SMU
SINGAPORE MANAGEMENT UNIVERSITY

School of
Computing and
Information Systems

IS616 – Applied Statistical Analysis with R
PROJECT REPORT

GREENHOUSE GAS EMISSIONS STUDY

Introduction

Fossil fuels, coal, oil and gas are by far the major contributors to global climate change, accounting for more than 75% of global greenhouse (GHG) emissions.[1] The main greenhouse gas emissions are carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O). Emissions of greenhouse gases trap the sun's heat, which can lead to global warming and climate change. Greenhouse gases have a wide range of environmental and health impacts and contribute respiratory diseases caused by air pollution, extreme weather, rising sea levels and global temperature.[2]

The first instrument to bring the United Nations Framework Convention on Climate Change (UNFCCC)'s envisioned GHG reduction goals into practical effect was the Kyoto Protocol, which came into force in 2005. The Protocol legally binds "Annex I" countries to reducing their GHG emissions in accordance with agreed targets. There are 42 "Annex I" countries and they are generally recognised as developed. "Non-Annex I" countries comprise developing countries.[3]

In 2015, the world agreed to pursue efforts to limit global temperature rise to 1.5 degrees Celsius above pre-industrial levels. Climate scientists have warned that crossing this threshold risks unleashing far more severe climate change effects on people, wildlife and eco systems.[4] Of concern is that the number of climate-related disasters has already tripled in the last 30 years, while the rate of global sea-level rise was 2.5 times faster during the period 2006 to 2016 compared to almost all of the 20th century. Meanwhile, over 20 million people a year are forced from their homes by climate change.[5]

A recent survey conducted by the United Nations Development Programme (UNDP) in 2021 found that nearly two-thirds of people in 50 countries across the main geographical regions believe that climate emergency is a global emergency. The level of belief is only slightly lower in developing countries than in developed countries. That said, only 59% who believed there is a climate emergency felt there was an urgency to respond. The remaining 41% were of the view that we should act slowly while learning more about what to do, that the world is already doing enough, or that we should do nothing. [6]

Overall Concept

Our objective is to study trends in the emission of carbon dioxide, methane and nitrous oxide over the period 2000 to 2019[1], using data made publicly available by the World Bank. Our main interest is in exploring the 20-year trends in GHG emissions and potential explanatory variables, comparing how these may differ between Annex I and Non-Annex I countries, and between geographical regions. Potential explanatory variables were population, Gross Domestic Product (GDP), the percentage of total energy consumed that is renewable, military expenditure as a percentage of government expenditure, a country's income classification as well as the export and import of goods and services as percentages of GDP.

We have also created an R Shiny app allowing users to discover for themselves some of what we have found during the course of our study. While climate science is complex and beyond the scope of our project, we hope to bring awareness at least of how GHG emissions from different groups and regions have been growing over the past 20 years. Providing more ways for the public to interact with data related to the main causes of climate change may be a useful way to engage them in the climate change conversation and to encourage their participation in its solutions.

[1] The most recent GHG emissions data available from the World Bank was for 2019.

Data Preparation and Methodology Overview

Of 4340 rows of data spanning 20 years, only 2816 were complete. Unsurprisingly, missing values were much more common amongst non-Annex I countries (42% of all non-Annex I rows) compared to Annex I countries (5% of all Annex I rows). However, as there are more non-Annex I countries, there remained 798 rows for Annex I countries and 2018 rows for non-Annex I countries. Missing data was however fairly distributed over the years, ranging between 34% to 40% of rows. The most frequently missing variable was that for military expenditure, followed by export and import figures. For descriptive analysis, we replaced missing values with the sample mean of its respective variable. For inferential analysis, all incomplete rows were excluded.

We began with data visualization techniques to better understand trends and identify potential points of interest. As each sample size was still more than 30 for each year, the Z-test was then used in the comparison of means between Annex I and non-Annex I countries. We used analysis of variance (ANOVA) to explore possible differences between the main geographical regions, and Tukey's honest significance test (Tukey HSD) to find out which pairs were significantly different. We then conducted multiple regression analysis to understand whether and how the independent variables we had selected might explain the volume of a country's GHG emissions.

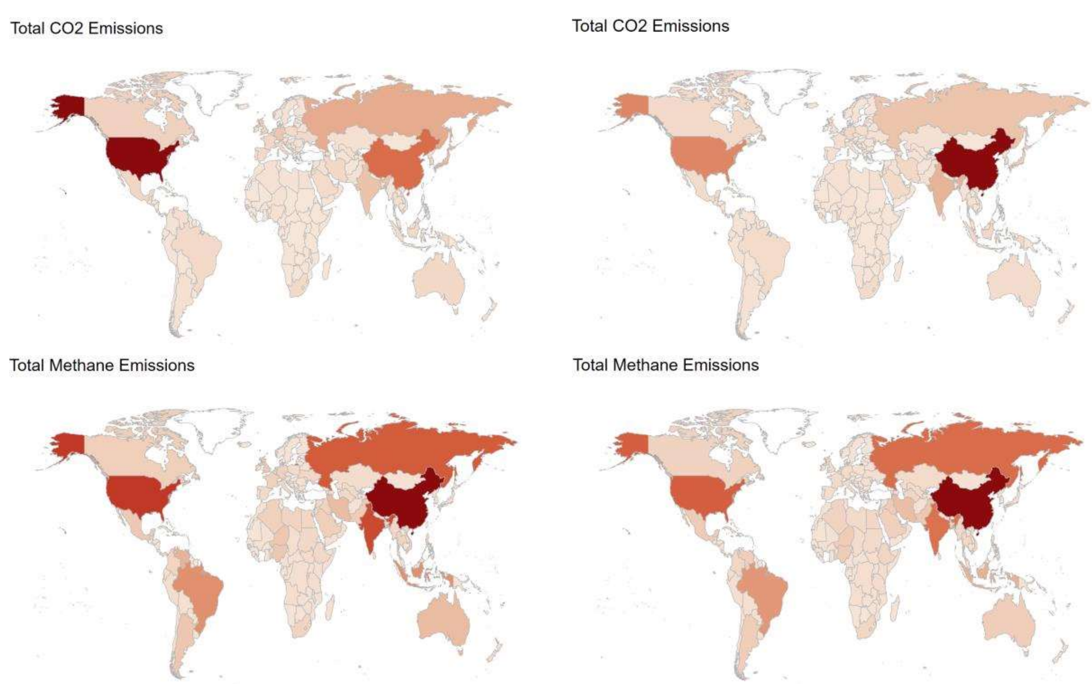
Descriptive Analysis

Cross-sectional

a) World view of emissions

To visualize the global distribution of GHG emissions and to provide a relative comparison of our independent variables across countries, world maps were plotted. For example, below are images of the world maps shown when an app user chooses the total CO_2 and CH_4 emissions in 2000 and 2019:

2000 **2019**



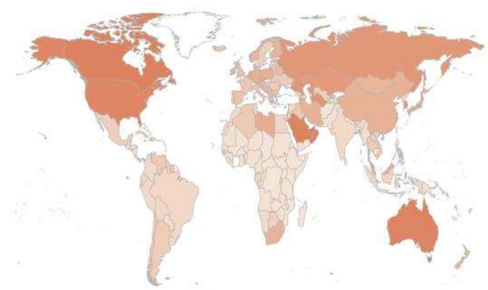
Colour scale:  kilotonnes (higher intensity reflects higher total emissions)

It is observed that the top emitters remained the same in 2019 as in 2000. In addition, it may be clearly observed that China overtook United States as the world's top emitter of carbon dioxide somewhere between 2000 and 2019 (the exact year, based on data visualized as world map on our app, was 2006).

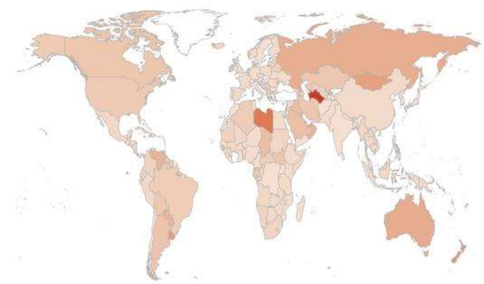
It may be alarming to see that there are a few non-Annex I countries amongst the top emitters, given that non-Annex I countries have less stringent GHG reduction targets to abide by. However, when the app user chooses to view emissions per capita instead, both China and India no longer appear as top emitters, and different main culprits appear instead (see images to the right).

To compell top non-Annex I emitters to reduce total emissions, it may seem fair that top emitters on a per capita basis are similarly compelled to do so.

CO2 Emissions Per Capita



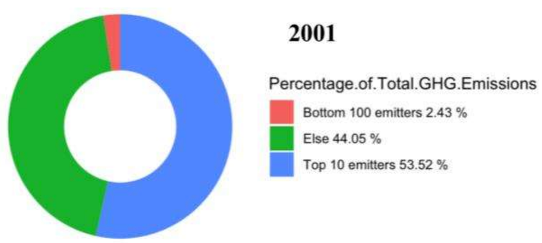
Methane Emissions Per Capita

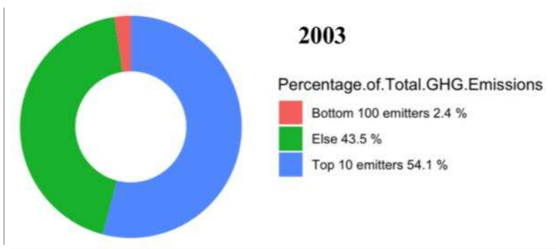


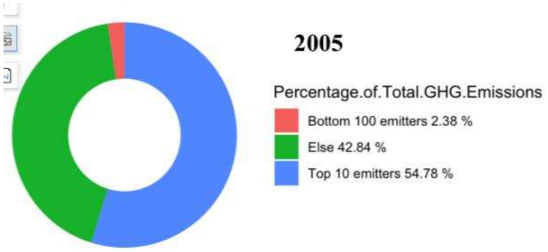
b) Total Greenhouse Gas Emissions (Top 10 emitters vs Bottom 100 emitters vs Else)

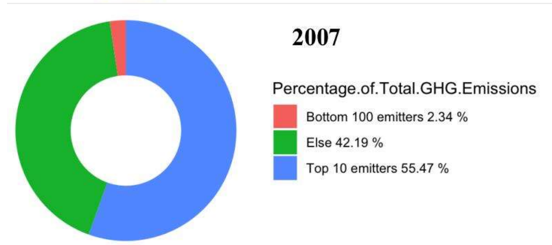
As countries implement targets, policies and pathways to reduce their GHG emissions, it is important to fully understand the global emissions picture and how it changes over time.[7]

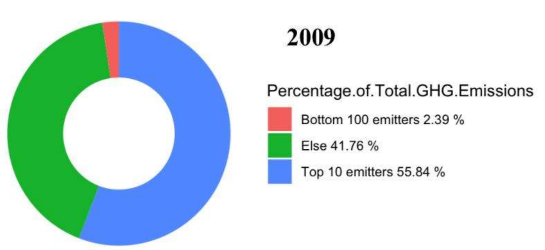
In this climate change data set, there are 217 countries in total. GHG emissions are first sorted by year, then divided into three groups: top 10 emitters, bottom 100 emitters, and remaining countries in between. A pie chart is plotted for each year. Given space constraints, only the odd years are shown:

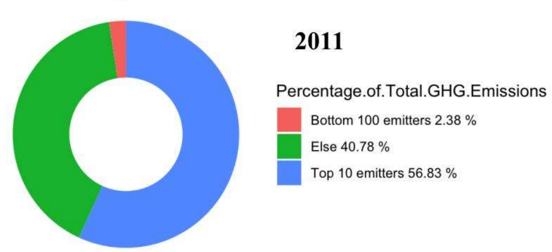


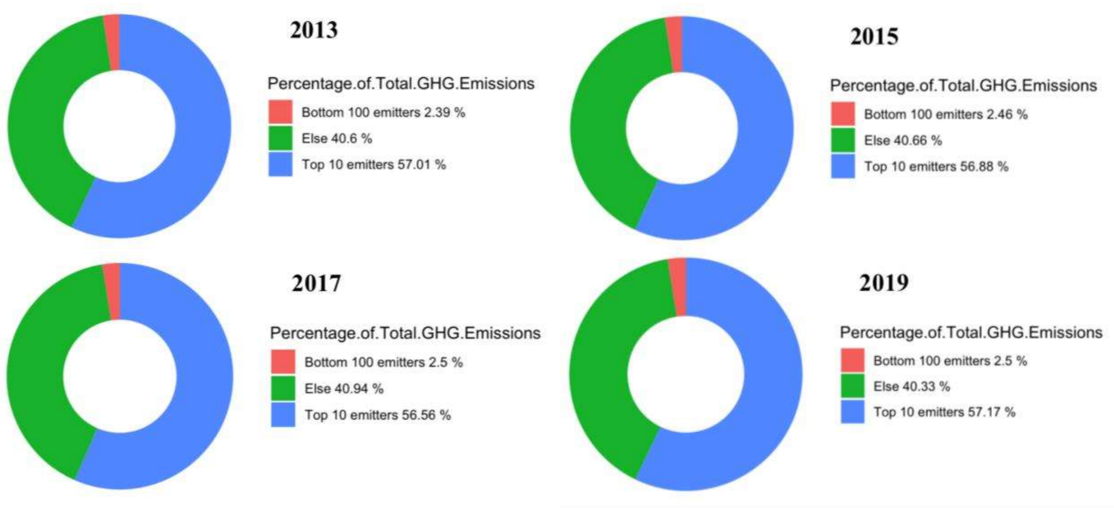








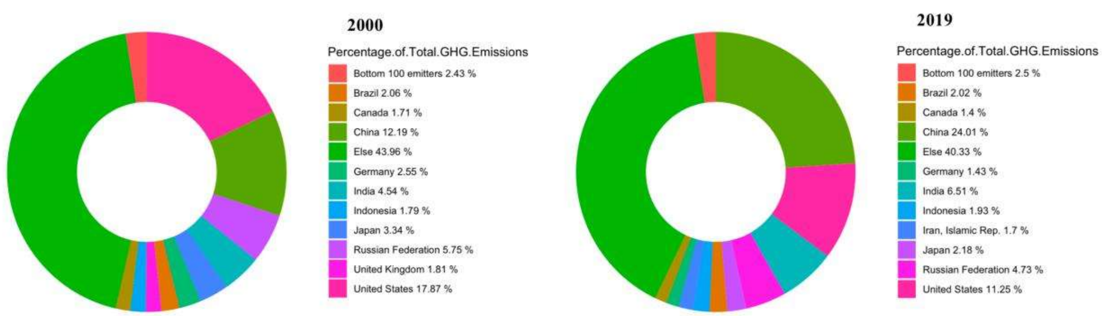




It is observed that total emissions from the top 10 emitters have exceeded half of the world's total GHG emissions, gradually increasing from 53.61% in 2000 (not shown) to 57.17% in 2019, among which 2014 (not shown) accounted for the largest proportion, reaching 57.3%. Total emissions of the bottom 100 countries are basically unchanged at 2.3% to 2.5%.

Through observation and calculation, it can be concluded that the world’s top 10 emitters contribute 23 times the GHG emissions of the bottom 100, which indicates that the top 10 emitters still need to take further effective measures to control their emissions. The world cannot successfully fight climate change without significant action from the top 10 emitters.[7]

In addition, in order to more specifically observe the proportion of GHG emissions of the top 10 emitters, we selected 2000 and 2019 and made the corresponding pie chart as follows.

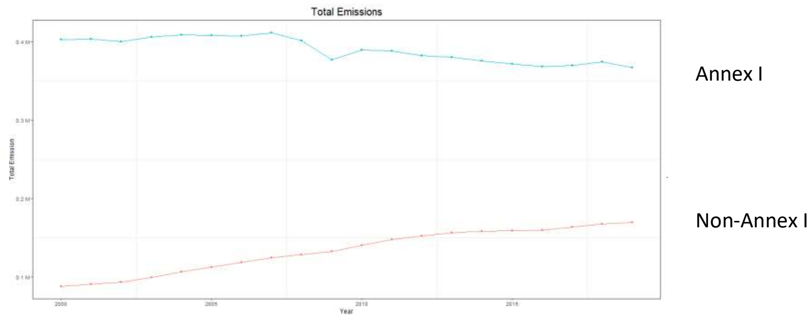


In 2019, compared to 2000, the top 10 emitters have changed, Iran replaced the United Kingdom as a top 10 emitter, China surpassed the United States to become the country with the highest proportion of emissions, and the top 3 emitters - China, the United States and Russia - remained unchanged. These data are essential to understanding the latest emissions trends and countries’ short- and long-term actions that will bend the emission curve downward.[7]

Time Series

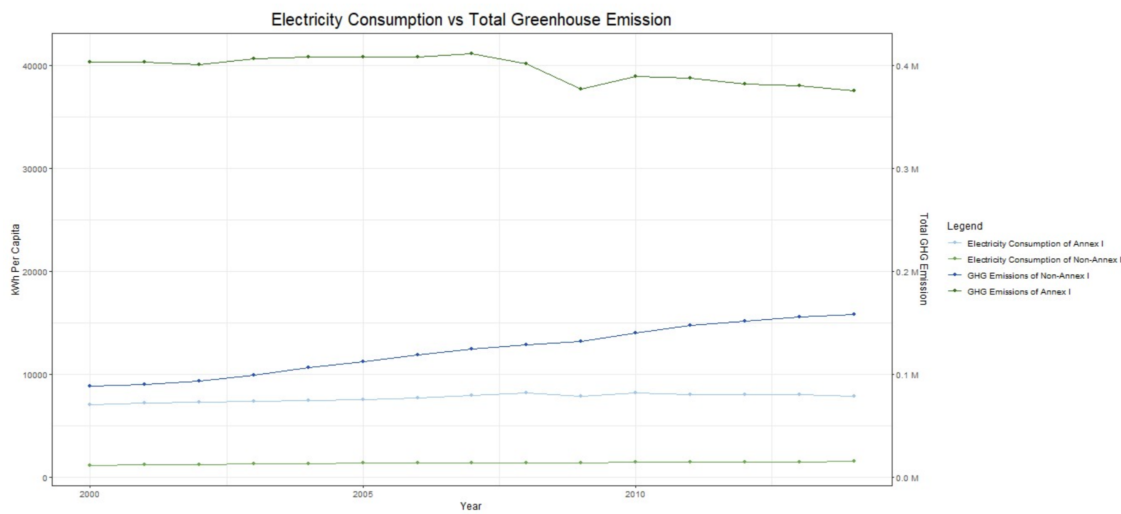
a) Average Total GHG Emissions (Annex I vs Non-Annex I)

In the period from 2000 to 2019, the average total GHG emissions of non-Annex I countries show a steady upward trend, with around 0.1 million tons of emissions in 2000 and 0.17 million tons of emissions in 2019. The average total emissions of Annex I countries are significantly higher than those of non-Annex I countries. Specifically, it peaked at 0.41 million tons in 2007 and dropped to the lowest in 2019 with 0.36 million tons.



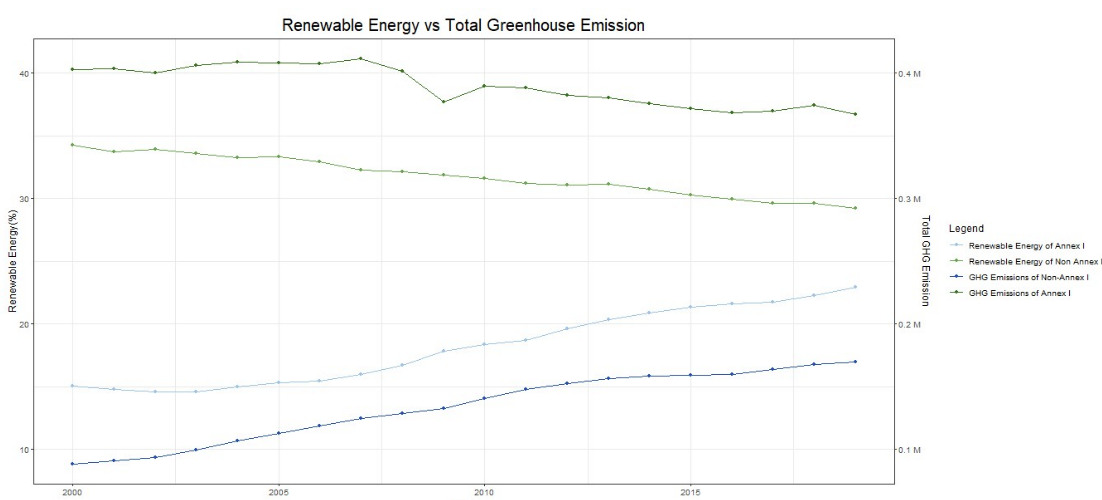
b) Average Electricity Consumption vs Average Total GHG Emission

While electricity consumption by Annex I countries has remained fairly constant, their GHG emissions have declined over the years. This could suggest increasing energy efficiency in these countries. In contrast, GHG emissions from non-Annex I countries appear to increase faster than electricity consumption. This could be due to decreasing energy efficiency, or GHG emissions from other sources (i.e. not from the generation of electricity).



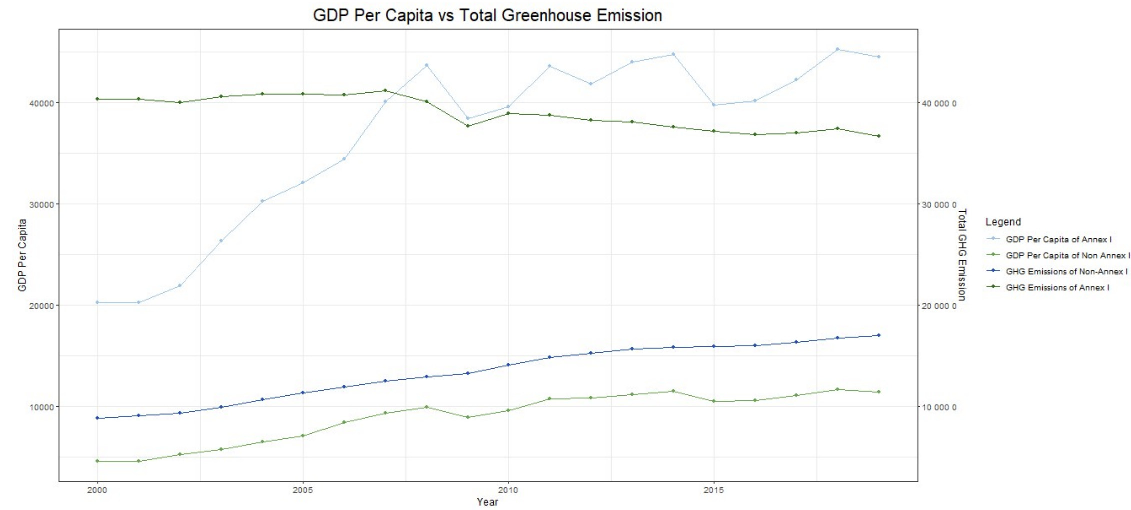
c) Average Renewables (as % of total energy consumption) vs Average Total GHG Emissions

The percentage of energy consumption that uses renewables is much higher among non-Annex I countries. Some studies have found a positive correlation between renewable energy consumption and CO_2 emissions among low-income countries, and a negative correlation between renewable energy consumption and CO_2 emissions among high-income countries[8].



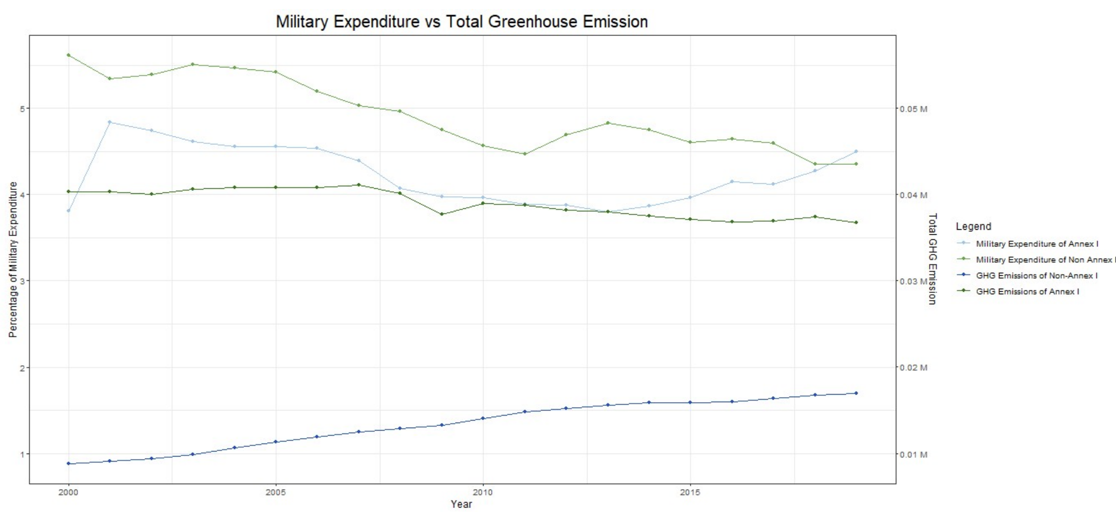
d) Average GDP per capita vs Average Total GHG Emissions

By 2019, Annex I GDP per capita had doubled while total GHG emissions were in gradual decline. However, non-Annex I countries total GHG emissions have increased with GDP per capita. This may suggest that both economic growth and climate change are priorities for Annex I, but only economic growth is a priority for non-Annex I.



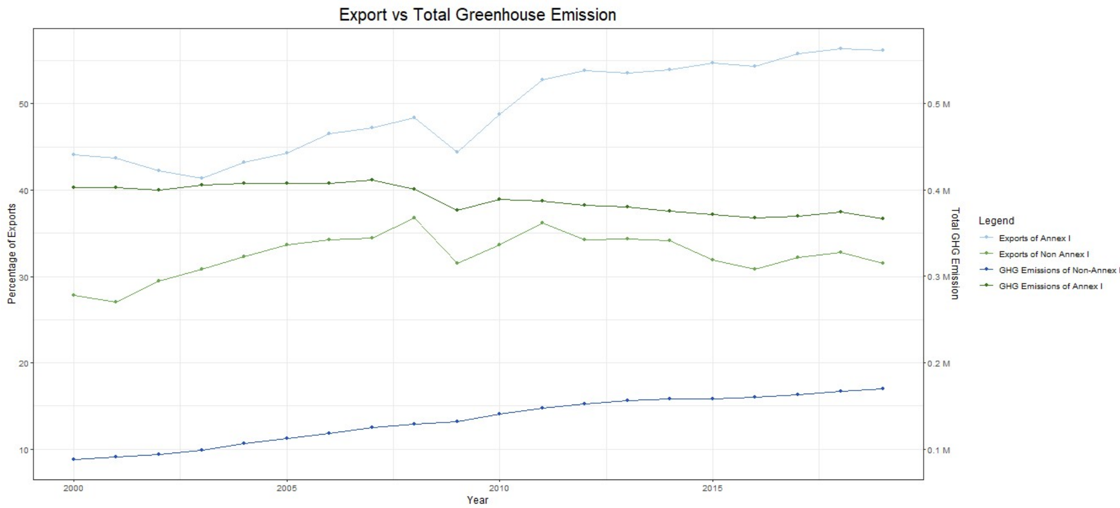
e) Average Military Expenditure (as % government expenditure) vs Average Total GHG Emissions

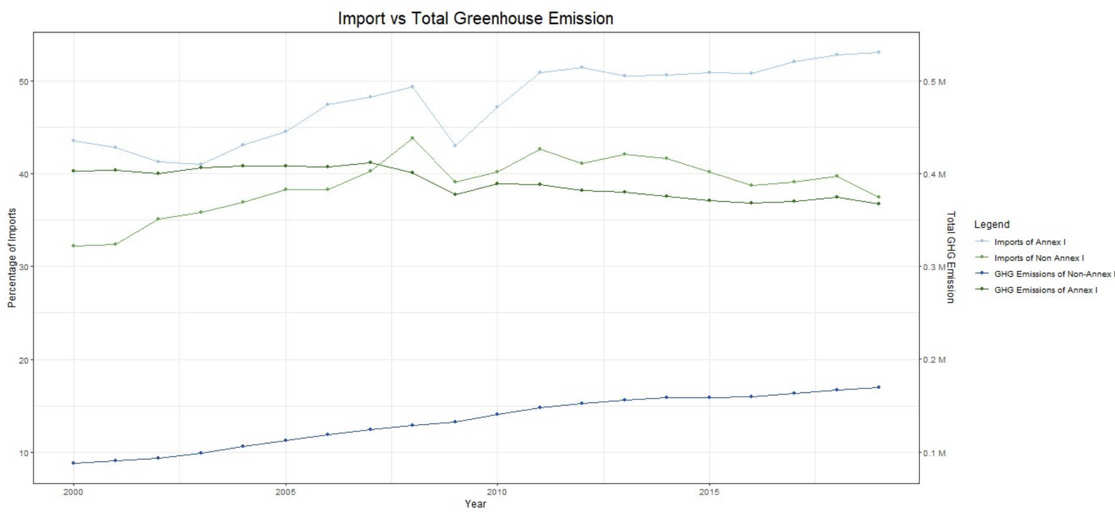
We were curious to see whether and how military expenditure as a percentage of total government expenditure might track emissions, as a way of potentially identifying national priorities. For Annex I, There is no observable relationship between military expenditure and GHG emissions. For non-Annex II, we see an overall decline in military expenditure while GHG emissions are increasing.



f) Average Imports/Exports (as % of GDP) vs Average Total GHG Emissions

We found that imports and exports had increased for Annex I countries over the period 2000 to 2019, even while GHG emissions declined. For non-Annex I countries, it appeared that imports, exports and GHG emissions all increased over the same period.





Inferential Statistics

Comparing two means

Comparing emissions from non-Annex I to Annex I Emissions

It is generally assumed that the populations in developed countries, being wealthier and thus consuming more, contribute more to global GHG emissions on a per capita basis, compared to populations in developing countries. At the same time, the Kyoto Protocol has bound developed countries to reducing GHG emissions since 2005. We wish to understand if there has been any change in the statistical difference between mean emissions from both groups since 2000.

We will therefore compare the mean emissions per capita from non-Annex I and Annex I countries. We will do so for the years 2000, 2010 and 2019, for four emissions categories: carbon dioxide, methane, nitrous oxide and total GHG emissions. As each sample size is over 30 and we do not have the population variance, we will use the Z-test and the sample standard deviation. The confidence level used is 95%. Our Shiny app allows the user to conduct these tests themselves, and the results are below:

H_0: $\mu_{\text{Annex I}} - \mu_{\text{non-Annex I}} \leq 0$
H_1: $\mu_{\text{Annex I}} - \mu_{\text{non-Annex I}} > 0$

RESULTS:	Reject null hypothesis? *			
Year	CO2	CH4	N2O	Total
2019	Yes	No	Yes	Yes
2010	Yes	No	Yes	Yes
2000	Yes	No	Yes	Yes

What was most surprising to us was discovering that **there was sufficient evidence to reject the claim that non-Annex I countries emitted less methane per capita compared to Annex I countries, for all three years**. Below are the results of analysis for methane emissions per capita in 2019:

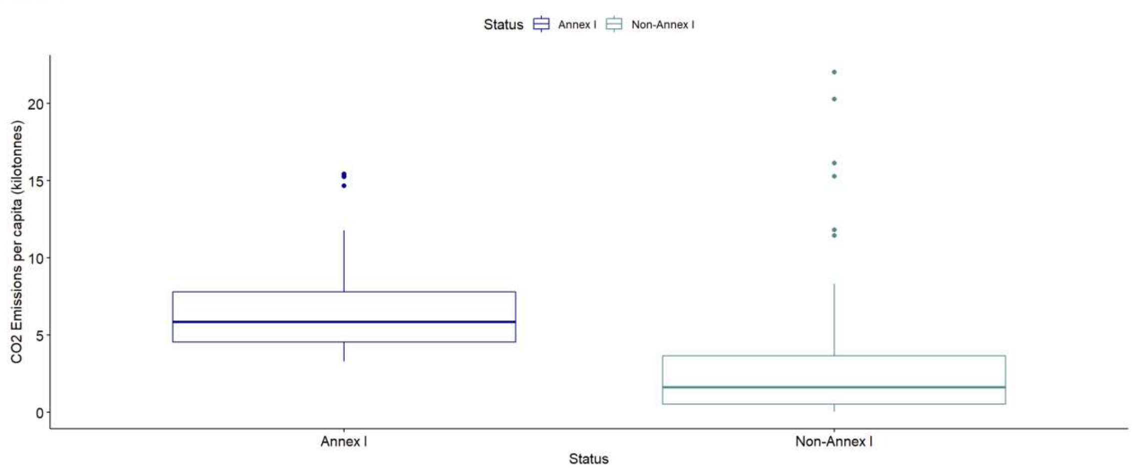
```
	Two Sample z-test

data:  AnnexI_2019[["Methane_emissions"]] and NonAnnexI_2019[["Methane_emissions"]]
z = -0.42692, p-value = 0.6653
alternative hypothesis: true difference in means is greater than 0
95 percent confidence interval:
 -0.5342252        Inf
sample estimates:
mean of x mean of y
 1.333345  1.443431
```

P-value is more than 0.05. There is insufficient statistical evidence to reject the null hypothesis.

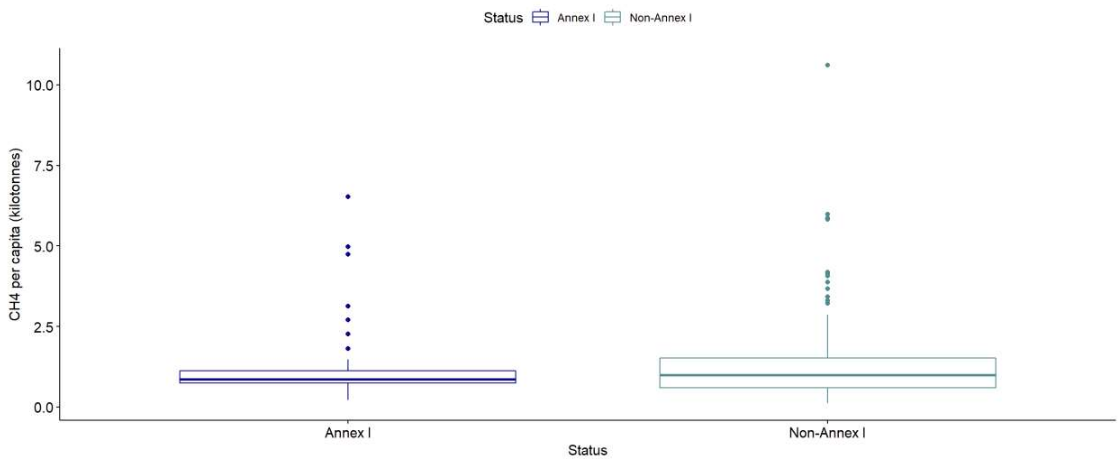
Further research informs us that methane is a powerful greenhouse gas that traps heat 28 times more effectively than carbon dioxide over a 100-year timescale. Our finding may therefore be interesting to developing countries to decide which GHG to address. As GHG reduction technologies can require significant investment, being able to focus on one type may help maximise returns on investment.

The boxplots generated to help visualise differences between the two groups were also of interest:

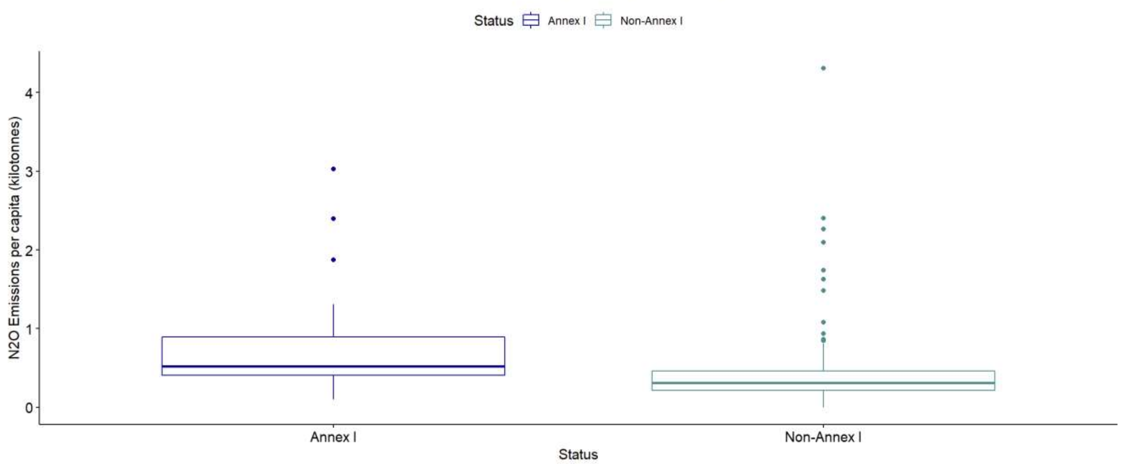
Claim: Non-Annex I countries emitted less Carbon Dioxide per capita compared to Annex I countries in 2019



Claim: Non-Annex I countries emit less Methane per capita compared to Annex I countries in 2019



Claim: Non-Annex I countries emit less Nitrous Oxide per capita compared to Annex I countries in 2019



As shown above, there were several outliers in the non-Annex I group, across all four emission categories, in 2019. The difference between the furthest outlier in each case and the median was between 5 to 10 times the value of the median. For Annex I, we see more outliers for methane (and for total GHG emissions, which is likely to be largely a result of being outliers for methane).

We therefore removed the outliers and repeated the Z-test on all four emissions categories for 2019. **The results were no different, i.e. there was sufficient evidence to support the claim in all categories except methane**. (Note: In our presentation, we said the result flipped for nitrous oxide. However, we were subsequently unable to repeat the result hence we retain our original conclusion.)

Analysis of variance

Comparing emissions across main geographical regions

The World Bank (our data source) uses six geographical categories: (i) East Asia and Pacific, (ii) Europe & Central Asia, (iii) Latin America & Caribbean, (iii) Middle East & North Africa, (iv) North America, (v) South Asia and (vi) Sub-Saharan Africa. The sizes of each sample varies greatly – there are 46 and 40 countries in groups (ii) and (vi) respectively, and only 5 and 2 countries in groups (v) and (vi).

Although equal sample sizes is not an assumption for ANOVA, we note that the unequal sizes including very small samples may result in reduced statistical power and reduced robustness to unequal variance. For this analysis, we have therefore regrouped (iii) and (v) together to form South Asia, Middle East & North Africa, and regrouped (i) and (iv) together to form Asia-Pacific. The resulting 5 groups and their sample sizes (for the year 2019) are shown to the right:

Asia-Pacific (AP)	21
Europe & Central Asia (ECA)	46
Latin America & Caribbean (LAC)	20
South Asia, Middle East & North Africa (SMN)	19
Sub-Saharan Africa (SSA)	40

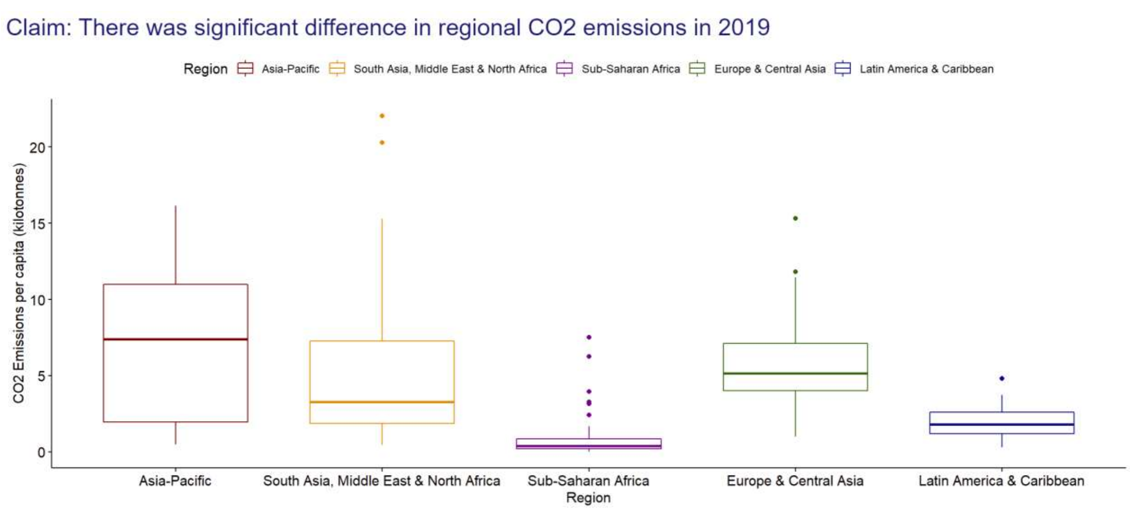
As before, analysis was conducted for the years 2019, 2010 and 2000. The results were not at all surprising: for all three years and all four emissions categories, a statistically significant difference in means across the five regions was observed.

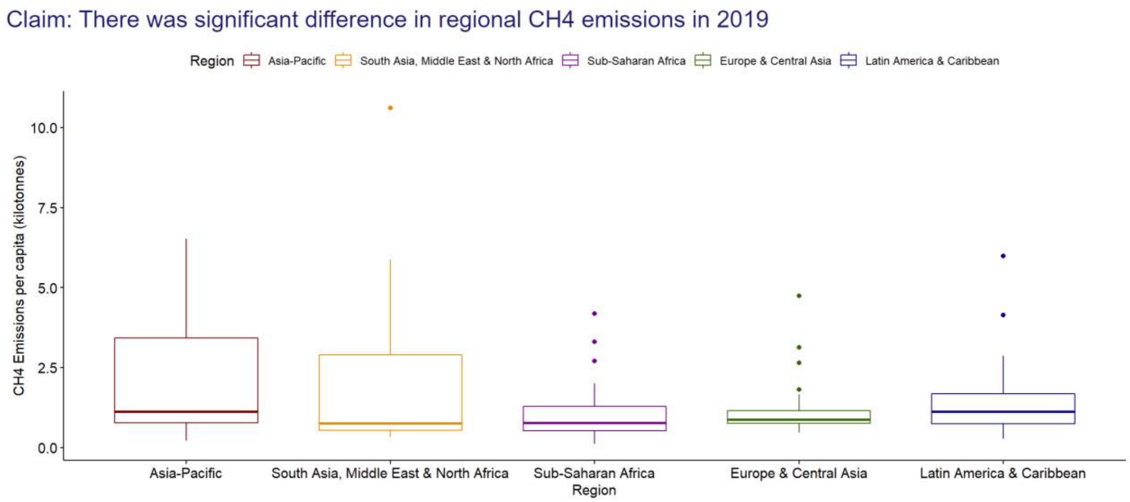
We then used Tukey HSD to understand which pairs in particular showed statistically significant differences. Regional pairs showing statistically significant differences in emissions per capita in 2019, at 95% confidence level

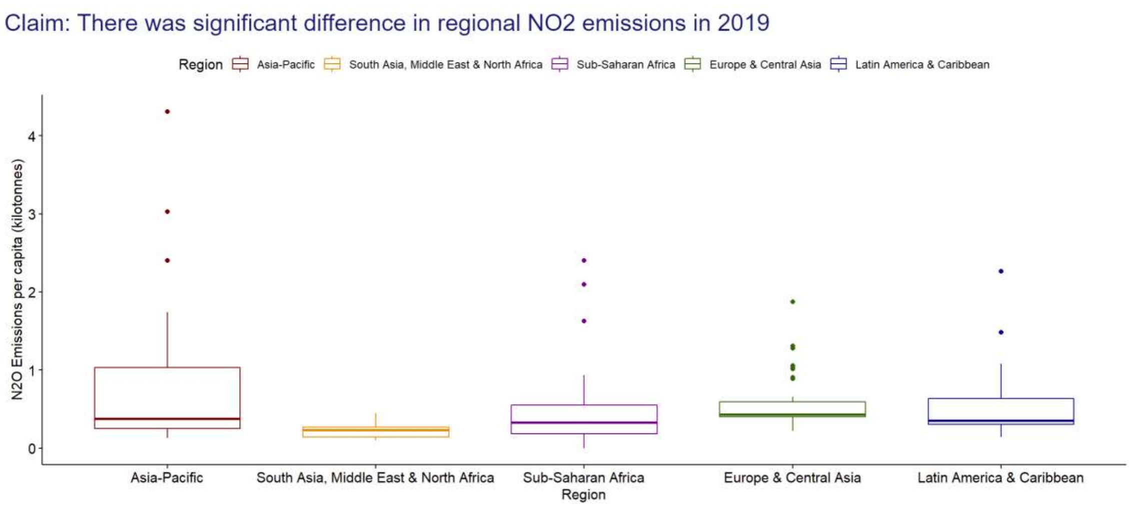
Carbon Dioxide *(p-value)*	Methane *(p-value)*	Nitrous Oxide *(p-value)*	Total GHG *(p-value)*
SSA-AP (0.0000001)	SSA-AP (0.0427336)	SMN-AP (0.0015615)	SSA-AP (0.0000003)
SSA-ECA (0.0000003)	-	SSA-AP (0.0437616)	SSA-ECA (0.0000629)
SSA-SMN (0.0000119)	-	-	SSA-SMN (0.0001372)
LAC-AP (0.0001759)	-	-	LAC-AP (0.0008731)
LAC-ECA (0.0027455)	-	-	SMN-LAC (0.0435688)
SMN-LAC (0.0046820)	-	-	-

As can be seen above, there are more pairs showing significant difference in the emission of carbon dioxide, than in the emission of methane or nitrous oxide. This appears to concur with earlier findings that there is insufficient evidence to support the claim that Annex I countries emit more methane and nitrous oxide than non-Annex I countries. In addition, Asia-Pacific is the only region seen as differing significantly from at least one other region in each category. Again, this concurs with earlier observations – 6 of the top 10 emitters are in the Asia-Pacific.

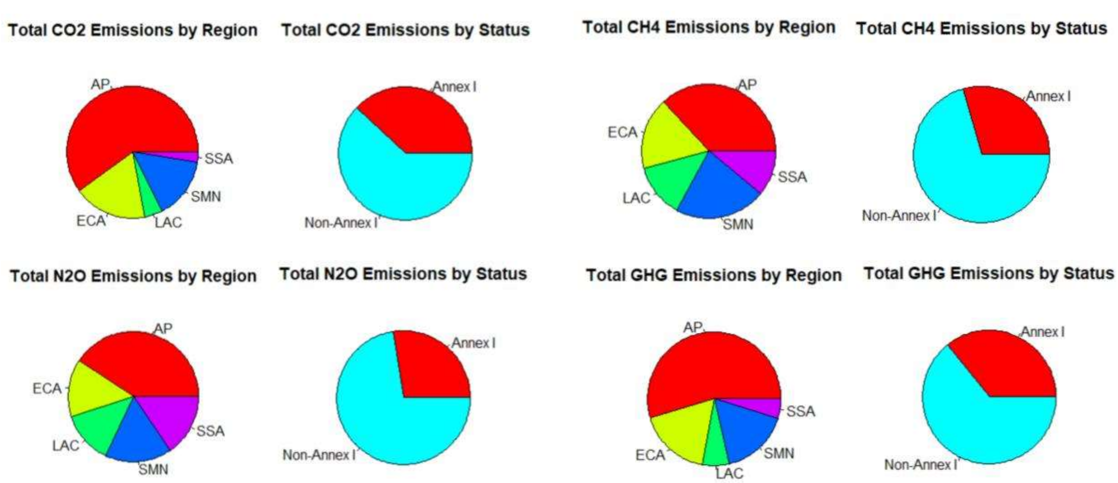
The relevant boxplots are shown below:







Comparing geographical regions may give rise to the question whether it might be more meaningful to policy decisions, to group countries by development status (as in Annex I and non-Annex I), or to group countries by geographical regions. We visually compare how global total emissions are divided using both categories, to see if there is anything of interest to note (this is not in the app):



It is difficult to draw any clear conclusions from this comparison. However, we note that Annex I countries comprise countries in North America, much of Europe as well as Australia and New Zealand.

From the pie charts, we see that AP and ECA (the regions where Annex I countries come from) make up well over half of total GHG emissions and, as a proportion of total emissions, is about twice the size of Annex I countries alone. Non-Annex I countries in AP and ECA seem to be emitting as much as the remaining three regions together (LAC, SMN and SSA). Though more research and analysis should be conducted, this preliminary observation prompts the question whether countries legally bound to more stringent emissions reduction targets should be expanded beyond the current Annex I.

Regression

As we had learned that top 10 emitting countries are responsible for almost 60% of total global GHG emissions, we built a prediction model using multiple linear regression to better understand how much variation can be accurately predicted by using various independent variables and the relative contribution of each independent variable in the total variance.

From our initial regression analysis of top 10 emitting countries, we have observed from regression diagnostics tools that there are significant amounts of outliers or influential data that make prediction results invalid. Upon further analysis, majority of these outliers belong to China and United States. As seen from the table below, for year 2019 excluding United States, China's total emission is more than the rest of the countries combined. United States' total emissions data is also found to have outliers especially for earlier years' data.

Country Name	Year	Total Greenhouse Emissions
China	2019	12435419.74
United States	2019	5827180.22
India	2019	3373120.07
Russian Federation	2019	2449629.96
Japan	2019	1127649.95
Brazil	2019	1047420
Indonesia	2019	998880.04
Iran, Islamic Rep.	2019	880990
Germany	2019	740230.02
Canada	2019	723410.02

Therefore, our regression analysis will be divided into two parts, firstly for only China and United States and secondly for the remaining 8 countries.

Regression Analysis 1

Before selecting variables into the regression model, correlations between variables should be examined to ensure multicollinearity does not exist.

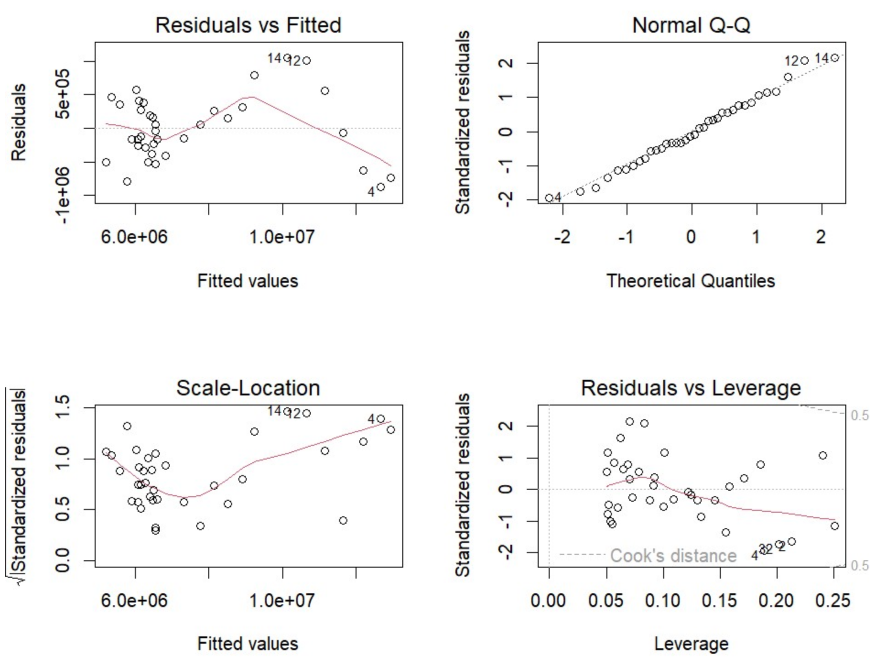
Correlation matrix for regression analysis 1

```
                 Renewable_Energy Population     Export     Import GDP_Per_Capita
Renewable_Energy        1.0000000  0.8432432  0.8821107  0.8167310     -0.6404118
Population              0.8432432  1.0000000  0.8105534  0.7402831     -0.4833977
Export                  0.8821107  0.8105534  1.0000000  0.9454311     -0.6700129
Import                  0.8167310  0.7402831  0.9454311  1.0000000     -0.7253539
GDP_Per_Capita         -0.6404118 -0.4833977 -0.6700129 -0.7253539      1.0000000
```

Correlation threshold for selecting variables is set at 0.8. The stepwise regression method is then employed in the predictive model, in order to find the subset of variables in the data set resulting in the best performing model that lowers prediction error. The model returns R-squared value of 0.9553 and adjusted R-squared value of 0.9511 which implies that by using three parameters in the result shown (Population, GDP per capita and Region), 95% of total variation in total GHG can be explained.

```
Coefficients:
                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)        -8.269e+07  4.973e+06 -16.630  < 2e-16 ***
Population          6.924e-02  3.749e-03  18.469  < 2e-16 ***
GDP_Per_Capita     -1.504e+02  1.669e+01  -9.012 2.71e-10 ***
RegionNorth America  7.510e+07  4.379e+06  17.152  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 505400 on 32 degrees of freedom
Multiple R-squared:  0.9553,	Adjusted R-squared:  0.9511 
F-statistic: 228.1 on 3 and 32 DF,  p-value: < 2.2e-16
```

Although R-squared and adjusted R-squared values seem to indicate that this is a fairly good model, further examination on regression diagnostics tools reveals that it might not be the case.



The diagnostics plots above suggest the model violated multiple linear regression assumptions (linearity of the data and homogeneity of variance of the residuals). The model may be further improved by non-linear transformation of predictors and removal of extreme values.

Regression Analysis 2

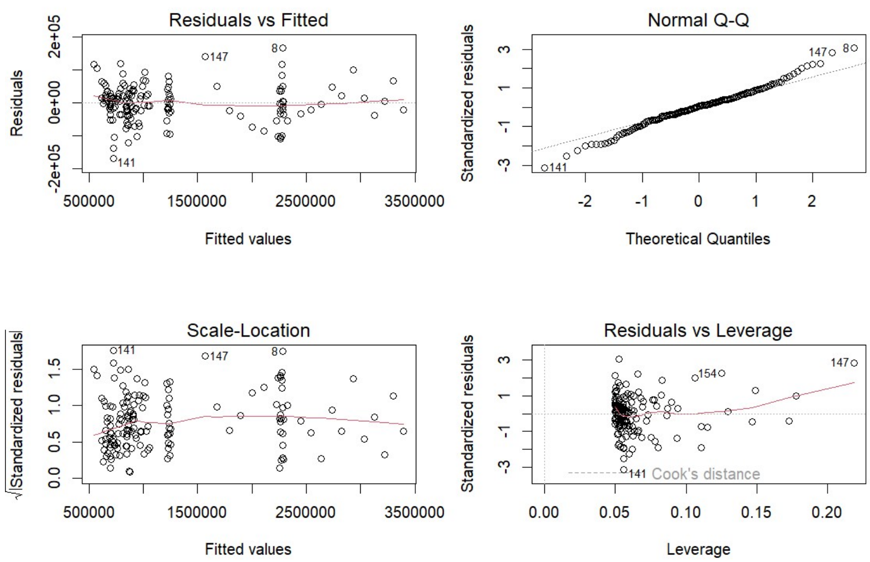
Correlation matrix for regression analysis 2

```
                 Renewable_Energy  Population     Export      Import GDP_Per_Capita
Renewable_Energy        1.0000000  0.47301664 -0.2822419 -0.12880606     -0.3606379
Population              0.4730166  1.00000000 -0.2781597 -0.09169113     -0.4510664
Export                 -0.2822419 -0.27815970  1.0000000  0.90095103      0.3040458
Import                 -0.1288061 -0.09169113  0.9009510  1.00000000      0.3789053
GDP_Per_Capita         -0.3606379 -0.45106641  0.3040458  0.37890534      1.0000000
```

For analysis 2, export and import are strongly correlated at correlation coefficient value of 0.9. Therefore, import will be eliminated from the variables for regression analysis.

```
Coefficients:
                                  Estimate Std. Error t value Pr(>|t|)    
(Intercept)                      4.822e+05  2.656e+04  18.157  < 2e-16 ***
Population                       6.332e-03  1.397e-04  45.341  < 2e-16 ***
Export                          -3.684e+03  1.057e+03  -3.487 0.000646 ***
IncomeGroupLower middle income  -1.122e+06  2.713e+04 -41.369  < 2e-16 ***
IncomeGroupUpper middle income   9.667e+05  2.257e+04  42.826  < 2e-16 ***
RegionEurope & Central Asia      2.484e+04  3.388e+04   0.733 0.464627    
RegionLatin America & Caribbean -1.676e+06  2.653e+04 -63.187  < 2e-16 ***
RegionMiddle East & North Africa 1.027e+06  2.963e+04  34.654  < 2e-16 ***
RegionNorth America              1.062e+05  3.013e+04   3.525 0.000566 ***
RegionSouth Asia                -4.549e+06  1.396e+05 -32.597  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 55820 on 146 degrees of freedom
Multiple R-squared:  0.9941,	Adjusted R-squared:  0.9938 
F-statistic:  2754 on 9 and 146 DF,  p-value: < 2.2e-16
```

The regression model has R-squared value of 0.9941 and adjusted R-squared value of 0.9938. Similarly to first regression analysis, diagnostics tools are utilized to test if the model is able to fulfil assumptions of regression analysis.



Diagnostics plots above show that the predictive model is able to meet the assumption requirements of multiple linear regression. However, there is a outlier data point (141) that has absolute standardized residual value greater than 3 and if removed, it might have potential influence on the regression results.

Conclusion

Some of our results were to be expected given what casual observers may know of greenhouse gas emissions. However, the following findings stood out:

- The top 10 GHG-emitting countries make up for over half of the world's total GHG emissions, and this has been slowly increasing over the period 2000 to 2019. The composition of the top 10 has remained largely unchanged over the same period, with only the United Kingdom replaced by Iran. In 2019, more than half of the top 10 emitters were from non-Annex I countries, i.e. countries that are not bound by more stringent GHG reduction targets.

- Many may assume that developed countries, having access to more financial resources and technologies, would use more renewable energy (as a percentage of total energy consumption) than developing countries. However, we find that the proportion of renewables in total energy consumption is generally higher for non-Annex I countries. That said, our comparison of total energy consumption vs GHG emissions for Annex I and non-Annex I countries suggest that Annex I countries may be becoming more energy efficient.

- While the view that Annex I countries emit more than non-Annex I countries on a per capita basis is statistically supported for carbon dioxide and nitrous oxide, it fails to hold for methane. Given the higher global warming potential of methane, it may be more impactful to for non-Annex I countries with high methane emissions to focus their limited resources on reducing methane instead of carbon dioxide. While

- Population, exports, whether or not an emitter is lower middle income or upper middle income, whether or not an emitter is in Latin America and the Caribbean, in the Middle East and North Africa, in North America and in South Asia, explains over 99% of the emitter's total GHG emissions.

Many of the independent variables we have chosen are either difficult or economically damaging to change (e.g. population, GDP, import, export) or cannot be changed (e.g. we cannot change an emitter's geographical location). For future work, we may wish to consider other variables such as the percentage of women in an emitter's national parliament or the percentage of the emitter's population that is tertiary educated. If they are shown to be negatively correlated to total emissions, certain policy actions might be taken to improve those percentages and thereby lower emissions.

Finally, we find that identifying the group most "responsible" for GHG emissions depends a lot on how the data is categorized: Annex I vs non-Annex I (or development status), top 10 emitters vs rest of world, by geographical regions, by income status, and so on. While categorization by development status might have been the only politically palatable option, our preliminary findings suggest that it is unlikely sufficient to reduce global emissions. Analysis that would demonstrate whether high emitters from developing countries are themselves bearing the brunt of climate change might help change the views of such countries on how they prioritize GHG reduction. For example, a world view visualization of emissions compared to one of the costs of climate change disasters, or comparing mean emissions from countries highly impacted by climate change with those from countries that are not. This would however require datasets quantifying the impact of climate change on individual countries, which we have yet to come across.

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