A Study into the Demographics Having the Greatest Carbon Footprint

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ABSTRACT

Our aim was to determine factors predicting greenhouse gas emissions per capita and to identify the demographics having the greatest carbon footprint. The relationship between socioeconomic trends and greenhouse gas emissions is controversial, given that many past studies evaluated only a single factor. We analyzed the relationship between global greenhouse gas emissions per capita and literacy rate, GDP per capita, urban population percentage, adolescent fertility rate, unemployment percentage, percent of agricultural land, research and development expenditure, renewable energy consumption, food production, population growth, mobile cellular subscriptions, air transport freight, and forest area. We gathered data from 217 countries spanning a period of 20 years; 1993 to 2012. We analyzed the data using multiple regression models. We concluded food production, renewable energy consumption, air transport, mobile cellular subscriptions, literacy rate, and population growth have the greatest impact on predicting greenhouse gas (GHG) emissions in our model, suggesting the demographic with the greatest carbon footprint are wealthy, educated people living in urban centers.

KEYWORDS

Climate change, greenhouse gas, carbon footprint, data science

INTRODUCTION

Greenhouse gas (GHG) emissions are the biggest contributor to climate change and global warming, especially since the start of the industrial era. Atmospheric carbon dioxide concentrations have risen from 280 ppm to 400 ppm in the past 150 years [1], and combined with the rises in concentrations of other greenhouse gases, has caused a 0.85 C (global mean) increase from 1880 to 2012 [1]. Although many studies have assessed greenhouse gas emissions and its relationship with climate change [1] [2] [3], socioeconomic trends in relation with greenhouse gas emissions are not well studied. Our aim was to determine which demographics produce the most greenhouse gases, and therefore propose policies to minimize the average greenhouse gas emissions per capita. Unlike past studies looking at a single or a few factors [4] [5] [6] [7] [8] [2] [9], this study analyzes 13 factors to compare and contrast their respective relationships with GHG per capita. The 13 factors analyzed were: literacy rate, GDP per capita, rural population percentage, urban population percentage, adolescent fertility rate (births per 1000 women ages 15 - 19), unemployment percentage, percent of agricultural land,

renewable energy consumption (% of final energy consumption), food production index, population growth (annual %), mobile cellular subscriptions, air transport freight, and forest area (% of total area). We picked these 13 factors because they had data spanning 20 years and are unique indicators under different World Bank categories [10] of economic and social development. We predict literacy rate, GDP per capita, and adolescent fertility will have the largest impacts on GHG emissions per capita because we hypothesize citizens of wealthier countries have greater access to resources and can afford to be more wasteful.

METHODOLOGY

We used the Python library, Pandas, to structure the data and SAS Visual Analytics [14] to assess the relationship between greenhouse gas (GHG) emissions per capita and 13 factors [1]. We extracted data spanning a 20-year period from 1993 to 2012 from the World Bank database for each factor [10]. We also extracted the total GHG emissions and global population datasets to calculate GHG emissions per capita. Using a Python library

called Pandas, we combined these two into a structure called a DataFrame. Iterating through each year in the DataFrame, we divided the GHG emission figure for the particular year by the year's population and multiplied by 1000 to convert the units from kilotons of GHG per capita to tons of GHG per capita. We then joined the tables and ran regression models using SAS Visual Analytics and scikit-learn [15] to determine if correlations exist between GHG emissions per capita and each factor. We quantified the strength of each correlation using the impact weights generated by our regression model. We used a 3:1 ratio for our training and testing set.

RESULTS

	GHG per capita (real)	GHG per capita (prediction)
1995	6.837476	7.564140
2005	7.245037	7.148353
1996	6.777399	7.300522
2001	6.513074	6.732983
1994	6.899806	7.321203

Figure 1. Predictions from the multiple regression model

With an r^2 value of 0.997, our model shows a strong correlation between the 13 indicators and GHG emissions per capita. Proceeding with testing the regression model, we can see in Figure 1 that the model produced results close to the actual GHG emission per capita output.

	Agricultural land	Forest area	Food production	Renewable energy consumption	Air transport	Mobile cellular subscriptions	GDP per capita	Literacy rate	Unemployment	Fertility rate	Population growth	Rural population	Urban population
Agricultural land	1	-0.2509	0.04036656	0.20593454	0.077884	-0.13520355	-0.15313	0.326422	0.595999249	-0.3189	-0.355565997	-0.04075927	0.0407593
Forest area	-0.250908	1	-0.9656218	0.64576591	-0.97093	-0.89173926	-0.86987	-0.98979	-0.262344972	0.994294	0.988629203	0.971059142	-0.9710591
Food production	0.0403666	-0.9656	1	-0.65822832	0.989691	0.976857072	0.964818	0.941793	0.085595542	-0.94548	-0.923287762	-0.99829437	0.9982944
Renewable energy consumption	0.2059345	0.6458	-0.6582283	1	-0.65083	-0.62460211	-0.67114	-0.58109	0.203056035	0.60508	0.607003787	0.676119976	-0.67612
Air transport	0.0778836	-0.9709	0.98969055	-0.65082552	1	0.953528965	0.939518	0.951921	0.135353907	-0.95617	-0.93341951	-0.98830226	0.9883023
Mobile cellular subscriptions	-0.135204	-0.8917	0.97685707	-0.62460211	0.953529	1	0.984884	0.859109	-0.036703319	-0.85921	-0.829061207	-0.97228335	0.9722833
GDP per capita	-0.153127	-0.8699	0.96481801	-0.67114274	0.939518	0.984884198	1	0.830173	-0.12901091	-0.83983	-0.798087407	-0.95651476	0.9565148
Literacy rate	0.326422	-0.9898	0.94179346	-0.58109239	0.951921	0.85910886	0.830173	1	0.315307582	-0.98712	-0.986103613	-0.94601475	0.9460147
Unemployment	0.5959992	-0.2623	0.08559554	0.203056035	0.135354	-0.03670332	-0.12901	0.315308	1	-0.3233	-0.365163284	-0.10913837	0.1091384
Fertility rate	-0.318902	0.9943	-0.9454827	0.605080056	-0.95617	-0.85920718	-0.83983	-0.98712	-0.32330044	1	0.990784702	0.950655133	-0.9506551
Population growth	-0.355566	0.9886	-0.9232878	0.607003787	-0.93342	-0.82906121	-0.79809	-0.9861	-0.365163284	0.990785	1	0.931198099	-0.9311981
Rural population	-0.040759	0.9711	-0.9982944	0.676119976	-0.9883	-0.97228335	-0.95651	-0.94601	-0.109138371	0.950655	0.931198099	1	-1
Urban population	0.0407593	-0.9711	0.99829437	-0.67611998	0.988302	0.972283347	0.956515	0.946015	0.109138371	-0.95066	-0.931198099	-1	1

Figure 3. Correlation matrix of Pearson correlation coefficient for the factors

	Model Weights
Agricultural land (% of land area)	1.161289e-01
Forest area (% of land area)	2.988346e+00
Food production index (2004-2006 = 100)	-5.358055e+00
Renewable energy consumption (% of total final energy consumption)	5.812910e-02
Air transport, freight (million ton-km)	5.707205e-01
Mobile cellular subscriptions (per 100 people)	-5.052614e-01
GDP per capita (current US\$)	1.199155e+00
Literacy rate, adult total (% of people ages 15 and above)	6.772573e-01
Unemployment, total (% of total labor force) (modeled ILO estimate)	-1.297599e-01
Fertility rate, total (births per woman)	-1.659450e+00
Population growth (annual %)	6.060881e-02
Rural population (% of total population)	-5.595735e+12
Urban population (% of total population)	-5.595735e+12

Figure 2. Weights generated by the multiple regression model

Figure 3 is a correlation matrix of our factors, it shows factors are not independent. This is significant because our model could be simplified by removing factors which have high Pearson's R with other factors.

DISCUSSION

Based on the standardized weights produced by our model, we found the indicators with the greatest impact on GHG emissions per capita are food production, renewable energy consumption,

air transport, mobile cellular subscriptions, literacy rate, and population growth. We correctly predicted literacy rate as having a large impact, but GDP per capita and adolescent births did not have as large of an impact as we predicted. However, we believe the results still suggest our assumptions are correct as it can be extrapolated that wealthy educated people living in urban centers pollute the most.

Literacy rate is correlated with higher education. A more educated populace tends to be wealthier. Wealthier people have more discretionary income to spend on luxury goods and services and tend to be more urbanized. It can be extrapolated people living in cities have easier and greater access to goods and services. Moreover, increased urbanization reduces carbon sinks. Thus, urban population growth also has a strong weight.

The correlation between food production and greenhouse gas emissions is likely due to an increasing global population and increasing standards of living [13]. Agriculture accounts for one-third of total anthropogenic GHG emissions [12].

As the world becomes more urbanized and wealthier, the demand for tourism and the transportation of food and goods increases. Current large-scale transportation methods burn fossil fuels and emit greenhouse gases. Hence, there is a strong correlation between air freight and GHG emissions.

This study matched findings from previous research [4] [5] [6] [7] [8] [2] [9] which studied the relationship between food production, irrigation, urbanization, air freight, and greenhouse gas emissions.

A weakness of our study is correlation does not imply causation. Moreover, data did not exist for some underdeveloped countries, possibly skewing the global average. Countries which made up each data set can be found here [10]. Unfortunately, each factor did not have the same number of countries so there were differing number of data points between regression analyses. Future studies should aim to determine if the correlations are causal. Due to the impracticalities of conducting controlled experiments, future studies could analyze temporal precedence to more accurately determine if a factor caused an increase in GHG emissions per capita. It would also be interesting for future studies to investigate if wealthier countries' investments in renewable energy mitigate their citizens' higher GHG emissions.

CONCLUSION

With weights greater than [5], our model suggests food

production, renewable energy consumption, air transport, mobile cellular subscriptions, literacy rate, and population growth have the greatest impact on GHG emissions. These factors are indicators of industrialization and purchasing power. Thus, we reaffirm the importance of balancing economic growth and sustainable development. Governments could target market sustainable consumption, balanced diets, and environmental stewardship to this demographic.

Future studies should aim to determine if the correlations are causal. Due to the impracticality of conducting controlled experiments, future studies could analyze temporal precedence to more accurately determine if a factor caused an increase in GHG emissions per capita.

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