AN EVALUATION WITH WINDOW ANALYSIS TO DETERMINE THE ENVIRONMENTAL EFFICIENCIES OF THE COUNTRIES THAT POLLUTE THE WORLD

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Abstract

As it is known, The Kyoto Protocol is an international agreement aims to reduce global warming and man-made greenhouse gas emissions. Approximately 160 countries entered into framework of the Kyoto Protocol and our world is polluted by about 50 countries mostly. The purpose of this study is to investigate values and the trends of performances of environmental/greenhouse gas emissions of these 50 most polluted countries in period of 2005-2015. At the same time, it is examined that the trend of the performance of Turkey in the concerned years. Window Analysis (WA) is a DEA and operational research (OR) based technique. DEA captures a moment photograph, each application is a cross-sectional analysis of data. In some applications, observations for DMUs are available over multiple time periods, so to perform an analysis where interest focuses on changes over time is important. WA gives us trend of changes of performance over time, and also details of the stability of performance.

Keywords: Data envelopment analysis, window analysis, nations, greenhouse gas emissions, performance
JEL Classification: C6,Q3,Q4

DÜNYAYI KİRLETEN ÜLKELERİN ÇEVRESEL ETKİNLİKLERİNİ BELİRLEMEK İÇİN PENCERE ANALİZİ İLE BİR DEĞERLENDİRME

Öz

Bilindiği gibi, Kyoto Protokolü küresel ısınmayı ve insan yapımı sera gazı salımını azaltmayı amaçlayan uluslararası bir anlaşmadır. Kyoto Protokolü çerçevesine yaklaşık 160 ülke girmektedir ve dünya çoğunlukla 50 ülke tarafından kirletilmektedir. Bu çalışmanın amacı, 2005-2015 döneminde ençok kirleten 50 ülkenin çevre ve sera gazı emisyonlarının değerlerini ve eğilimlerini araştırmaktır. Aynı zamanda Türkiye'nin bu zaman dilimindeki performans eğilimini ve kararlılığını incelemektir. Window Analizi bir tür Veri Zarflama Analizi'dir ve yöneylem araştırması tabanlı bir tekniktir. Veri Zarflama Analizinde veriler kesitsel olarak analiz edilirler. Bazı uygulamalarda ise karar verme birimleri için gözlemler çoklu zaman dilimlerinde mevcuttur. Bu nedenle farklı zaman içindeki değişimlere odaklı bir analiz yapmak önemlidir. Window analizi zaman içindeki performans değişimlerinin eğilimini ve performans kararlığının detaylarını sunmaktadır.

Anahtar Kelimeler: Veri zarflama analizi, window analizi, sera gazı emisyonu, performans
JEL Sınıflandırması: C6,Q3,Q4

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1. Introduction

Recently, global warming and climate change have emerged as two main issues in the scientific and political agenda. It is widely accepted that these environmental problems represent a serious threat for the life conditions of hundreds of million people. The risk of climate change due to emissions of greenhouse gas (GHG) from fossil fuels is considered to be the main environmental threat (Demirbas, 2003). The accelerating use of fossil fuels since the industrial revolution and rapid destruction of forests have led to a significant increase in the anthropogenic GHGs (Tunc et al., 2007). The Kyoto Protocol can be cited as the most important agreement which seeks to limit the countries' emissions within a time horizon (Tunc et al., 2007). The Kyoto marks an important turning point in efforts to promote the use of renewable energy as a key strategy for reducing GHG emissions worldwide. Turkey has signed the Kyoto Protocol on February 17th, 2009. To reach the level envisaged in the protocol, the status of GHG emissions should be reviewed and strategic plans must be made within the context of the compliance with protocol. Turkey is obliged to fulfill the liabilities of GHG emissions as a candidate country of the European Union (EU)(Sözen and Alp, 2009).

Environmental efficiency assessment is one of the most important ways to quantitatively evaluate the performance of and interaction between economy and environment. Many efficiency analysis techniques have been proposed to calculate Environmental Efficiency (EE). Based on the production possibility frontier theory, these methods can be mainly divided into two types: parametric and nonparametric. The representatives of the parametric and nonparametric methods are stochastic frontier analysis (SFA) (Aigner et al., 1977; Meeusen and Broeck, 1977) and data envelopment analysis (DEA) (Charnes et al., 1978), respectively. SFA employed regression analysis to estimate the relationship between inputs and outputs. The efficiency of peer decision making units (DMUs) is decomposed into two parts: a stochastic error term and a systematic inefficiency term. In contrast to SFA, DEA method does not need to specify the functional relations between inputs and outputs. DEA is a nonparametric approach for measuring the relative efficiency of DMUs that have multiple inputs and outputs. Compared with SFA, DEA is easier to use in various circumstances with multiple variables (Lee et all, 2014; Reinhard et all, 2000; Zofío and Prieto, 2001; Mandal and Madheswaran 2010; Agrell and Bogetoft, 2005).

Window Analysis (WA) is a DEA and operational research (OR) based technique. DEA captures a moment photograph, each application is a cross-sectional analysis of data. In some applications, observations for DMUs are available over multiple time periods, so to perform an analysis where interest focuses on changes over time is important. WA gives us trend of changes of performance over time, and also details of the stability of performance.

2. Literature Rewiev

Data envelopment analysis (DEA) has gained great popularity in energy and emissions modeling during the past decades. Most research articles studied on DEA are on the linkages among CO2 emissions, energy consumption and gross domestic product growth. (Zhou et al., 2008; Honma and Hu, 2008; Honma and Hu, 2009; Ramakrishnan, 2006; Lozano and Gutierrez, 2008).

Numerous literature have studied environmental efficiency using the DEA method. Table 1. listed some of the existing studies on environmental efficiency. The majority of them focused on the country-level or provincial-level EEs, while few of them paid much attention to the city-level EE analysis.

Table 1: **Literature Rewiev**

Researcher	Method	Study area	Input	Output
Ramakrishnan 2006	DEA	1988-2001 World	World GDP, energy consumption	CO2
Zhou et al. 2007	Non-radial DEA, Malmquist	26 OECD countries, 1995–1997	Labor	GDP, CO2, SOx, NOx, CO
Chien and Hu 2007	DEA	45 countries, 2001 and 2002	Labor, capital, energy	GDP
Lozano and Gutierrez 2008	DEA	26 Countries from World	Population and GDP	Greenhouse Gases
Honma and Hu 2008	Malmquist	47 prefectures of Japan	Real GDP, capital, energy, Oil, Gas, Coal, Coke	Total Income
Honma and Hu 2009	DEA	17 sectors in Japanese economy	Labor, capital, energy	Value added in each sector
Sözen and Alp, 2009	DEA	EU countries and Turkey	Primary energy, energy consumption by sectors	GHG, SO2, NO, CO2 and others
Halkos and Tzeremes 2013	Bootstrapped DEA	110 countries, 2007	Labor, capital	GDP, CO2
Li et al. 2013	DEA, Tobit	Beijing, 2005–2009	Labor, capital, energy	GDP, waste water, solid waste
Wang et al. 2013	DEA window analysis	29 provinces in China, 2000–2008	Labor, capital, energy	GDP, CO2, SO2
Zhou et al. 2013	Entropy SBM DEA	30 provinces in China, 2005–2010	Labor, capital, energy	Power capacity, SO2, NOx, CO2
Yang and Wang 2013	DEA	29 provinces in China, 2000–2007	Labor, capital, energy	GDP, CO2
Changet al.2013	SBM DEA	30 provinces in China, 2009	Labor, capital, energy	value-added of transportation sector, CO2
Song et al. 2013	SBM DEA, Tobit	29 provinces in China, 1998–2009	Labor, capital, energy	GDP, waste water, solid waste, waste gas
Wang et al. 2013	Non-radial DDF	28 provinces in China, 2005–2010	Labor, capital, energy	GDP, CO2
Wang et al. 2013	Meta-frontier, DEA	211 cities in China, 2008	Labor, capital, energy	GDP, SO2
Zhou et al. 2013	Weighted SBM	27 industrial sectors in China	Industry investment, employees, coal, oil, gas	industry production, solid wastes, waste gas, waste water
Song and Guan 2014	SESBM, Malmquist	Wanjiang demonstration area, 2010 and 2011	Population, capital, energy	GDP, industrial SO2
Woo et al. 2015	DEA, Malmquist	31 OECD countries, 2004–2011	Labor, capital, energy	GDP, CO2

The majority of sduies focused on the country-level or provincial-level EEs, while few of them paid much attention to the city-level EE analysis. Understanding city-level EEs can help us gain a better understanding of regional imbalance, which is beneficial for making decisions towards regional development strategy, especially for economic zones. There are also some researchers focusing on city-level EE assessment.

3. Data, Variables and Model

Approximately 160 countries entered into framework of the Kyoto Protocol and our world is polluted mostly by about 50 countries. The purpose of study is to investigate values and the trends of performances of environmental/greenhouse gas emissions of these 50 most polluted countries in period of 2005-2015. At the same time, it is examined that the trend of the performance of Turkey in the concerned years. Data are taken from Wold Bank statistics site.

50 countries which most polluted the World are the following: Argentina, Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Chile, China, Czech, Denmark, Egypt, Finland, France, Germany, Greece, Hungary, India, Indenosia, Iran, Ireland, Israel, Italy, Japan, Kazakhstan, Korea, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Norway, Pakistan, Peru, Philippines, Poland, Portugal, Romania, Russia, Saudi Arabia, South Africa, Spain, Sweden, Thailand, Turkey, Ukrania, UK, US, Vietnam, Venezuella.

In this study, when calculating dynamic performance changes of 50 countries the following variables that generally used in literature were selected. These are: Economic (labour and capital), environmental (freshwater) and energy inputs with a desirable output (GDP) and three undesirable outputs greenhouse gases (CO2,methane and nitrous oxide emissions etc.). The directions of undesired variables have been changed in a suitable way.

Table 2: **Summary Statistics of Variables and Model's Inputs and Outputs**

Variables	Input/Output in Model	Mean	Std. Deviation	Minimum	Maximum
Labor total	I	52763853,36	131503911,71	2184332	806498521
Freshwater	I	67,24	143,20	,65	761,00
Capital	I	19761,28	17704,22	813,70	67223,02
Energy	I	3012,82	1787,35	457,13	7247,23
CO_2	O	6423,23	969,76	99,20	6713,00
Methane	O	1726,48	274,30	99,70	1848,58
NO_2	O	641,03	97,15	99,83	685,24
GDP	O	28574,00	15591,72	5041,71	61471,57

The gases that hold the heat in the atmosphere are called the greenhouse gas. These are:

Carbon dioxide (CO2): is the primary greenhouse gas emitted through human activities. While CO2 emissions come from a variety of natural sources, human-related emissions are responsible for the increase that has occurred in the atmosphere since the industrial revolution. Carbon dioxide enters the atmosphere through burning fossil fuels (coal, natural gas, and oil) for energy and transportation, Although certain industrial processes and land-use changes also emit CO2.), Solid waste, trees and wood products, and also as a result of certain chemical reactions (e.g., manufacture of cement). Changes in CO2 emissions from fossil fuel combustion are influenced by many long-term and short-term factors, including population growth, economic growth, changing energy prices, new technologies, changing behavior, and seasonal temperatures.

And overall growth in emissions from electricity generation, and increased demand for travel and transportation.

Methane (CH4): Methane is emitted during the production and transport of coal, natural gas, and oil. Methane emissions also result from livestock and other agricultural practices and by the decay of organic waste in municipal solid waste landfills.

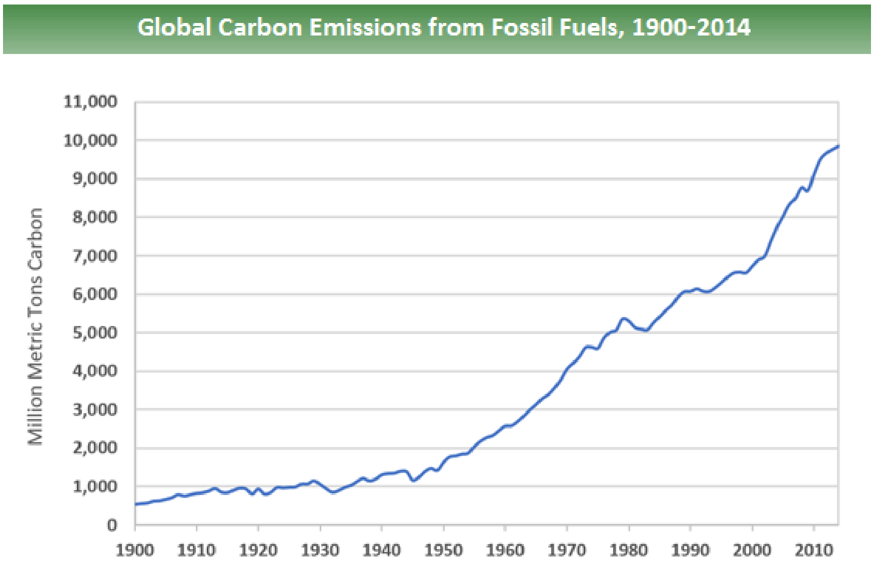
Agricultural activities, waste management, energy use, and biomass burning all contribute to CH4 emissions.

Nitrous oxide (N2O): Nitrous oxide is emitted during agricultural and industrial activities, as well as during combustion of fossil fuels and solid waste.

3.1. Trends in Global Emissions

Global carbon emissions from fossil fuels have significantly increased since 1900. Since 1970, CO2 emissions have increased by about 90%.

Graph 1: **Global Carbon Emissions from Fossil Fuels, 1900-2014**

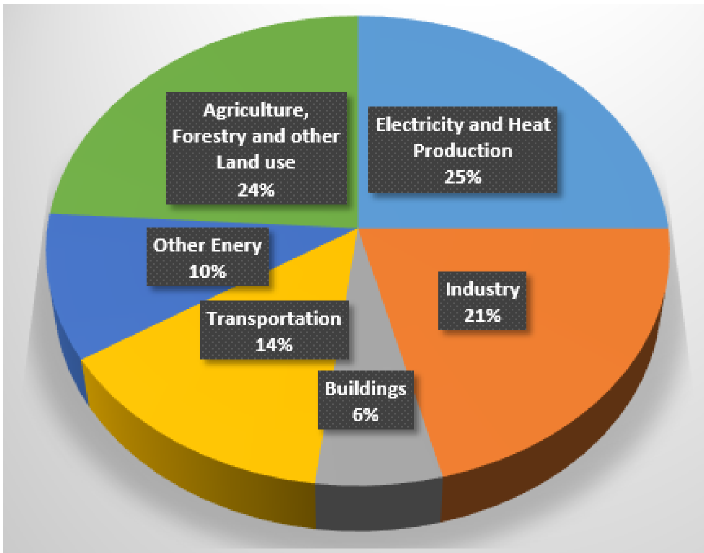


Source: Boden, T.A., Marland, G., and Andres, R.J. (2017). Global, Regional, and National Fossil-Fuel CO2Emissions. Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, Tenn., U.S.A. doi 10.3334/CDIAC/00001_V2017

3.2. Global Emissions by Economic Sector

Global greenhouse gas emissions can also be broken down by the economic activities that lead to their production.

Graph 2:**Greenhouse Gas Emissions by Sectors**



Source: IPCC (2014) Exit based on global emissions from 2010. Details about the sources included in these estimates can be found in the Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.

•Electricity and Heat Production (25% of 2010 global greenhouse gas emissions): The burning of coal, natural gas, and oil for electricity and heat is the largest single source of global greenhouse gas emissions.

•Industry (21% of 2010 global greenhouse gas emissions): Greenhouse gas emissions from industry primarily involve fossil fuels burned on site at facilities for energy. This sector also includes emissions from chemical, metallurgical, and mineral transformation processes not associated with energy consumption and emissions from waste management activities. (Note: Emissions from industrial electricity use are excluded and are instead covered in the Electricity and Heat Production sector.)

•Agriculture, Forestry, and Other Land Use (24% of 2010 global greenhouse gas emissions): Greenhouse gas emissions from this sector come mostly from agriculture(cultivation of crops and livestock) and deforestation. This estimate does not include the CO2 that ecosystems remove from the atmosphere by sequestering carbon in biomass, dead organic matter, and soils, which offset approximately 20% of emissions from this sector.

•Transportation (14% of 2010 global greenhouse gas emissions): Greenhouse gas emissions from this sector primarily involve fossil fuels burned for road, rail, air, and marine transportation. Almost all (95%) of the world's transportation energy comes from petroleum-based fuels, largely gasoline and diesel.

•Buildings (6% of 2010 global greenhouse gas emissions): Greenhouse gas emissions from this sector arise from onsite energy generation and burning fuels for heat in buildings or cooking in homes. (Note: Emissions from electricity use in buildings are excluded and are instead covered in the Electricity and Heat Production sector.)

•Other Energy (10% of 2010 global greenhouse gas emissions): This source of greenhouse gas emissions refers to all emissions from the Energy sector which are not directly associated with electricity or heat production, such as fuel extraction, refining, processing, and transportation.

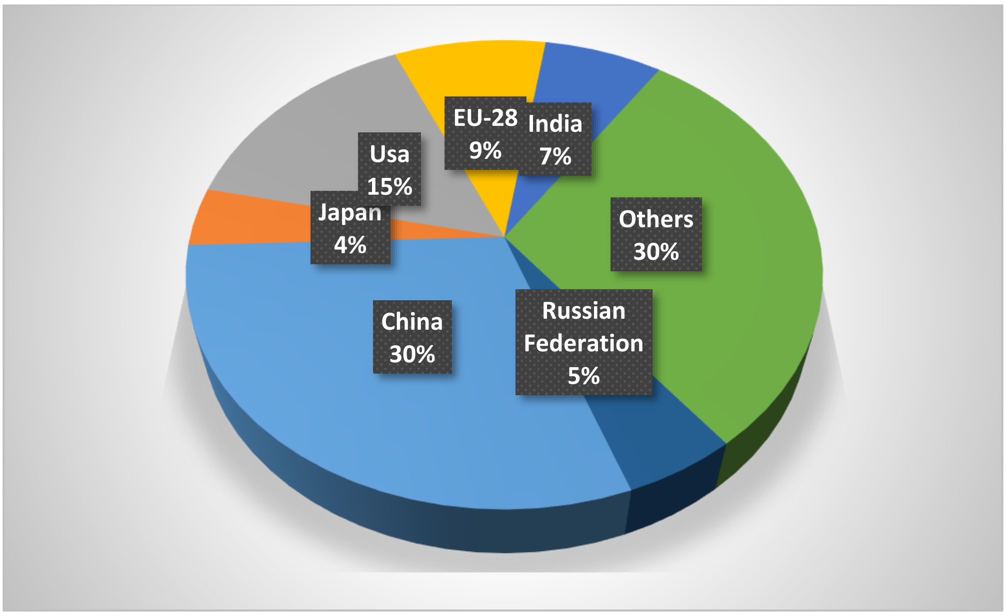
3.3. Emissions by Country

In 2014, the top carbon dioxide (CO2) emitters were China, the United States, the European Union, India, the Russian Federation, and Japan.

These data include CO2 emissions from fossil fuel combustion, as well as cement manufacturing and gas flaring. Together, these sources represent a large proportion of total global CO2 emissions.

Emissions and sinks related to changes in land use are not included in these estimates. However, changes in land use can be important: estimates indicate that net global greenhouse gas emissions from agriculture, forestry, and other land use were over 8 billion metric tons of CO2 equivalent,or about 24% of total global greenhouse gas emissions(www.epa.gov,https://www.epa.gov/ghgemissions/global-greenhouse-gas-emissions-data references 1-2-3).

Graph 3: **Emissions by Country**



Source: Boden, T.A., Marland, G., and Andres, R.J. (2017). Global, Regional, and National Fossil-Fuel CO2Emissions. Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, Tenn., U.S.A. doi 10.3334/CDIAC/00001_

4. Model

4. 1. Data Envelopment Analysis

A nonparametric technique known as Data Envelopment Analysis (DEA) , developed by Charnes, Cooper, and Rhodes (CCR, Charnes et al., 1978) and based on Farrell's efficiency measurement opinion. While Farrell's original idea is concerned with one input and one output, but the DEA method of Charnes, Cooper, and Rhodes can related the case where organizations (i.e. decision making units, (DMUs)) use multiple inputs to produce multiple outputs simultaneously. A DMU is defined as the concrete or intangible systems responsible for transforming inputs into outputs, and whose performance is evaluated. Examples of such units to which DEA has been applied are as follows: nations, banks, hospitals, schools, airports, tax offices, libraries, universities or their departments and also environment and energy organizations (Emrouznejad et al., 2008; Ray, 2004; Cook and Seiford, 2009; Sözen and Alp, 2009; Alp and Sözen, 2011). Note that one advantage of DEA is that it can be applied to not-for-profit organizations participating in public programs.

DEA is a powerful new methodology for organizing and analyzing data and for identifying best practice frontiers. The basic idea of DEA is to identify the most efficient decision making unit/s among all DMUs. The most efficient DMU is called a Pareto-optimal unit and is considered the standard for comparison for all other DMUs. DEA uses linear programming technique to determine the efficiency frontier. The points, which lie on the frontier comprises the efficient companies DMUs and the inefficient companies DMUs lie below the frontier.

The aim of DEA is to quantify the distance to the efficient frontier for every DMU. The measure of performance is expressed in the form of efficiency score. After the evaluation of the relative efficiency of the present set of units, DEA shows how inputs and outputs have to be changed in order to maximize the efficiency of the target DMU. DEA suggest the benchmark for each inefficient DMU at the level of its individual mix of inputs and outputs.

DEA models can be classified by two criteria: Type of scale effects and model orientation. The first criterion determines the assumptions concerning the scale effects accepted in the model (constant returns to scale (CRS), or variable returns to scale (VRS)). The model orientation approach indicates whether the objective is the minimisation of input(s), such as the cost of production, or the maximisation of a particular output, such as profit. In this study we used the input-oriented CCR (CRS) model. Using these model, the efficiency score is determined by holding output constant and assessing to what extent inputs would have to be improved (decresad) in order for a DMU to be considered efficient.

The dual form of CCR (CRS) input-oriented model (1) is as follows:

$$\begin{aligned}
&\min \quad h_o = \phi - \varepsilon.\sum_{r=1}^{s} S_r{}^{+} - \quad \varepsilon.\sum_{i=1}^{m} S_i^{-} \\
&Subject\,to \\
&\qquad \phi.y_{ro} - \sum_{j=1}^{n} \lambda_j x_{rj} - S_r^{+} = 0 \\
&\qquad \sum_{j=1}^{n} \lambda_j y_{ij} - S_i^{-} = y_{io} \\
&\qquad \lambda_{j,}\, S_i^{-},\, S_r^{+} \geq 0 \\
&\qquad j = 1,\dots,n,\;\; i = 1,\dots,m,\;\; r = 1,\dots,s
\end{aligned} \tag{1}$$

Where the subscript o represents the DMU being assessed and efficiency score of DMUo. xij, yrj denotes the input i and output r of DMU_i, respectively. ε is an arbitrary small “non-Arcimedian” number. are the slacks in the ith and the r th input and output and n, m and s are the number of DMUs, inputs, and outputs respectively.

From the dual CCR model, input augmentation is accomplished through the variable. If is less than 1.0 (or 100) and / or the slacks are not zero, then the DMU under investigation is inefficient, To improve and shift the DMU towards onto the frontier, a proportional decrease of for all inputs is required, followed poteantially, by an adjustment of individual slacks.

4.2. Window Analysis

In many DEA applications cross-sectional data were used. Each DMU unit is observed only one time in the studies. If multi-period data exist, in combination with the individual efficiency of each DMU, it is often important to perform a panel data analysis where the focus is on changes in efficiency over time. However, for this purpose, one approach to performing longitudinal analysis is to compare cross-sectional performance series across the number of time periods in the study. This approach introduces variability into the analysis because it treats the performance of a DMU in each time period as independent from its performance in the previous period. Also, with this approach it is not feasible to ascertain trends in performance or to observe persistence of efficiency or inefficiency, where the window analysis approach corrects some of these problems. In such a setting, it is possible to perform DEA over time using a moving average analogue (of time series), where a DMU in each different time period is treated as a distinct DMU. Specifically, a DMU’s performance in a particular period is contrasted with its performance in other periods in addition to the performance of the other DMUs (Cooper et al.). While ordinary DEA results table can be named as “static table”, window analysis results table is regarded as “dynamic table”.

5. Application

In this study Window Analysis solutions of most polluted coutries were obtained by Efficiency Measurement System software (EMS 1.3.0 version from Dortmund University). The average, standard deviation, and range statistics of each country's performance scores were calculated. And according to these statistics ranked in decreasing order. Results are at Table 3.

Table 3: **Distribution Of Performance Scores and Other Statistics of Most Polluted Countries of World**

DMU	Mean	SDeviation	Max	Min	Range	Rank
China	25,59%	1,04%	28,15%	24,11%	4,04%	1
US	35,40%	1,40%	37,52%	32,70%	4,82%	2
India	45,06%	2,24%	50,57%	42,27%	8,30%	3
Brazil	55,18%	11,12%	76,31%	44,22%	32,09%	4
Canada	55,26%	2,02%	58,18%	51,64%	6,54%	5
Argentina	56,89%	2,34%	60,98%	53,92%	7,06%	6
Korea	57,73%	6,50%	67,61%	48,13%	19,48%	7
Japan	58,25%	2,58%	64,25%	54,17%	10,08%	8
Indenosia	58,67%	1,41%	61,14%	55,14%	6,00%	9
Mexico	62,92%	4,10%	68,95%	54,92%	14,03%	10
South Africa	65,03%	2,05%	70,64%	63,00%	7,64%	11
France	67,17%	1,78%	70,67%	63,68%	6,99%	12
Australia	67,39%	1,57%	70,54%	65,14%	5,40%	13
Russia	70,85%	6,92%	80,16%	52,08%	28,08%	14
Germany	72,43%	2,17%	76,35%	67,66%	8,69%	15
Poland	78,01%	3,00%	83,81%	73,46%	10,35%	16
Turkey	78,75%	2,80%	83,68%	72,29%	11,39%	17
Sweden	79,66%	2,56%	83,43%	73,45%	9,98%	18
Netherlands	80,49%	3,01%	85,92%	76,34%	9,58%	19
Belgium	81,78%	2,52%	86,80%	76,22%	10,58%	20
UK	82,83%	3,00%	88,13%	77,99%	10,14%	21
Spain	84,03%	3,09%	89,45%	76,52%	12,93%	22
Italy	84,27%	3,19%	88,95%	76,13%	12,82%	23
Venezuella	84,87%	4,74%	95,42%	78,90%	16,52%	24
Thailand	86,99%	1,28%	89,72%	84,64%	5,08%	25
Finland	90,04%	1,89%	93,36%	87,49%	5,87%	26
Iran	91,23%	2,55%	97,34%	88,38%	8,96%	27
Austria	92,14%	3,26%	96,58%	83,73%	12,85%	28
Chile	93,51%	6,47%	100,00%	83,94%	16,06%	29
Greece	97,81%	2,83%	100,00%	91,53%	8,47%	30
Norway	97,96%	3,07%	100,00%	90,09%	9,91%	31
Portugal	98,79%	2,01%	100,00%	91,32%	8,68%	32
Saudi Arabia	98,88%	1,47%	100,00%	94,77%	5,23%	33
Malaysia	98,96%	1,23%	100,00%	95,84%	4,16%	34
Romania	99,01%	1,51%	100,00%	94,32%	5,68%	35
Hungary	99,18%	1,40%	100,00%	95,74%	4,26%	36
Ukrania	99,53%	1,58%	100,00%	92,74%	7,26%	37
Peru	99,65%	0,70%	100,00%	97,53%	2,47%	38
Vietnam	99,79%	0,42%	100,00%	98,77%	1,23%	39
New Zealand	99,86%	0,46%	100,00%	97,93%	2,07%	40
Czech	99,92%	0,32%	100,00%	98,50%	1,50%	41
Bulgaria	99,95%	0,24%	100,00%	98,89%	1,11%	42
Israel	99,97%	0,13%	100,00%	99,37%	0,63%	43
Kazakhstan	99,98%	0,09%	100,00%	99,57%	0,43%	44
Denmark	99,99%	0,06%	100,00%	99,71%	0,29%	45
Ireland	100,00%	0,00%	100,00%	100,00%	0,00%	48
Morocco	100,00%	0,00%	100,00%	100,00%	0,00%	48
Philippines	100,00%	0,00%	100,00%	100,00%	0,00%	48
Egypt	100,00%	0,00%	100,00%	100,00%	0,00%	48
Pakistan	100,00%	0,00%	100,00%	100,00%	0,00%	48

The ten worst environmental / greenhouse gas emissions performers from these 50 countries, are the following respectively (with respect to mean): China, USA, India, Brazil, Canada, Argentina, Korea, Japan, Indenosia and Mexico.

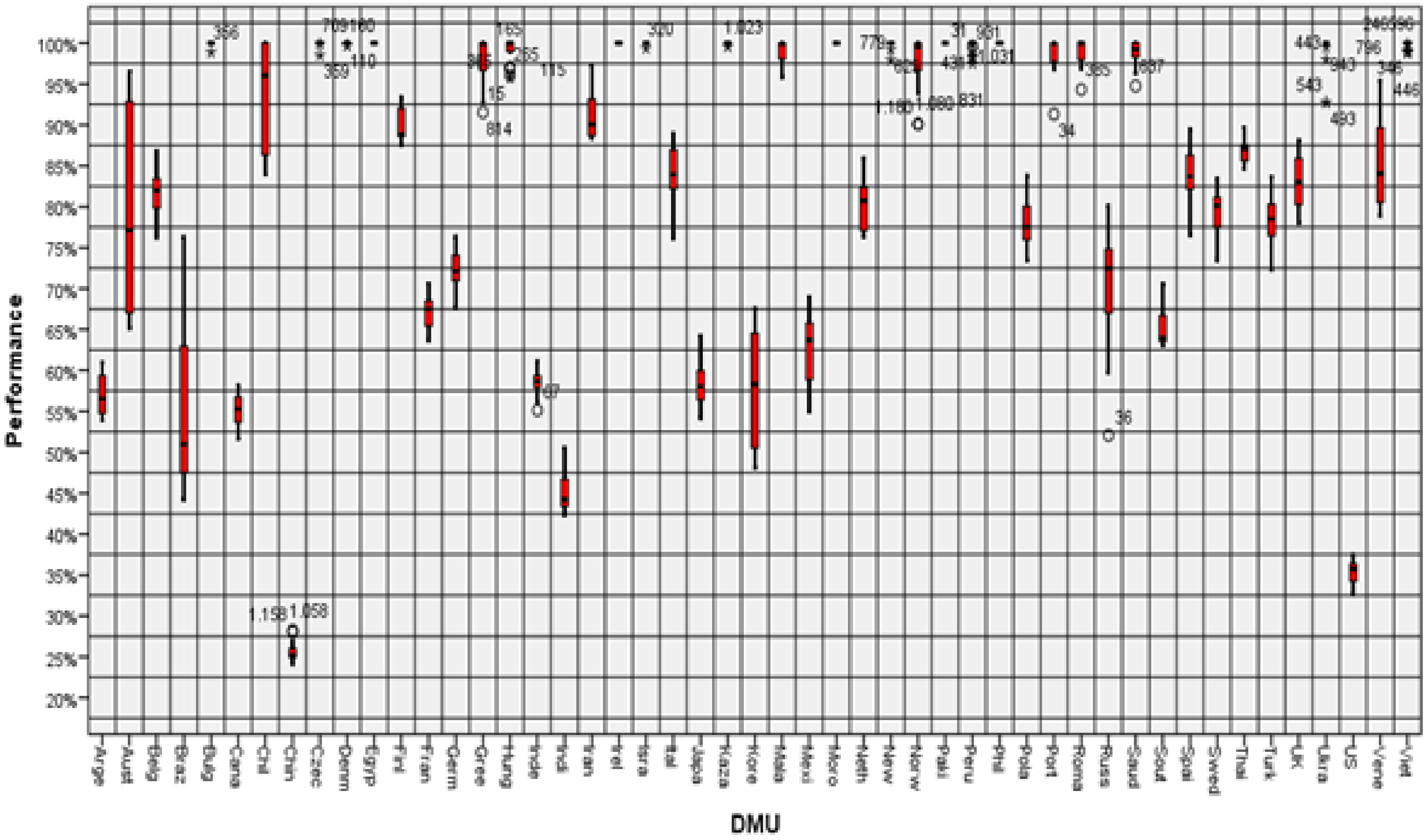
Five countries were found efficient throughout the period. These are: Ireland, Morocco, Philippines, Egypt, and Pakistan.

The boxplot graph which gives us a plenty information about performance scores of the countries which are minimum, maximum, approximate value of mean (median), distribution of 25 percent slices, variability, homogeneity and skewness of data is in the below.

According to Graph 4, the countries with the two worst performance scores belong to China and USA.

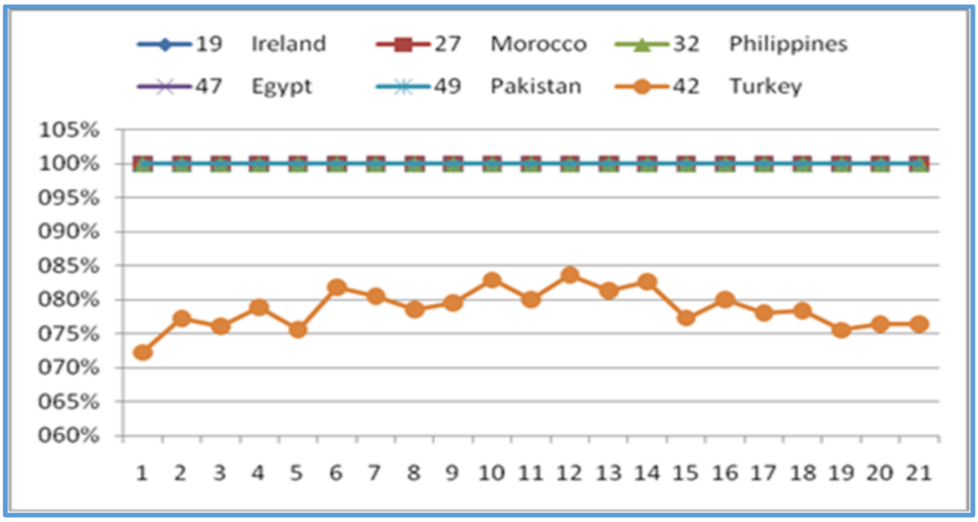
The two highest variability in performance scores belong to Australia and Brazil.

Graph 4: **Boxplot of Performance Skores of 50 Countries**



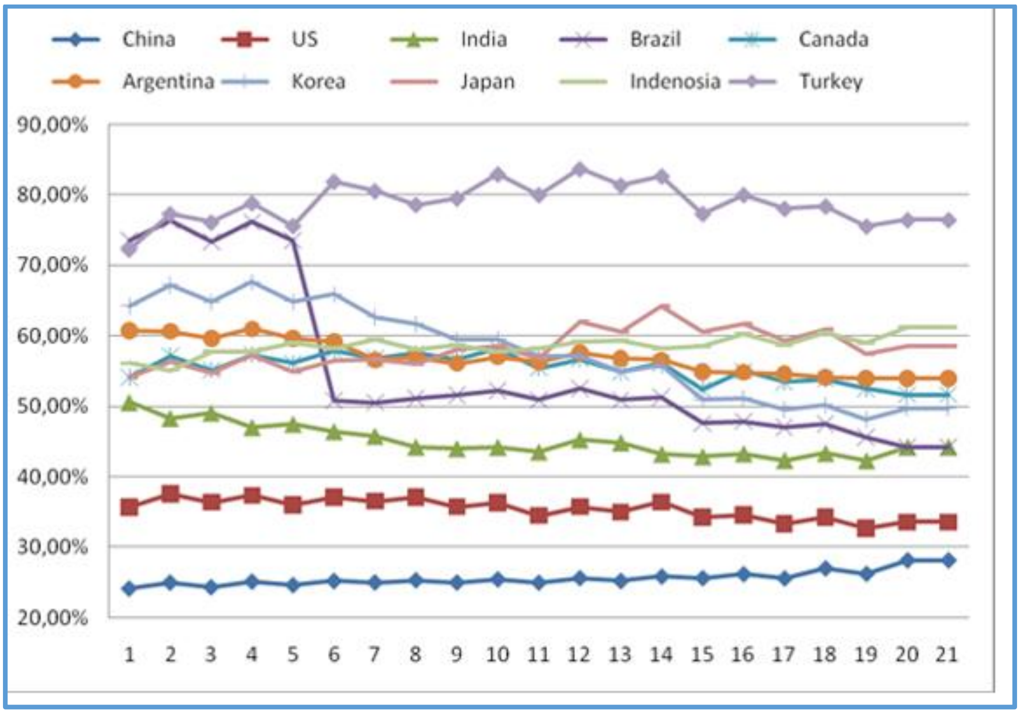
Stability and trend of EE scores of efficient countries (Ireland, Morocco, Philippines, Egypt, and Pakistan)and Turkey in the following Graph 5. The situation of the efficient countries is most desirable. In the study, ten years time period was taken into consideration. In the WA application, two performance scores were calculated for each year - with a logic of moving averages in the time series analysis- and an extra performance score for the last year. Thus, 21 performance scores were obtained for each DMU.

Graph 5:**Stability And Trend of EE Scores of Efficient Countries and Turkey**



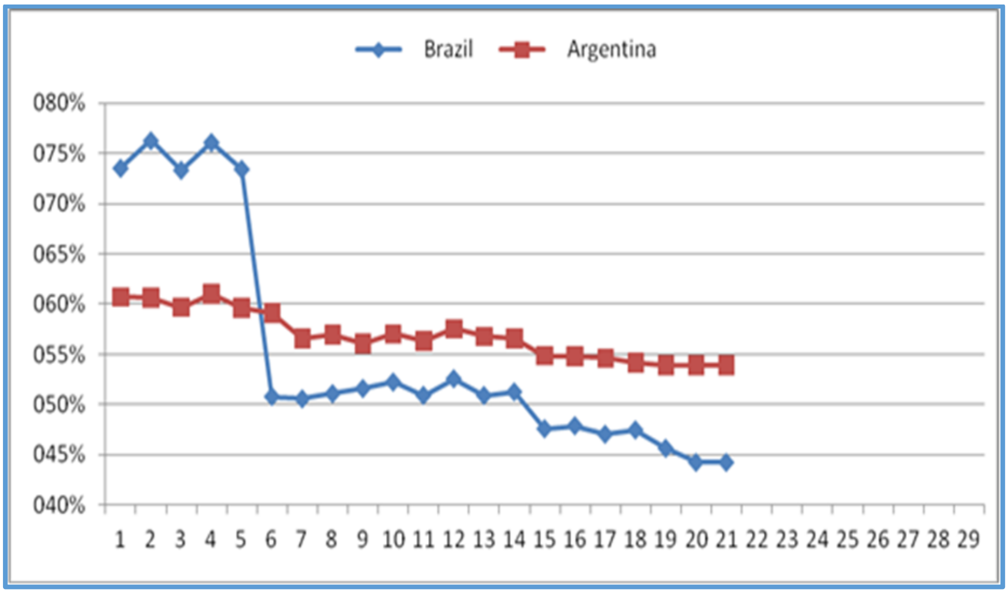
Stability and trend of EE scores of worst 10 coutries (China, USA, India, Brazil, Canada, Argentina, Korea, Japan, Indenosia and Mexico) and Turkey in the following Graph 6.

Graph 6:**Stability and Trend of EE Scores of Worst 10 Countries and Turkey**



Stability and trend of EE scores of Brazil and Argentina in the following Graph 7.

Graph 7:**Stability and Trend of Brazil and Argentina**



Rapid and major changes, as well as the decline in the environmental performance trends of countries, are considered absolutely negative. As can be seen in Graph 7, Brazil's environmental performance score showed a significant decline over a certain period of time. The reason of this is that, in that time zone, forest fires and land use for agriculture. This is also a reason for the variation which is quite high in Brazil's environmental performance scores (standard deviation and range, 11,12%, 32,09% respectively). And also Argentina has a continuously decreasing environmental performance trend.

6. Conclusion and Discussion

Apart from a few countries (Australia, Brazil, etc.) there is so much change in the EE performance of the countries. Wide range of dispersion, sudden alterations and steadily decreasing trend are undesirable for efficient countries throughout the process. Countries with the widest range of change are: Brazil, Russia, Korea, Venezuella and Mexico.

The five worst environmental performers with respect to mean from these 50 countries are the followings: China, USA, India, Brazil and Canada (25,59%, 35,40%, 45,06%, 55,18%, 55,26%) respectively.

The ranking of five countries with the best environmental efficiency performance over the years studied is as follows: Ireland, Morocco, Philippines, Egypt and Pakistan with score 100%.

Turkey's ranking among these countries is 34 and values are as follows: Mean=78.75, Standart deviation=2.8, Max=83.68, Min=72.29 and Range=11.39. The aggregate average statistics of the other countries considered in the study are as follows: 82,58%, 19,56%, 24,11%, 100,00%, 75,89% respectively.

Turkey should focus on renewable energy sources that will reduce the solid fuels it uses to increase its EE performance. To this end, in 2017, Turkey has been committed to increasing wind energy investments to a record level. Moreover, the institution of nuclear and new hydroelectric power plants is on the agenda of Turkey.

The average performance of the fifty countries between 2005 and 2015 was 82.63%. This result suggests that for a better world these countries should reduce greenhouse emissions by mean 17.37%.

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