-0.643627	1.029973	-0.624897	0.5320
PS_CHANGE	1.666996	0.581733	2.865569	0.0042
AV_INV	0.034680	0.044262	0.783513	0.4333

McFadden R-squared	0.187168	Mean dependent var	0.278689
S.D. dependent var	0.450203	S.E. of regression	0.404607
Akaike info criterion	1.076676	Sum squared resid	18.82629
Schwarz criterion	1.237562	Log likelihood	-58.67724
Hannan-Quinn criter.	1.142023	Deviance	117.3545
Restr. deviance	144.3773	Restr. log likelihood	-72.18867
LR statistic	27.02287	Avg. log likelihood	-0.480961
Prob(LR statistic)	0.000143		

Obs with Dep=0	88	Total obs	122
Obs with Dep=1	34		

Dependent Variable: PROB

EV-AIR

Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)

Date: 04/18/18 Time: 13:28

Sample (adjusted): 2 196

Included observations: 121 after adjustments

Convergence achieved after 4 iterations

Coefficient covariance computed using observed Hessian

GLM adjusted covariance (variance factor =0.986970164726)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.416574	2.209127	1.999239	0.0456
LN_GDP	-0.729646	0.323745	-2.253767	0.0242
EVAIR_2000	-0.020913	0.012033	-1.738028	0.0822
HDI_2000	0.031771	0.025785	1.232126	0.2179
FGE_CHANGE	1.554651	0.774462	2.007395	0.0447
PS_CHANGE	0.194003	0.401154	0.483612	0.6287
AV_INV	0.015752	0.033853	0.465291	0.6417

McFadden R-squared	0.107192	Mean dependent var	0.388430
S.D. dependent var	0.489420	S.E. of regression	0.467592
Akaike info criterion	1.308566	Sum squared resid	24.92526
Schwarz criterion	1.470306	Log likelihood	-72.16823
Hannan-Quinn criter.	1.374255	Deviance	144.3365
Restr. deviance	161.6658	Restr. log likelihood	-80.83290
LR statistic	17.32934	Avg. log likelihood	-0.596432
Prob (LR statistic)	0.008146		

Obs with Dep=0	74	Total obs	121
Obs with Dep=1	47		