Atmospheric Variables
and their Impact on Climate Change

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1. Introduction

It is a well researched fact that the human emission of greenhouse gasses is largely responsible for the warming of global temperatures. The burning of fossil fuels, which has been rapidly accelerating since the start of the industrial revolution, has had far-reaching effects on the Earth's climate. Despite the overwhelming scientific consensus that observed changes in the Earth's climate are directly caused by human activity, there is a small but vocal minority that continues to deny the link between human activity and climate change.

This minority uses flawed justifications for the argument that climate change and human activity are not significantly correlated, often in the aims of pushing a political or personal agenda. One of the most common arguments used by climate change deniers is the claim that the Earth's climate has changed at various points in the planet's history and that observed temperature differences are simply part of a naturally occurring cycle. The cyclical nature of El Niño, a global weather phenomenon caused by the shifting of ocean currents in the South Pacific Ocean, is often used by climate change deniers as a justification to show that observed temperature changes are simply a part of this naturally occurring cycle.[1] El Niño is known to cause rising temperatures, droughts, and extreme weather phenomena in the roughly 2-5 year cyclical period in which it occurs. The climate change deniers will argue that changes in the Earth's climate are being caused by the weather cycle of El Niño, and that this cycle is the driving force behind observed changes in the planet's climate.

The goal of this research paper is to use data about the phenomenon of El Niño and greenhouse gas emissions to determine the specific effects that these factors have had on changing Earth's climate. The analysis specifically identifies how global average temperatures and sea levels have been affected, comparing the cumulative recorded impact of El Niño to the impact of greenhouse gas concentrations.

2. Data

Two climate datasets were combined into a single dataset for the analysis. These datasets contain information about average global greenhouse gas concentrations, average global temperatures, and average sea levels. Regression analysis and model fitting was used to establish the correlations among the variables.

The first dataset is a record of climate variables compiled from May 1983 to December 2008 that was published on Kaggle. This data was gathered on a monthly basis and contains the atmospheric concentrations of specific greenhouse gasses, including carbon dioxide (CO_2), nitrous oxide (N_2O), methane (CH_4), trichlorofluoromethane (CCl_3F-) and dichlorodifluoromethane (CCl_2F_2 -). The greenhouse gas data was recorded by the ESRL/NOAA Global Monitoring Division.

Besides greenhouse gas concentrations, this dataset includes additional atmospheric variables that have a known impact on atmospheric temperatures. These variables are the measurements of the TSI (total solar irradiance), recorded by the SOLARIS-HEPPA project, and the MEI (Multivariate El Niño Southern Oscillation Index), recorded by the ESRL/NOAA Physical Sciences Division, as well as atmospheric aerosol concentrations.

The TSI is a measure of the sun's energy deposition in the Earth's atmosphere and is highly dependent upon events such as sunspots and solar flare ups. The MEI is a variable created by researchers at the NOAA to measure the strength and impact of the El Niño cycle oscillation. The MEI variable is a combined Empirical Orthogonal Function of five different variables (sea level pressure (SLP), sea surface temperature (SST), zonal and meridional components of the surface wind, and outgoing longwave radiation (OLR) over the tropical Pacific basin.[2] This combination of atmospheric and oceanic variables is used to determine the cumulative effect of El Niño weather events.

Information from this dataset is used to establish the relationship between greenhouse gas concentrations and temperature changes, and more specifically, the impact of El Niño on temperature changes using the recorded MEI data. The strength of the relationship between the MEI and global temperature changes are explored in the analysis, establishing whether this variable contributes in a meaningful way towards temperature changes, and how it compares to the impact on temperatures caused by greenhouse gas emissions.

The second dataset is a record of average global sea levels, created by Australia's Commonwealth Scientific and Industrial Research Organization in collaboration with NOAA. The sea level is measured on a yearly basis from 1880-2015.

The dataset used in the analysis joins these two climate datasets, combining the sea level change data with the atmospheric and temperature data. To match the timespan of the records, atmospheric concentrations, average temperatures and non-atmospheric variables, which were recorded on a monthly basis, are averaged by year, and the sea level changes are subsetted from 1983-2008. This combined dataset is used to analyze the impact of the MEI on both temperature changes and sea levels.

3. Analysis

The goal of this research paper is to use data about the phenomenon of El Niño and greenhouse gas emissions to determine the specific effects that these factors have had on changing Earth's climate. The impact these variables have on the average global temperature and the global sea level are identified specifically. The relationships between the dataset variables are also analyzed.

3.1 Exploratory Visualizations

Both datasets were imported as csv files into R and were properly formatted and free of any obvious errors or deviations. In terms of data cleaning, the different time spans of the datasets had to be taken into account, as well as the time increments. To match the timespan of the records, atmospheric concentrations, average temperatures and non-atmospheric variables, which were recorded on a monthly basis, are averaged by year, and the sea level changes are subsetted from 1983-2008.

Exploratory visualizations were generated to see how the data was distributed. Plots of each variable against temperature and plots of each variable against sea level were generated to determine the nature of the relationship between variables.

3.2 Linear Regression

Linear regression analysis using the ordinary least squares method (OLS) was performed to more accurately determine the relationship between dependent and independent variables. Two OLS linear regressions were performed, one with temperature as a response variable and the other with sea level as a response variable. All other variables from the dataset were used as predictor variables.

$$Y = \beta_0 + \beta_1 X + \varepsilon$$

Equation 1. Basic setup of a linear regression equation. Y is all the observed values for the dependent variable, β_0 is the y-intercept (bias), β_1 is the slope (coefficient), X is all observed values of the independent variable, and ε is the error.

Additional analyses checked if the linear model contained any OLS (Ordinary Least Squares) violations. Both datasets were checked for violations of linearity, violations of constant variance, and violations of normality. The OLS violation analysis was conducted on the uncombined average temperature dataset, and was later conducted on the combined dataset.

To inspect violations of normality, residuals were plotted side-by-side against individual predictors. A histogram of residuals with a best fitting normal curve, followed by an ordered value plot of the residuals vs quantiles of the standard normal distribution (Q-Q plot) were included to inspect violations of normality. A Shapiro-Wilk test was also carried out on the residuals to inspect normality violations. A component-plus-residual plot was generated to inspect violations of normality. Correlations between variables were also examined using an index plot of residuals, a regression of successive residuals, and computation of the Durbin-Watson statistic. The most relevant graphs and charts that were generated are included in the appendix. Points that were outliers in the dataset were omitted to eliminate any bias in the model.

3.3 Model Fitting

The datasets were checked for outlying values, influential points, and leverage points, which were removed from the model. These points, if included in the model, will modify the estimated coefficients of the regression model by a significant amount.

The model was split into a test and training data set, and the MSPE (Mean Squared Prediction Error) was calculated. Variables were removed from the model, and the MSPE was calculated for a total of four refitted models. The MPSE, BIC (Bayesian Information Criterion) and AIC (Akaike Information Criterion) were used to determine which of these models are the best fit.

Multicollinearity between variables was examined by generating a correlation plot, and calculating the VIF (Variance Inflation Factor). After the removal of multicollinearity, a final reduced model was created that would best describe the relationships between variables.

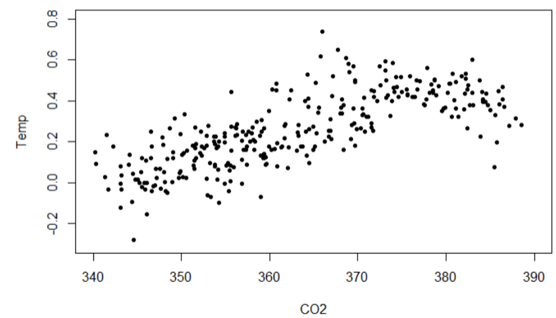
4. Results

Exploratory visualizations, OLS regression, and model fitting were used on two datasets. The first using temperature as a response variable and the second using sea level as a response variable.

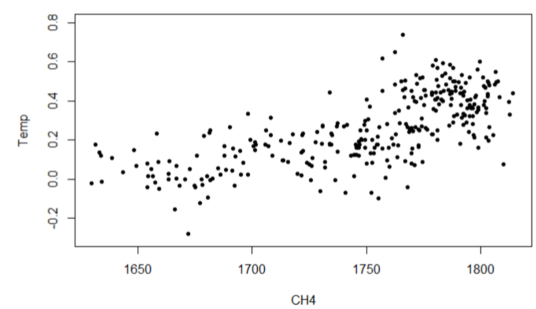
4.1 Exploratory Visualizations: Temperature

An initial look at the relationship between variables in the temperature dataset when plotted against temperature suggests that the correlation between individual greenhouse gas concentrations and temperature is mostly linear. The plot of the TSI and temperature and the MEI and temperature suggests that there is no obvious correlation.

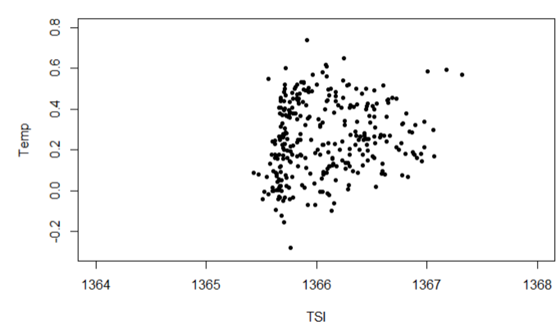
The plot with concentration of aerosols in the atmosphere also shows that there is no obvious correlation.



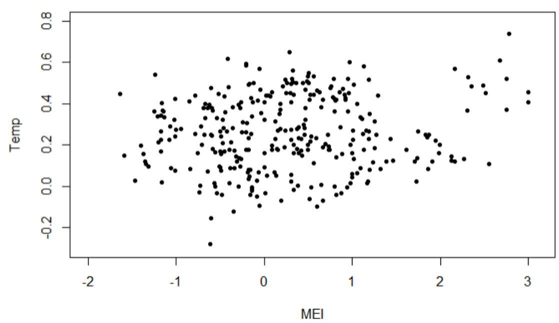
Plot of CO_2 concentrations and temperature. This visualization suggests a possible linear relationship.



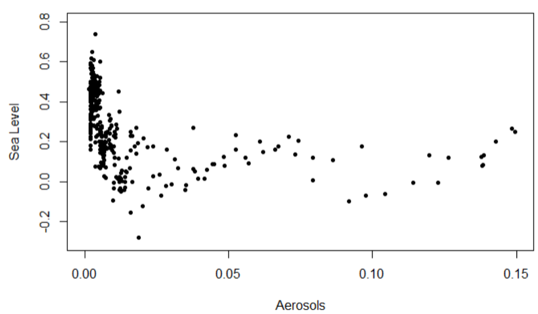
Plot of CH_4 concentrations and temperature. This visualization suggests a possible linear relationship. The other greenhouse gasses, when plotted against the temperature variable, show a similar distribution of data points.



Plot of the TSI and temperature. This visualization suggests that there is no obvious relationship between the variables.



Plot of the MEI and temperature. This visualization suggests that there is no obvious relationship between the variables.



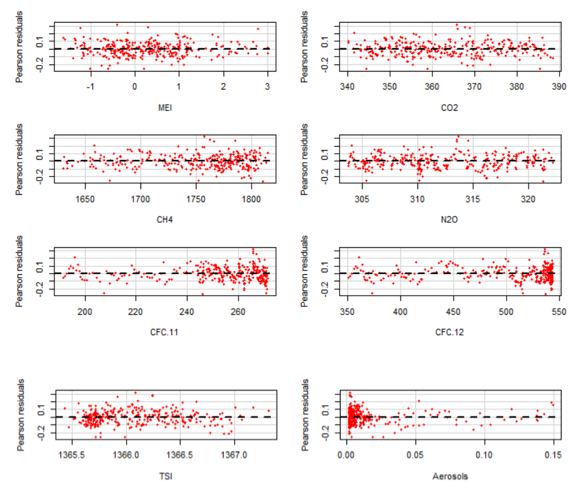
Plot of aerosol concentrations and temperature. This visualization suggests that there is no obvious relationship between the variables.

4.2 OLS Model: Temperature

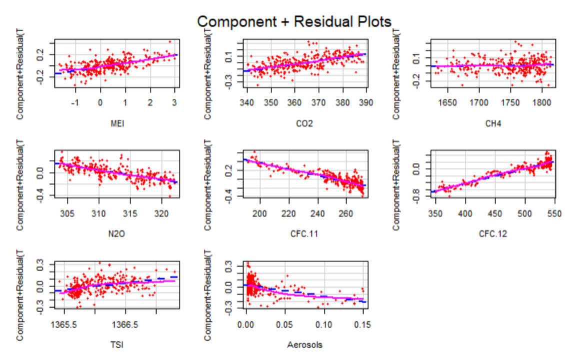
An OLS model was fitted with average temperature as the response variable, and the remaining variables as predictors. In order to confirm the validity of the OLS model, tests were conducted to identify possible OLS violations such as violations of linearity, normality, and constant variance. The generated charts show that there are possible violations of OLS assumptions on the non-greenhouse gas predictor variables.

The plot of residuals against individual predictors on one plot side-by-side shows that the residuals on the MEI, TSI, Aerosol, CFC-1, and CFC-2 predictors possibly violate the constant variance assumption.

The other greenhouse gas variables appear to have a normal distribution of residuals.



Plot of predictor residuals shows that the MEI, TSI, Aerosol, CFC-1 and CFC-2 variables appear to violate constant variance assumptions. Other greenhouse gas predictor variables appear to be normally distributed.



Component-plus- residual plot suggests that the linear relationship in the Aerosol, TSI, and CH_4 variables is less strong than for the other predictors.

Prior to the removal of outlying points and multicollinearity among the predictor variables, the p-values from the summary of the fitted model suggest a strong linear relationship with the average temperature for certain predictor variables.

```
F-statistic: 110.5 on 8 and 298 DF,  p-value: < 2.2e-16


Call:
lm(formula = Temp ~ MEI + CO2 + CH4 + N2O + CFC.11 + CFC.12 +
    TSI + Aerosols, data = climate_data)

Residuals:
     Min       1Q   Median       3Q      Max
-0.26228 -0.05868  0.00051  0.05718  0.32170

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.277e+02  1.919e+01  -6.654 1.36e-10 ***
MEI          6.632e-02  6.186e-03  10.722  < 2e-16 ***
CO2          5.207e-03  2.192e-03   2.375   0.0182 *
CH4          6.371e-05  4.977e-04   0.128   0.8982
N2O         -1.693e-02  7.835e-03  -2.161   0.0315 *
CFC.11      -7.278e-03  1.461e-03  -4.980 1.07e-06 ***
CFC.12       4.272e-03  8.763e-04   4.875 1.77e-06 ***
TSI          9.586e-02  1.401e-02   6.844 4.38e-11 ***
Aerosols    -1.582e+00  2.099e-01  -7.535 5.86e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.09182 on 299 degrees of freedom
Multiple R-squared:  0.744,     Adjusted R-squared:  0.7371
F-statistic: 108.6 on 8 and 299 DF,  p-value: < 2.2e-16
```

The low p-values for the MEI, CFC-11, CFC-12, TSI and Aerosol suggests that these variables are strongly correlated with temperature, while CO_2, CH_4, and N_2O are not significant in the model. This indicates the presence of multicollinearity that needs to be addressed in the model.

4.3 Model Fitting: Temperature

In order to address the presence of multicollinearity, certain predictor variables had to be removed in order to prevent distortion in the model. Various reduced models were created, and the MPSE was calculated for each model, along with the AIC, BIC and the VIF. These criteria were used to determine which predictor variables were collinear, and to determine which reduced model is the best fit.

A total of three models were created. In the first model, all predictors were present. In the second model, CH_4 was removed as a predictor, and in the third model, N_2O was removed as a predictor.

MPSE values for the models:

Model 1:0.008290668
Model 2: 0.008267023
Model 3: 0.008023906

The MPSE continued to decrease as predictor variables were removed from the model. Model 2, however, had the highest R-squared value of the three models. The values of the calculated AIC and BIC for the three models suggest that the first model, with all predictors present, is the best model fit.

The presence of multicollinearity among the predictor variables was determined through the calculation of the VIF (Variance Inflation Factor) for each one of the variables.

Variance Inflation Factors:

MEI	1.241354
CO_2	27.592306
CH_4	18.679286
N_2O	64.125795
CFC-11	31.414659
CFC-12	92.410267
TSI	1.129745
Aerosols	1.379048

After the removal of CFC-12 from the model, which had the highest VIF value, N_2O became the variable with the largest VIF score. N_2O was then removed from the model, which reduced the p-value of CO_2 to a statistically significant value. This implies that N_2O and CO_2 were strongly collinear.

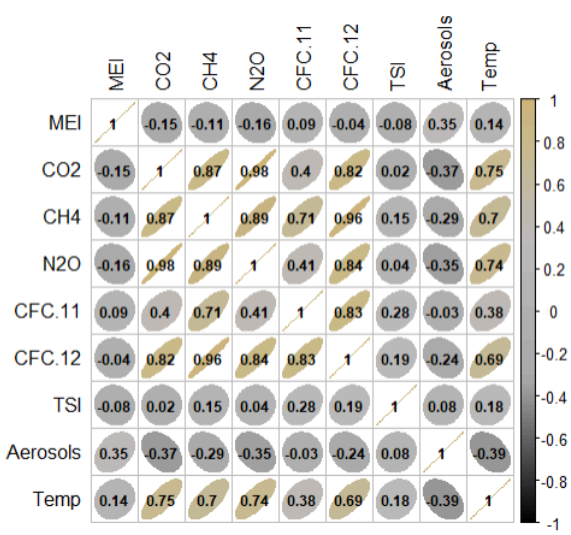
With the removal of these collinear predictors, the model was reduced to a total of six predictors.

Variance Inflation Factors:

MEI	1.225206
CO_2	26.927900
CH4	11.712265
CFC.11	3.611181
TSI	1.125155
Aerosols	1.335312

```
Call:
lm(formula = Temp ~ MEI + CO2 + CH4 + CFC.11 + TSI, data = climate_data)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.34324 -0.05541 -0.00278  0.06437  0.38107 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -1.222e+02  2.159e+01  -5.659 3.54e-08 ***
MEI          5.400e-02  6.639e-03   8.134 1.09e-14 ***
CO2          8.767e-03  1.267e-03   6.921 2.70e-11 ***
CH4          9.846e-04  4.573e-04   2.153   0.0321 *  
CFC.11      -1.139e-03  5.714e-04  -1.994   0.0471 *  
TSI          8.624e-02  1.581e-02   5.455 1.02e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1045 on 302 degrees of freedom
Multiple R-squared:  0.665,	Adjusted R-squared:  0.6594 
F-statistic: 119.9 on 5 and 302 DF,  p-value: < 2.2e-16
```

Summary of the final reduced model.



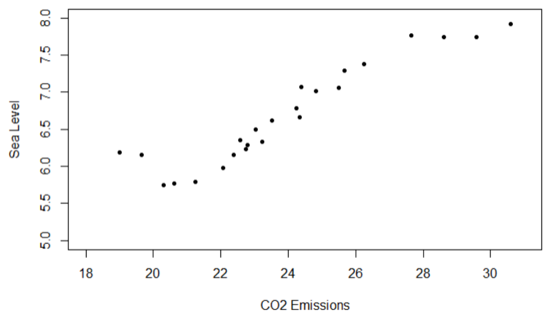
Correlation plot of variables.

The final, reduced model with six predictors shows that MEI, CO_2, and TSI have statistically significant p-values. CH_4 and CFC-11 were less significant than the other predictors but still had an influence on temperature.

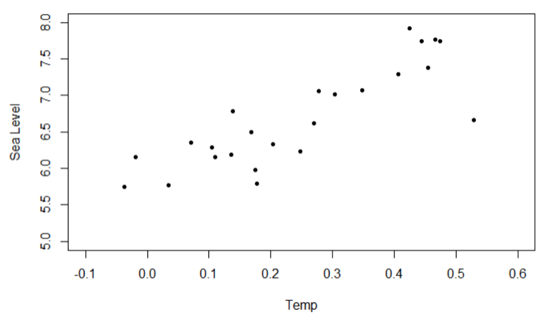
4.4 Exploratory Visualizations: Sea Level

The same set of analyses was performed on a second, combined dataset, where the same predictors were used, with the addition of average temperatures and yearly CO_2 emissions as predictors. The chosen response variable was sea level.

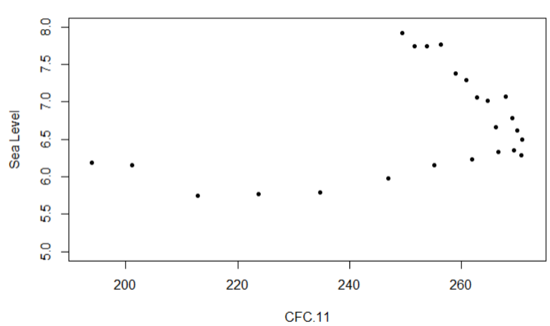
An initial look at the relationship between variables in the sea level dataset suggests that the correlation between individual greenhouse gas concentrations and temperature is mostly linear. The plot of the CO_2 and temperature appear to be mostly linear. The plot with concentration of aerosols in the atmosphere and also the plot of the MEI shows that there is no obvious correlation.



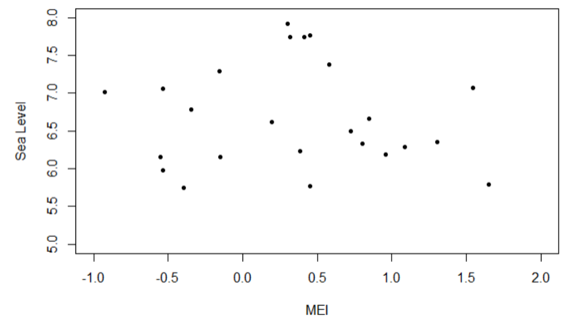
Plot of CO_2 concentrations and sea level. This visualization suggests a possible linear relationship.



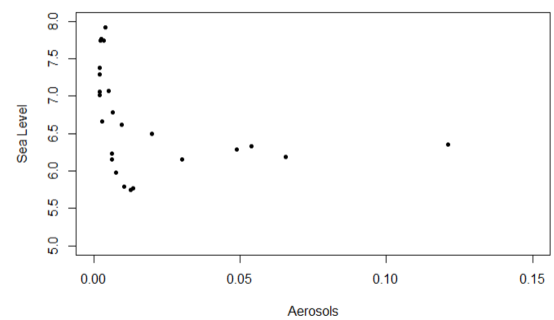
Plot of temperature and sea level. This visualization suggests a possible linear relationship.



Plot of the CFC-11 and sea level. This visualization suggests that there is no obvious relationship between the variables.



Plot of the MEI and sea level. This visualization suggests that there is no obvious relationship between the variables.



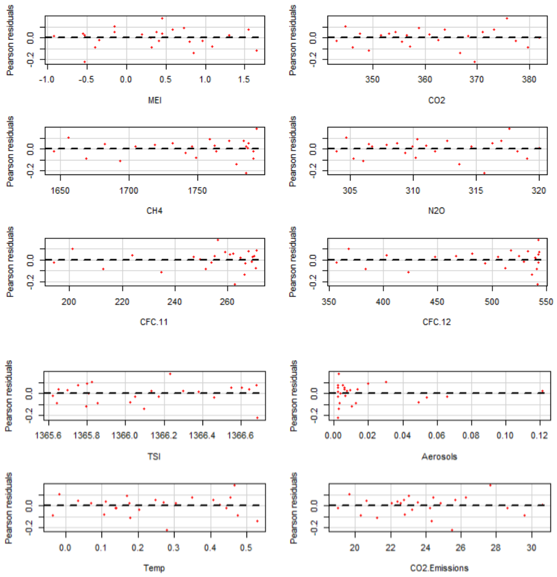
Plot of aerosol concentrations and sea level. This visualization suggests that there is no obvious relationship between the variables.

4.5 OLS Model: Sea Level

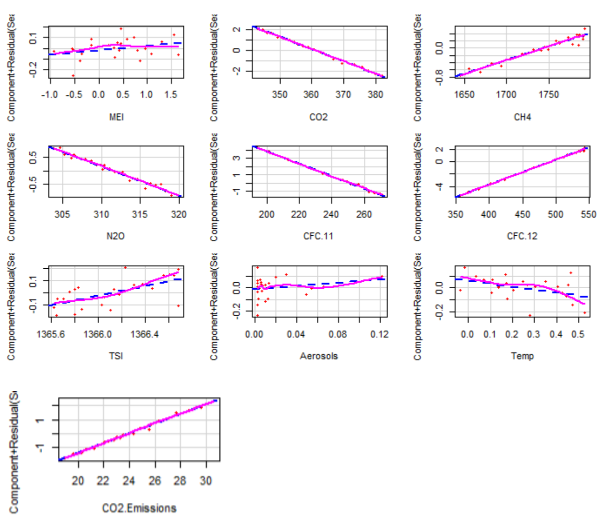
An OLS model was fitted with average sea level as the response variable, and the remaining variables as predictors. In order to confirm the validity of the OLS model, tests were conducted to identify possible OLS violations such as violations of linearity, normality, and constant variance. The generated charts show that there are possible violations of OLS assumptions on the non-greenhouse gas predictor variables.

The plot of residuals against individual predictors on one plot side-by-side shows that the residuals on the MEI, TSI, Aerosol, CFC-1, and CFC-2 predictors possibly violate the constant variance assumption.

The other greenhouse gas variables appear to have a normal distribution of residuals.



Plot of predictor residuals shows that the MEI, TSI, Aerosol, CFC-1 and CFC-2 variables appear to violate constant variance assumptions. Other greenhouse gas predictor variables appear to be normally distributed.



Component-plus- residual plot suggests that the linear relationship in the Aerosol, TSI, MEI and temperature variables is less strong than for the other predictors.

Prior to the removal of outlying points and multicollinearity among the predictor variables, the p-values from the summary of the fitted model suggest a strong linear relationship with sea levels for three predictor variables.

```
Call:
lm(formula = Sea.Level ~ MEI + CO2 + CH4 + N2O + CFC.11 + CFC.12 +
    TSI + Aerosols + Temp + CO2.Emissions, data = climate_data)

Residuals:
     Min       1Q   Median       3Q      Max
-0.22147 -0.04486  0.02270  0.05226  0.18288

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)   -2.143e+02  1.555e+02  -1.378  0.19144
MEI            4.060e-02  6.930e-02   0.586  0.56799
CO2           -1.181e-01  7.534e-02  -1.568  0.14096
CH4            7.487e-03  1.041e-02   0.719  0.48488
N2O           -1.097e-01  1.186e-01  -0.926  0.37152
CFC.11        -7.460e-02  1.392e-02  -5.359  0.00013 ***
CFC.12         3.966e-02  9.646e-03   4.112  0.00122 **
TSI            2.018e-01  1.208e-01   1.671  0.11868
Aerosols       6.937e-01  1.497e+00   0.463  0.65083
Temp          -2.494e-01  5.945e-01  -0.419  0.68172
CO2.Emissions  3.517e-01  1.002e-01   3.509  0.00385 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1175 on 13 degrees of freedom
Multiple R-squared:  0.9831,    Adjusted R-squared:   0.97
F-statistic: 75.44 on 10 and 13 DF,  p-value: 7.682e-10
```

The low p-values for CFC-11, CFC-12 and CO_2 Emissions suggests that these variables are strongly correlated with temperature, while CO_2, CH_4, and N_2O are not significant in the model.

4.6 Model Fitting: Sea Level

In order to address the presence of multicollinearity, certain predictor variables had to be removed in order to prevent distortion in the model. Various reduced models were created, and the MPSE was calculated for each model, along with the AIC, BIC and the VIF. These criteria were used to determine which predictor variables were collinear, and to determine which reduced model is the best fit.

A total of four models were created. In the first model, all predictors were present. In the second model, the MEI was removed as a predictor, in the third model, CH_4 was removed as a predictor and in the fourth model, temperature was removed as a predictor.

MPSE values for the models:

Model 1:	43.1513
Model 2:	43.15076
Model 3:	43.23849
Model 4:	43.30424

The MPSE continued to increase as predictor variables were removed from the model. Model 4, however, had the highest F-statistic value of the three models. The values of the calculated AIC and BIC for the three models suggest that the first model, with all predictors present, is the best model fit.

The presence of multicollinearity among the predictor variables was determined through the calculation of the VIF (Variance Inflation Factor) for each one of the variables.

Variance Inflation Factors:

MEI	4.003457
CO_2	2379.776787
CH_4	466.751509
N_2O	1152.850069
CFC-11	420.309771
CFC-12	1132.392225
TSI	5.361813
Aerosols	4.044157
Temp	16.114499
CO_2 Emissions	276.464400

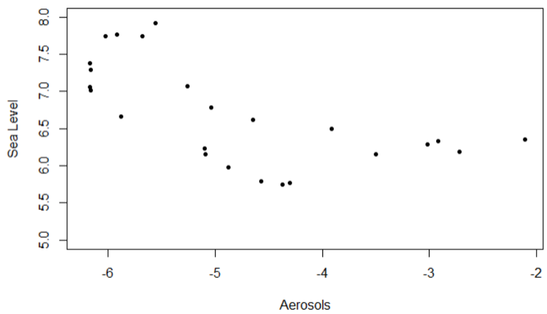
After the removal of CO_2 from the model, which also was shown to be highly collinear with CO_2 emissions in the correlation plot, only one of the two values were retained. CO_2 was removed since it has the highest VIF. Successive variables with high VIF were removed from the model until a reduced model with only six remaining predictors was generated. The reduced model contains the MEI, N_2O, CFC-11, the TSI, aerosols and temperature as predictors.

```
Call:
lm(formula = Sea.Level ~ MEI + N2O + CFC.11 + TSI + Aerosols +
    Temp, data = climate_data)

Residuals:
     Min       1Q   Median       3Q      Max
-0.32265 -0.08625 -0.02820  0.10450  0.29935

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 80.692850 184.536870   0.437   0.6674
MEI         -0.037433   0.084932  -0.441   0.6650
N2O          0.137736   0.018809   7.323 1.19e-06 ***
CFC.11      -0.005564   0.002139  -2.601   0.0186 *
TSI         -0.084673   0.133732  -0.633   0.5351
Aerosols     2.364215   2.175988   1.087   0.2924
Temp         0.517414   0.626920   0.825   0.4206
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1822 on 17 degrees of freedom
Multiple R-squared:  0.9468,	Adjusted R-squared:  0.928
F-statistic: 50.38 on 6 and 17 DF,  p-value: 6.742e-10
```

Summary of the final reduced model.

The final, reduced model with six predictors shows that the model is not a good fit. This is likely due to the fact that some of the predictor variables violated some of the OLS assumptions. Because the model didn't produce a good fit, additional non-linear transformations were applied to the model in the attempt to produce a model with a better fit.

The CFC-12 and CH_4 variables were squared, the aerosol variable was changed logarithmically, and a cube root transformation was applied to the CO_2 emissions variable. This resulted in a more linear relationship between these variables and the sea level.



Aerosol concentrations when plotted against the sea level are now more linear than before the transformation.

After these transformations were applied, a new model was created. Predictors that showed multicollinearity were removed, and the best model was chosen based on the MSPE, AIC, BIC, and VIF values.

```
Call:
lm(formula = Sea.Level ~ MEI + CFC.11 + Aerosols + Temp + CO2.Emissions,
    data = climate_data2)

Residuals:
    Min      1Q  Median      3Q     Max
-0.4555 -0.1024 -0.0105  0.1417  0.2514

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)    8.032260   0.593548  13.533 7.12e-11 ***
MEI           -0.093408   0.082852  -1.127  0.27438
CFC.11        -0.002038   0.001997  -1.021  0.32078
Aerosols       0.207781   0.067955   3.058  0.00678 **
Temp           1.025504   0.602878   1.701  0.10615
CO2.Emissions  0.538419   0.067564   7.969 2.59e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1873 on 18 degrees of freedom
Multiple R-squared:  0.9404,	Adjusted R-squared:  0.9239
F-statistic: 56.84 on 5 and 18 DF,  p-value: 2.144e-10
```

Summary of the final reduced model after non-linear transformations were applied on some of the predictors.

CO_2 emissions were found to be strongly correlated with the sea level response variable, along with aerosols to a lesser extent. Neither the MEI nor the temperature had a significant correlation with the sea level, although they did exhibit some influence.

5 Conclusion

Overall this report gained insight into the impact of various atmospheric variables on both global temperatures and the sea level. The analysis showed that the MEI variable, which measures the impact of the El Niño cycle, did exhibit a strong correlation with rise in atmospheric temperatures, along with atmospheric CO_2 concentration. Changes in sea level were found to be most strongly impacted by CO_2 emissions. Average global temperatures and the MEI did not exhibit a strong correlation, but were found to have some impact.

5.1 Limitations and Further Analysis

The relationship between the MEI and average temperatures would require further investigation to determine how strongly temperature is impacted by the MEI as compared to CO_2 levels, which was also found to be a very strong predictor of rising temperatures. There is a possibility that the MEI might not be the best measure of the El Niño to be used in this specific analysis. One of the surprising finds of this analysis was that average global temperatures did not exhibit a strong correlation with rising sea levels. This implies that there are other confounding variables that influence sea levels that have not been accounted for in the model. Further research about climate cycles would need to be done in order to determine which predictors should also be included in the model fit in order to account for the complexities of climate cycles.

To address the argument used by climate change deniers, the main analysis of this report found that although the combined effects of El Niño are correlated with rising temperatures, this does not mean that the effects of greenhouse gas concentrations can be disregarded. Due to the complexity of global climate systems, it can be difficult to determine the exact effects of El Niño on the variability of climate factors such as temperature and sea level rises. The argument that observed changes in global temperatures are caused solely by the effect of El Niño are false since greenhouse gas concentrations were also found to have a strong influence on temperatures.

6 Appendix

Links to datasets:

Dataset 1 (Average Temperatures): https://www.kaggle.com/datasets/econdata/climate-change

Dataset 2 (Sea Level): https://datahub.io/core/sea-level-rise

6.1 Graphs and Visualizations

Most relevant graphs and visualizations have been included in the report. All other graphs and visualizations from the analysis can be generated through running the code.

6.2 Code

All code and datasets used are attached as files to the assignment submission.

6.3 References

1. “Fake News Tries to Blame Human-Caused Global Warming on El Niño | Dana Nuccitelli.” *The Guardian*, Guardian News and Media, 5 Dec. 2016, www.theguardian.com/environment/climate-consensus-97-per-cent/2016/dec/05/fake-news-tries-to-blame-human-caused-global-warming-on-el-nino

2. Team, PSL Web. “Multivariate Enso Index Version 2 (Mei.V2).” *PSL*, psl.noaa.gov/enso/mei/. Accessed 17 Dec. 2023.