Investigating the Effects of Socio-Economic Development and Population on a Country's Climate Protection Performance

Abstract

Climate change, population growth, and socioeconomic development are linked through complex feedback loops. Understanding these relationships is critical for future climate projections and mitigation strategies. This paper investigates the relationship between a country's development and its climate protection performance. The effects of selected socioeconomic and population factors are tested on countries' Climate Change Performance Index (CCPI). Model selection was used to determine the factors which have a significant impact on CCPI. CCPI scores were highest in countries with a high rate of school enrolment, high GDP per capita, low digital technology usage and low population growth.

Introduction

Climate change, socio economic development, and population change are intertwined. Of importance is the bidirectional causality between economic development and CO_2 emissions (Mardani et al., 2019). 'Developed' nations are often heralded as low emission countries with strong climate mitigation policies. They are defined as having a high human development index (HDI) characterised by high education levels and high national income per capita, pointing towards high rates of labour participation and low levels of unemployment (United Nations Development Programme, 2015). They are also characterised as having a low population growth, low population density and high life expectancy (World Bank, 2023). The aim of this study is to investigate which socioeconomic and population factors have the strongest relationship with Climate Change Performance Index (CCPI) to evaluate the factors that influence the outperformance of 'developed' nations over others.

This study analyses the 2019 CCPI scores, socioeconomic factors, and population measures for 45 countries. CCPI, a measure of a country's climate performance across four categories: greenhouse gas emissions, renewable energy use, conventional energy use and climate policy was used as the explanatory variable (CCPI, 2018). 7 socioeconomic and 4 population factors (see Table 1) from World Bank Databank (2023) were selected and used as the response variables. It was hypothesized that countries with developed conditions have higher CCPI scores. These developed conditions assumed a high rate of school enrolment, gender parity index of school enrolment, digital technology usage, labour force participation, GDP per capita, life expectancy, and sex ratio as well as low unemployment, GDP growth, population growth and population density.

Variables	**Mean ± SD**	**Variable**	**Mean ± SD**
CCPI Score	51.09 ± 13.14	GDP Growth (%)	2.41% ± 1.68%
Ratio of School Enrolment (%)	101.66% ± 6.16%	GDP per capita (US$)	US$ 31836 ± US$ 25100
Gender Parity Index of School Enrolment (females per males)	1.00 ± 0.028	Life Expectancy (years)	78.94 ± 4.08
Digital technology usage (% of population)	82.72% ± 12.16%	Sex Ratio at Birth (male births per female births)	1.06 ± 0.014
Rate of Labour Participation (% of population)	72.96% ± 7.42%	Population Growth (%)	0.51% ± 0.73%
Unemployment (% of population)	6.28% ± 4.54%	Population Density (people per sq. km)	112.76 ± 118.50

Table 1: List of all variables with central tendency measures (SD = Standard Deviation)

Methodology

To investigate the factors impacting CCPI scores, a stepwise backwards model selection was performed to find the minimum adequate model. The maximal model was fitted with the CCPI score as the explanatory variable and the selected variables (Table 1) as the main effects. Non-significant effect terms were successively removed, and models compared using an analysis of variance.

Variables were scaled to satisfy the assumptions. The diagnostic plots of the minimum adequate model were examined and none of the assumptions were violated. The minimum adequate model included the main effects of ratio of school enrolment, digital technology usage, GDP per capita and population growth.

<u>Results</u>

CCPI scores, socioeconomic and population measures from 48 countries for 2019 were analysed. The central tendency measures for all the variables are reported in Table 1.

Countries with high ratio of school enrolment, high GDP per capita, low population growth and low digital technology usage were found to have high CCPI scores. A stepwise backwards model selection produced a minimum adequate model with a significant model equation containing the response variables: ratio of school enrolment, digital technology usage, GDP per capita and population growth (F-value=8.094, df=(4, 40), p-value<0.001) with an adjusted R^2 of 0.39. The model equations for all the main effects are given below (see Table 2 & Figure 1):

Ratio of School Enrolment = 7.24*(CCPI Score) + 51.09
Digital technology usage = -5.07*(CCPI Score) + 51.09
GDP per Capita = 4.49*(CCPI Score) + 51.09
Population Growth = -8.04*(CCPI Score) + 51.09

Coefficient	**Estimate ± SE**	**t-value**	**p-value**
Intercept	51.09 ± 1.53	33.46	p<0.001
Ratio of School Enrolment	7.24 ± 1.73	4.19	p<0.001
Individuals using Internet	-5.07 ± 2.02	-2.51	p<0.05
GDP per Capita	4.49 ± 2.01	2.23	p<0.05
Population Growth	-8.04 ± 1.75	-4.60	p<0.001

Table 2: Coefficients of the minimum adequate model

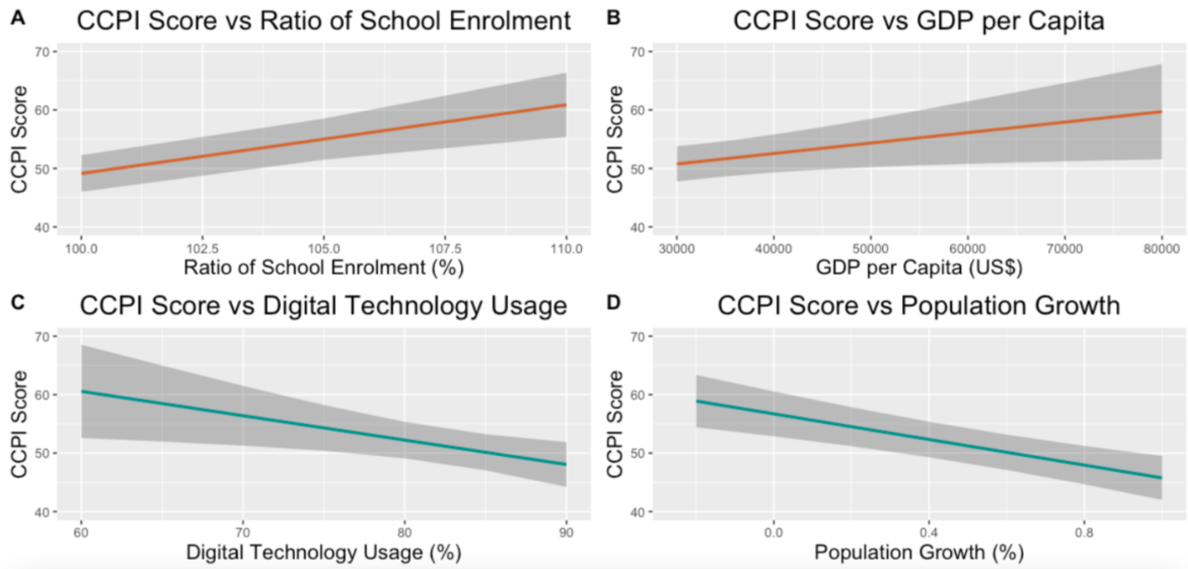

Figure 1: Trends of the main effects with CCPI score. Shaded area reflects the 95% confidence interval

<u>Discussion</u>

Countries with a higher CCPI score were found to have a higher rate of school enrolment, higher GDP per capita, lower digital technology usage and lower population growth. These results are mostly in accordance with past studies. School enrolment has been found to positively impact human capital, reducing CO_2 emissions (Bano et al., 2018). Increase in usage of digital technology has led to rapid increase in energy consumption and CO_2 emissions (Gelenbe & Caseau, 2015). Increases in population growth has been found to result in increased CO_2 and energy consumption (Dong et al., 2018). Of interest is the relationship between GDP per capita and climate mitigation which has been found to follow a U-shaped curve reaching a tipping point as countries approach the status of 'developed' (Heidari, Turan Katircioğlu & Saeidpour, 2015). This could suggest a threshold of GDP per capita beyond which a country has resources to direct towards climate protection. The results above point towards a positive trend between GDP per capita and climate mitigation and could suggest that majority of the countries analysed have crossed the hypothesized tipping point.

Countries with high CCPI scores contain higher rates of school enrolment, higher GDP per capita and lower population growth which is consistent with a 'developed' country. But they exhibit lower digital technology usage, which though logical due to increased energy consumption and CO_2 emissions, is contrary to the hypothesis. Developed countries exhibit increased digital technology usage (World Bank, 2023) but it may not reflect on its CCPI score due to several reasons. It is possible that developed countries use more sustainable technologies which does not lead to energy consumption and greenhouse gas emissions. Additionally, digital technology usage was measured as a ratio of population utilising technology and this could have affected the analysis. In developing countries a lower proportion of the population uses digital technology, despite the growing digital sector hence, possibly skewing the results.

Conclusions and Future Works

These results could act as stepping stones for future mitigation plans. Improving GDP per capita and increasing school enrolment could point towards increasing a country's climate protection. Switching towards more sustainable technologies would also be highly crucial in the upcoming years. Drawbacks of this paper include the adoption of a simplistic model with no interacting terms and the presence of limited datapoints. In the future, the trends of socioeconomic and population factors on climate protection across multiple years could be studied for a wider range of countries

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Reflection

This project was an extremely interesting assignment for me as it gave me the freedom of choosing my research question and dataset. The first challenge came up in choosing the dataset. The first dataset I chose was an incomplete and messy dataset and I lost some time working through it before I realised it could not be used. This gave me my first learning experience, always study the dataset and be clear on the hypothesis/research question before proceeding.

The second challenge encountered was time management, which was also the biggest challenge. Though I had charted out a plan and given myself a couple of days for each task, the plan I made was not robust. Some tasks took longer than others, leaving me no buffer room approaching the deadline. The last 2 days leading up to the deadline for a bit tensed due to improper time management but I was able to complete the assignment without giving up on food or sleep. So the second learning experience was the important of better time management and leaving more buffer room when charting out a plan

The third learning experience during the course of this project was the skill of reporting the results from a statistical analysis. This task which I expected to take half a day dragged on to two days since I was having lots of doubts with the acceptable standards of reporting the stats. I had to spend some time first revising the course notes before I could proceed. Our EEC tutors were also extremely helpful in this regard as they cleared some of the doubts.

The fourth learning experience for me was the art of scientific communication. I asked 3 of my friends to proofread my report for me and I realised that each of them had different criticisms and takes on my report. Though they did agree on some points, they had their differences too. This is when I realised that scientific communication is a fine art. Trying to convey information across to different groups of people is quite an intense challenge and requires a lot of practice.

The last learning experience was the importance of double checking everything last thing before submitting. Because of this, I was able to detect a major error in my code that seeped into my report and presentation as well. Thankfully I had detected it well in advance to give me time to edit it and submit.

Overall, I had lots of fun doing the miniproject especially since it gave me the opportunity to study a field that I'm extremely interested in. It also gave me the chance to learn useful technical skills such as coding in R, statistical analysis, model interpretation, report writing and presentation skills. It also gave me an opportunity to hone soft skills such as time management and problem solving skills.