Statistical Analysis of Renewable and Non-renewable Energy Consumption against Population Growth

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Abstract. Global population has significantly tripled in the last 50 years. The increasing population rate has led to increasing energy consumption, consequently, increasing Greenhouse Gas (GHG) emissions, which is the leading cause for global warning that endangers survival chances for living species. However, recent interest surged in renewable energy for clean and sustainable power production and consumption. With the deployment of renewable energy in the past years, dependence on fossil fuel was supposed to have declined, and consequently, GHG emissions, especially CO\textsubscript{2}. The aim of this research is to study the effect of population growth against fossil fuel consumption producing these emissions, in addition to the impact of renewable energy consumption that alternatively reduces GHG emissions. The outcome of the proposed topic represents comprehensive findings that relate population growth with global energy consumption against GHG emissions over the past few decades. This is achieved based on recent statistical applications and methodologies including linear regression models, and prediction models, which are applied to study the interaction of annual CO\textsubscript{2} emissions, energy consumption, and population during, almost, the past fifty years. Additionally, according to the results, the presented null hypothesis is rejected as the current trend does not comply with the Paris agreement.

1. Introduction

1.1. Study significance

Recently, there has been a dramatic change in new-born rates and countries’ population. There were less than 1 billion people on the earth before 1800 A.C. After the Second World War, the world population started to increase by a billion person every 12-15 years. In addition, nowadays, the population continues to grow by more than 80 million person every year, however, it is most likely to continue growing for the rest of the century [1]. The United Nations (UN) makes a projection estimation for the future population every two years. The latest projection shows a population of 9.7 billion and 10.9 billion in 2050 and 2100, respectively. There are many factors leading to this growth, such as life expectancy. According to the UN, life expectancy at birth increased from 48 years in 1950 to 69 years in 2010, and it is expected to continue to rise in the next four decades [2]. This is due to the improvement in healthcare, food availability and new technologies that help enhance the standard of humans’ lives. The population growth is reflected on energy consumption over the years. Some researchers believe that energy consumption will increase by 50% to sustain humanity by 2050 [3]. The energy consumption has increased from 28TWh in 1950 to 158TWh in 2018, which shows the significant effect of the population growth.
growth on energy consumption [3]. Many energy resources are consumed to fulfil electrical energy demands of humanity. Most of these resources are not environmentally friendly, such as coal, oil and natural gas [3]. Non-renewable resources are considered as primary energy resources in the world. One example of negative implications of non-renewable resources affecting the environment is the Greenhouse Gases (GHG) emitted when burnt to produce energy. GHG emissions cause climate changes that lead to the increase of the global temperature by 1℃ [3]. As a result, population growth and energy consumption could have an indirect impact on health, as well as other environmental events, such as sea-level rise and disrupted water systems. However, renewable energy resources can be used as a replacement in order to reduce GHG emissions.

1.2. Study objective and overview of the paper
This research aims to study the measures and relations between the world population and non-renewable energy consumption. In addition, an attempt to measure the effectiveness of consuming renewable energy in reducing GHG emissions is presented.

The remainder of this paper is organized into four sections as follows: Section 2 presents the literature review; Section 3 describes the proposed methodology and collection methods; Section 4 presents and analysis the results; and Section 5 discusses and concludes the paper.

2. Literature review
In general, the dependency of energy consumption on population has been of a large focus in recent research [4]. An empirical analysis is presented by Salim and Shafiei [4] addressing the influence of urbanization expansion (i.e. concentration of population and economic activities in urban areas) on the consumption of renewable and non-renewable energy. The analysis was conducted using the STIRPAT (STochastic Impacts by Regression on Population, Affluence, and Technology) model in the Organization for Economic Co-operation and Development (OECD) countries from 1980 to 2011. The methodology included the empirical model, the economic approach, and the panel causality test. Data types included variables like the total population, industrialization, population density, Gross Domestic Product (GDP) per capita, and renewable and non-renewable energy consumption. As a result, it was found that the consumption of non-renewable energy is significantly and positively influenced by urbanization, whereas urbanization does not noticeably influence the consumption of renewable energy in OECD countries. In other words, the main energy resource remains fossil fuels in developed countries despite of the recent increase of renewable resources usage.

York et al. [5] was the first to adopt the STIRPAT model to show that population is a major key factor of the energy consumption. Begum et al. [6] have investigated the variables of GDP growth, energy consumption and population growth on CO₂ emissions in Malaysia using econometric approaches.

Another instance is India where population growth has led to a relatively fast rate of energy consumption [7] that is fulfilled by fossil fuels. Tripathi et al. [7] have presented an overview of renewable energy effective contribution in the provision of sustainable power supply in India. Shafiei and Salim [8] have proposed a comparative analysis of renewable, non-renewable energy and CO₂ emissions. Apergis and Payne [9] have adopted the Panel Error Correction (PEC) model in order to show bidirectional causality between energy consumption (renewable and non-renewable) and economic growth.

Another work in [10] has showed causal relationships between CO₂ emissions, GDP, and energy consumption over 1980–2010. In specific, bidirectional causality using Short-run Granger causality tests was presented. They also verified the U-shaped Environmental Kuznets Curve (EKC) hypothesis using long-run Fully Modified Ordinary Least Squares (FMOLS) and Dynamic Ordinary Least Squares (DOLS) estimates.

Although the presented related work addresses the influence of population on energy consumption, however, very few have explicitly addressed parametric, non-parametric, and normality/Equal Uniformity tests. The paper aims to present comprehensive findings that relate population growth with global energy consumption against GHG emissions over the past few decades. This is achieved based on recent statistical applications and methodologies.

3. Methodology
In this research paper, the aim is to understand the relation between population, energy consumption based on non-renewable energy sources, GHG emissions and the introduction of renewable energy sources into the equation. The used data is summarized in Table 1. It should be noted that all the described data belong to “Ratio Scale” data type as division can be applied throughout different years to investigate growth phenomenon. The data is also non-stationary time-series that is yearly collected where an increasing growth is present in the three datasets.

Table 1. Used datasets for statistical analysis.

| Dataset Name                        | Years included                  | Data Type                                                                 |
|-------------------------------------|---------------------------------|---------------------------------------------------------------------------|
| Population Growth by World Region   | 1950 – 2019 per country         | Population Count                                                          |
| [11]                                | -10000 – 2019 for the world     |                                                                           |
| Energy Consumption by Source        | 1965 – 2018 per country         | Oil, Coal, Gas, Hydropower, Nuclear, Solar, Wind & Other renewables       |
| [12]                                | 1965 – 2018 for the world       | combined (all in Terawatt-hours = TWh)                                    |
| Annual CO₂ Emissions by Region      | 1959 – 2017 per country         | Carbon Dioxide (CO₂) tonnes                                              |
| [13]                                | 1751 – 2017 for the world       | (tonne = metric ton)                                                     |

The number of years per country was not consistent. However, 1959 was the minimum common between all.

The analysis mainly targets the world’s population from the year 1965 until 2017 since these are the years that are common between the 3 datasets. However, at some point, specific continents are pinpointed to establish whether huge advancements in producing energy from renewable sources is reached based on their published visions.

The data is sourced from the same website “Our World in Data” governed by University of Oxford where it was first created by Max Roser as the leading author.

4. Analysis and results

4.1. Parametric vs. non-parametric & normality/equal uniformity test (for parametric analysis only)

The kind of tests that fit the research data are non-parametric since the normality assumption is not asserted. Figure 1 shows both (a) population growth and (b) annual CO₂ emissions, failing the normality test with \( \alpha = 0.05 \), where the attained P-value is much lower.

![Figure 1. Normality test on (a) Population growth, (b) Annual CO₂ emissions.](image)

Thus, for the aforementioned datasets, it is more suitable to go for non-parametric tests that do not assume that data comes from a normally distributed set.

4.2. Hypothesis definition
The Paris agreement was introduced by the UN in an effort to save earth from the imminent threat of global warming, and it aims to decrease the earth’s total temperature by 1.5°C by 2030. In order to meet this target, the UN said that the CO₂ emissions should drop 7.6% every year in this decade. The percentage is to be used as a comparison benchmark to compare the goal to what will happen if the current CO₂ emission trendline. In this paper, this will be put into test by defining the following null hypothesis and alternative hypothesis:

- \( H_0 \): Intervention of renewable energy sources with the existence of non-renewable energy sources will reduce GHG emission such as CO₂ before 2030.
- \( H_A \): Intervention of renewable energy sources with the existence of non-renewable energy sources will not reduce GHG emission such as CO₂ before 2030.

4.3. Statistical analyses and results

4.3.1. Correlation. Since the used data failed the normality test, then it would be safer to use the Spearman correlation test. Some of the correlation results are shown figure 2, where it can be seen that Population & CO₂ emissions are highly correlated. Further tests are implemented and discussed in the Discussion sections.

![Spearman correlation](image1)

(a) Matrix Plot of Population, CO₂ Emission
(b) Matrix Plot of CO₂ Emission, Renewable energy/total energy

Figure 2. Spearman correlation (a) population & CO₂ emissions; (b) CO₂ emissions & renewable energy/total energy.

4.3.2. Linear regression models. After seeing the correlation results, it is evident that there is high correlation between population, energy consumption and CO₂ gas emissions. Therefore, to have a better understanding of the nature of their relationships, a linear regression model is created between each variable for a group of continents as shown in figure 3.

It is worth noting that the data are not compatible for the Asia and Oceania regions, and for the Americas (North, Central and South) such that they were not fully independent. Thus, for energy consumption versus vs. population, Asia Pacific and Middle East energy consumption are summed to represent Asia & Oceania discarding the countries in the Commonwealth of Independent States (CIS) common between Asia & Europe. Similarly, for the Americas, they are considered as a single continent to make the datasets more compatible and easier to represent [12].

5. Discussion

5.1. Correlation

First the basic correlations are calculated in order to establish if the use of regression is possible. Since the population does not follow a normal distribution, Spearman correlation is used. After calculating the correlation between world’s population and the CO₂ emissions, it is found that they are much correlated \( (r = 0.996 \text{ and } P\text{-Value} < 0.001) \) leading to reject the null hypothesis of the non-significance of the data.
Figure 3. Linear regression model for each continent between (a) energy consumption vs. population; (b) CO$_2$ emissions vs. population; (c) CO$_2$ emissions vs. energy consumption.

Then, the correlation between population and energy consumption is calculated ($r = 0.999$ and P-Value $< 0.001$). Moreover, a significant correlation between CO$_2$ and energy consumption is found ($r = 0.998$ & P-Value $< 0.001$). An extra correlation is done between CO$_2$ emissions vs. the ratio of renewable energy to the total energy in order to investigate if the world is being conscious of CO$_2$ emissions and started leaning towards using renewable clean energy as shown in figure 2(b). The correlation is found...
to be 0.881 with a P-Value < 0.001 which means that there is an incentive of increasing renewable energy consumption since CO\(_2\) emissions have increased. However, renewable energy as of 2017 only represents around 9.4\% of total energy which is not enough. Also, the ratio is rapidly increasing in the last years, but the CO\(_2\) emissions are not decreasing, which indicates that the deployed renewable energy is not replacing existing fossil fuel-based consumption.

5.2. Linear regression models

5.2.1. Energy consumption vs. population. It can be seen from figure 3(a) that Africa has the lowest energy consumption with respect to its very gradual population growth. Unlike to Africa, it can be noticed that Europe and Americas show a significant and rapid increase in their energy consumption against their population growth. On the other hand, Asia and Oceania demonstrate the highest population growths during the period 1965-2017. This is accompanied with the highest energy consumption rates outstanding all the other continents. On another note, Asia and Oceania show a nearly exponential energy consumption rate in the most recent years. In other words, the figure shows that population growth is a key factor in the prediction of futurist energy consumption rates, where Asia is predicted to be the highest energy-consuming continent.

As shown in table 2, a summary of the linear regression models created in figure 3(a) can be seen. In all the models, the general behavior is linear with R\(^2\) values in the range of 0.89 to 0.99 with Europe’s model being the least fitting one. In this case, linear regression can be declared as a viable tool to model global energy consumption against increasing population.

5.2.2. Annual CO\(_2\) emissions vs. population. CO\(_2\) emissions vs. population analysis for the continents groups is shown in figure 3(b), where a causation relationship can be deduced. It is evident that half of the population is residing within the Asia and Oceania region, which can account for some of the CO\(_2\) emissions, mainly in China and India. However, China is considered the main contributor of CO\(_2\) emissions where they produce more than half of the total Oceania and Asia region’s CO\(_2\) emissions in (2017) [13]. For Africa, their CO\(_2\) emissions are much lower, and it can be due to the industrial delay this continent is witnessing with respect to the advancements in other continents. Nonetheless, they have the minimum CO\(_2\) emissions, and they are contributing the least to global warming. On the other hand, for a similar population to the one in Africa, both Europe and the Americas almost have 4-6 times the CO\(_2\) emissions that Africa has. It is worth noting that they have lower population than Asia and Oceania, yet they have a lot of emissions with respect to the number of people in these continents. In Europe, their aim towards reducing their CO\(_2\) emissions is starting to pay-off and that can be noticed in figure 3(c) as well.

A summary of the of the linear regression’s models for CO\(_2\) emissions vs. population are shown in table 2. For instance, Asia and Oceania show relatively linear behavior with R\(^2\) = 0.894. Also, Africa demonstrates linear behavior with R\(^2\) equal to 0.978. On the other hand, the model for Europe does not show any signs of linearity (R\(^2\) = 0.014) between CO\(_2\) emissions and population which indicates reduction in their CO\(_2\) production. The Americas, on the flipside, show linear behavior with R\(^2\) = 0.899.

5.2.3. Annual CO\(_2\) emissions vs. energy consumption. CO\(_2\) emissions vs. annual total energy consumption analysis is shown in figure 3(c), where it is clear that there is a causation relationship between them for all the continent. However, Europe shows a significant drop in the CO\(_2\) emissions. For the other continents, the amount of consumed energy increases linearly with increasing annual CO\(_2\) emissions. Asia and Oceania have the highest energy consumption among the continents, which justifies the huge amount of CO\(_2\) emitted per year. The underlying reason is the continents’ large population and the existence of heavy industrial activities in Asia, such as in China, India, and Singapore, where some of these businesses originally come from USA and Europe [14]. However, Africa shows the least amount of total CO\(_2\) emissions due to low energy consumed when compared with other continents, and this may relate to the high percentage of poor countries in Africa. For the Americas, there is a strong linear relationship between the consumed energy and the emitted CO\(_2\). They are both huge due to the population numbers, in addition to the fact that it contains the USA, which is considered as one of the
leading countries in the industrial fields. Moreover, in Europe, the effect of integrating renewable energy resources is reflected on the amount of CO₂ emitted. It is clear from the graph that the consumed energy increased, but the CO₂ emissions decreased, which shows the advantage of using renewable resources in reducing CO₂ emissions.

A summary of the linear regression’s models for CO₂ emissions vs. energy consumption are shown in table 2. Like the previous demonstration, Europe exhibits non-linear behavior with R² = 0.0876. The remaining continents show remarkable linearity with R² values over 0.99. Overall, these models can be utilized to predict CO₂ emissions based on energy consumption in the Americas, Africa, and Asia and Oceania.

| Variables | Energy Consumption vs. Population | CO₂ Emissions vs. Population | CO₂ Emissions vs. Energy Consumption |
|-----------|-----------------------------------|-----------------------------|-------------------------------------|
| Asia & Oceania | $y = 2.57723 \times 10^{-5}x - 5.06792 \times 10^4$ | $y = 5.65601x - 1.09667 \times 10^{10}$ | $y = 220620x + 1.76483 \times 10^8$ |
| Africa | $y = 4.92643 \times 10^{-5}x - 7.25858 \times 10^2$ | $y = 1.21461x - 3.96305 \times 10^7$ | $y = 247043x + 8.40428 \times 10^7$ |
| Americas | $y = 4.10020 \times 10^{-5}x + 9.84031 \times 10^2$ | $y = 7.1523x + 1.37328 \times 10^6$ | $y = 176853x + 1.07547 \times 10^6$ |
| Europe | $y = 1.14473 \times 10^{-5}x - 5.94836 \times 10^4$ | $y = 3.11983x + 4.39458 \times 10^6$ | $y = 63881x + 5.22763 \times 10^6$ |

5.3. Prediction

In order to assess the goal set by the Paris agreement and compare it with the current trend, a linear regression model is built using Minitab. The model is between CO₂ emission (tonnes) and time (years) using the data points ranging in (1965 to 2017). The linear model is:

$$CO₂ Emissions = 4.44 \times 10^8 \times year - 8.60 \times 10^{-11}$$ (2)

From this model, two values are calculated. The values of CO₂ emissions in both 2020 and 2030, assuming the continuation of the current trendline. The CO₂ emission in 2020 and 2030 is estimated to be $3.688 \times 10^{10}$ tonnes and $4.132 \times 10^{10}$ tonnes, respectively. The goal setpoint by Paris agreement was calculated using a complex interest function using the decay percentage of 7.6% and a duration to be 10 years. In doing so, the Paris agreement setpoint can be calculated for CO₂ emission in 2030:

$$CO₂ Emissions(2030) = CO₂ Emissions(2020)(1 - rate of decay)^{duration}$$ (3)

According to the calculation, the CO₂ emission in 2030, following the current trendline, is around 2.5 times the CO₂ emission listed in the Paris agreement, the listed Paris agreement goal threshold if reached, irreversible damage would be done to the earth’s climate.

6. Conclusion

All in all, the aim of this study is achieved by understanding the relation between population, energy consumption, GHG emissions, and the reflection of renewable resources in reducing GHG emissions. A clear linear causation relation is deduced between the population and energy consumption in all continents, where Asia and Oceania have the highest population number compared to other continents. A deeper look into energy consumption and CO₂ emissions was done at each continent showing that Asia and Oceania outstand other continents in the energy consumption rates. They also were found to have the highest rates of CO₂ emissions amongst the other continents. This is due to the high population of these continents and due to the heavy industrial actvates in these areas. On the other hand, Africa has the lowest CO₂ emissions due to its low population and consumed energy compared to other continents. A prediction model was done using linear regression in order to study the CO₂ emissions, and compare it to the goal set by the Paris agreement in order to reduce the climate change by 1.5°C. Based on the previous calculations, the null hypothesis is rejected as the current trend cannot comply with the Paris agreement. It is also worth noting that the database and its data availability is one of the biggest
limitations encountered as the authors were not able to handle the analysis for each of the continents separately. In addition, the range of the utilized dataset was between (1965-2017), where the lower bound is induced by the energy consumption dataset [12], and the upper bound is induced by the CO$_2$ emission dataset [13]. Future work would be to study the energy consumption of each country by itself and investigate the implementation of renewable energy in each country and its impact on GHG emissions.

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