Multiple Regression Term Project:

Annual CO_2e Emissions

Fahd Chaudry

Anna Reimer

Travis Tkachyk

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Brad Quiring

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Introduction

Carbon dioxide equivalent (CO_2e) is an emissions scale used to compare different emissions. This is done through converting the different emissions to a comparable carbon dioxide amount based on their respective global warming potential. An emission's global warming potential is a measure of the effect of that greenhouse gas on our atmosphere. Carbon dioxide equivalent is therefore a useful measure of the cumulative amount of emissions that a country is releasing.

Using multiple regression, we will analyze 115 different countries to determine how closely our selected variables of each country correlate to the respective carbon dioxide equivalents. If our independent variables show a strong enough correlation with carbon dioxide equivalents, a country could potentially use these variables as a carbon dioxide equivalents predictor. The ability for a country to accurately predict its carbon dioxide equivalents would allow for analysis on their policies and regulations to reduce their emissions output. This could have many positive benefits for that country, such as, avoiding costly environmental trade tariffs and promoting trade with other countries.

Variables that we believe make an impact on a country's CO_2e emissions include **total population, urban population, population density, total gross domestic product (GDP), land cover, gross national income (GNI), and median household income**. Population is widely considered a major player in emissions levels and climate change (Jorgenson & Clark, 2013, p. 1), and population density has been found to affect per capita CO_2 emissions in a study completed by Ohlan in 2015 (p. 1426). In a 2010 report on climate change, The World Bank discusses the role economic growth and urbanization play in emissions (p. 15). The report states that urban areas have a significant impact on climate change and emissions, due to the economic activity that is concentrated in those areas. Mitić, Ivanović, and Zdravković (2017) completed a study that analyzed the relationship between GDP and CO_2 emissions in 17 transitional countries. They found that "...on average, a 1% change in GDP leads to a 0.35% change in CO2 emission for the considered group of countries" (p. 13). Based on research, a country's GNI seems to be a strong predictor of emissions. According to Ritchie (2018), the richest 50% of countries contribute to 86% of global emissions (para. 4). The type of land cover determines whether the area is a carbon source or a carbon sink. Carbon sinks, which are land cover areas that absorb more carbon than they release as carbon dioxide, are crucial in reducing overall emissions of an area (IPCC, 2019, p. 2; Fern, 2016, para. 1). Finally, it has been shown that as household income increases in China, emissions levels are also increasing, indicating a correlation that will be tested herein (Golley & Meng, 2012, p. 2).

Research Question

Can the total population, urban population density, the density of the country's total population, GDP, GNI, land cover, and median household incomes be used to predict CO_2e emissions?

Research Hypothesis

There is significant correlation that each of the following; total population of a country, urban population levels, the density of the country's population, the GDP, GNI, land cover, and median household income, can be used to predict CO_2e emissions, as they individually and collectively correlate and have an effect on CO_2e emissions. This relationship exists because there exists a very strong correlation between each of those independent variables, and the dependent variable of carbon dioxide emissions.

Our research hypothesis will be our alternative hypothesis. Our null hypothesis will be that there is no correlation between CO_2e and our chosen variables and they are therefore not a good predictor of CO_2e. A Type I error is that the null hypothesis is true, that there is no correlation between CO_2e and our chosen variables, but we reject it. This could give false guidelines for predicting CO_2e which could cause further damage to the environment and cost governments money. A Type II would be accepting a false null hypothesis, stating that there is no correlation between CO_2e and the chosen variables, when in fact there is. This could result in the loss of a useful prediction model that would help potentially reduce global emissions. Both errors are potentially costly so we will set the level of significance to 5%.

Results

Outliers

China, India, and the United States of America were sources of outliers for almost all of the independent variables. Because of this, we have removed those data points from the raw data. No other outliers were removed as any other removal made a negligible impact on the validity of the model. The standardized residuals on the simple linear regression model were above 2, which is how we decided they were outliers in the data.

Individual Analysis of Independent Variables

The analysis was begun by running each independent variable independently against the dependent variable. In doing this, we found that artificial surface land cover was the only variable that seemed to have a strong correlation individually to annual emissions, based on the correlation coefficient of 0.89. The coefficient of determination for artificial surface land cover shows that for this individual simple regression model, 79% of the variation in annual CO_2e emissions can be explained by the area of artificial surfaces that make up the total land area of a country. Population, GNI, cropland, and tree cover individually had moderate correlations to the dependent variable. Population, GNI, cropland, artificial surfaces, urban population density, median household income, and tree cover all had p-values below our alpha of 5%, which indicates that these variables are, in the individual models, significant predictors of annual CO_2e emissions. We can also see that, when the variable's regression is run individually, the standard error is quite high. For example, the population regression showed a standard error of 235. This standard error means that, for this model, on average, the estimate of CO_2e emissions deviates 235Mt from the actual level of CO_2e emissions. Full data for each regression can be found in Appendix B.

Original Multiple Regression Model

The first overall regression model, with all variables included, appears strong. The standard error of the regression is considerably smaller than the simple regressions run on each variable. This indicates that there is less error when more variables are included. The p-value of the model is well below our established alpha of 5%, which indicates that, for this model, there is a significant relationship between annual CO_2e emissions and the independent variables. The correlation coefficient of 0.95 indicates that the model shows a strong, positive relationship between annual CO_2e emissions and the independent variables. The adjusted coefficient of determination of 0.88 determines that the nine independent variables can explain 88% of the variation in annual CO_2e emissions. The standard error for this model is 105, which is considerably lower than the standard error for the individual simple regressions. This means that when the regression is run together, there is less error. As we move forward in the analysis, we will be able to determine which of the independent variables are the most reliable predictors.

When we run the full multicollinearity test to find the Variance Inflation Factor (VIF) scores for each X variable, we find that there is no multicollinearity with any of the variables. This means that none of the independent variables have a significant correlation with each other.

When determining which of the variables are the strongest, variables with the highest p-values above our established alpha of 5% are removed one at a time, and the regression is rerun each time to evaluate the p-values. Following this process, we will be left with a simplified model that includes only those predictor variables that show strong correlation. As shown in table 1, which shows the p-values for each independent variable, total GDP has a very high p-value at 0.8277, which indicates it should be removed from the model.

Population	GDP	Population Density	Urban Population Density	GNI
0.0005	0.8277	0.7571	0.1164	0.0001

Median Household Income	Land Cover - Cropland	Land Cover - Tree Cover	Land Cover - Artificial Surfaces
0.3750	0.5706	0.0000	0.0000

Table 1

When GDP was removed, and the regression ran again, the correlation coefficient and adjusted coefficient of determination remained high at 0.95 and 0.89, respectively. This process continued where population density, land cover - cropland, median household income, and urban population density were removed one by one due to high p-values. Full data for each regression can be found in appendix B.

The final regression model proved that population, GNI, land cover - tree cover, and land cover - artificial surfaces were all strong predictors of annual CO_2e emissions. Each variable had a p-value well below our established alpha of 5%. The final model had a correlation coefficient of 0.94, which shows a strong, positive relationship between the dependent and independent variables. The model's adjusted coefficient of determination of 0.8864 indicates that the remaining four predictor variables can explain 88.6% of the variation in annual CO_2e emissions. The standard error for the final model is 104, which is just slightly lower than the standard error for the original regression. This means that, on average, for this model, the estimate of CO_2e emissions deviates 104Mt from the actual level of CO_2e emissions. The p-value for the regression is 0.0000, well below the 5% alpha, which means that we can conclude that, for this model, there is a significant relationship between annual CO_2e emissions and the four predictor variables. After removing the variables with low correlation, the adjusted r2 only decreased by approximately 1%, so the model is still strong. The equation for the final regression is as follows:

$$\mathbf{Y = 5.906 + 0.00000102x_1 + 0.000000000115x_2 + 0.103x_3 + 17.335x_4}$$

This regression equation allows us to predict, for this sample, how emissions will change based on changes in the other variables. The following is an explanation of how the equation works (1 Megatonne is equal to 1,000,000 metric tons):

- For every population increase of 1 million people, annual CO_2e emissions will increase by 1.02 metric tons, if the other variables remain constant.
- For every increase of $1,000,000 in GNI, annual CO_2e emissions will increase by 0.000115 metric tons, if the other variables remain constant
- For every increase of 1000km^2 of tree cover, annual CO_2e emissions will increase by 0.103Mt, if all other variables remain constant
- For every increase of 1000km^2 of artificial surface cover, annual CO_2e emissions will increase by 17.335Mt, if all other variables remain constant

Confidence and Prediction Intervals

These confidence and prediction intervals were created using random given data points to illustrate how the intervals might be used. The slope confidence interval represents an estimate of the true population slope for the variables, on average. The second confidence interval represents an estimate of the average annual CO_2e emissions for the given value of the independent variable. The prediction interval represents an estimate of the actual annual CO_2e emissions for the given value of the independent variable.

<u>Population</u>

Slope Confidence Interval: $0.0000005 < \beta 1 < 0.0000015$

We are 95% confident that the population slope is somewhere between 0.0000005 and 0.0000015. This means that for every increase in population of 1 person, annual CO_2e emissions would be expected to increase by somewhere between 0.0000005Mt and 0.0000015Mt, on average. A more simple way to put this would be that for every increase of 1,000,000 people, annual CO_2e emissions would be expected to increase by somewhere between 0.5 metric tons and 1.5 metric tons, on average.

Confidence Interval: $170.7 < Y < 350.6$

We are 95% confident that for a given population of 250,000,000, the average annual CO_2e emissions for that country would be somewhere between 170.7 and 350.6Mt.

Prediction Interval: 35.7 < Y < 485.6

We are 95% confident that for a given country with a population of 250,000,000, the annual CO_2e emissions would be somewhere between 35.7 and 485.6Mt.

Gross National Income

Slope Confidence Interval: 0.00000000007 < β1 < 0.00000000016

We are 95% confident that the population slope is somewhere between 0.00000000007 and 0.00000000016. This means that for every increase in GNI of $1, annual CO_2e emissions would be expected to increase by somewhere between 0.00000000007Mt and 0.00000000016Mt, on average. A more simple way to put this would be that for every increase in GNI of $1,000,000, annual CO_2e emissions would be expected to increase by somewhere between 0.00007 metric tons and 0.00016 metric tons, on average.

Confidence Interval: 189.0 < Y < 282.6

We are 95% confident that for a given GNI of $2 trillion, the average annual CO_2e emissions for that country would be somewhere between 189.0 and 282.6Mt.

Prediction Interval: 24.4 < Y < 447.2

We are 95% confident that for a given country with a GNI of $2 trillion, the annual CO_2e emissions for that country would be somewhere between 24.4 and 447.2Mt.

Land Cover - Tree Cover

Slope Confidence Interval: 0.079 < β1 < 0.13

We are 95% confident that the population slope is somewhere between 0.079 and 0.13. This means that for every increase in total tree cover of 1000km2, annual CO_2e emissions would be expected to increase by somewhere between 0.079Mt and 0.13Mt, on average.

Confidence Interval: 434.1 < Y < 604.1

We are 95% confident that for a given total area of 5,000,000km2 of tree cover, the average annual CO_2e emissions for that country would be somewhere between 434.1 and 604.1Mt.

Prediction Interval: 296.1 < Y < 742.1

We are 95% confident that for a given total area of 5,000,000km2 of tree cover, the annual CO_2e emissions for that country would be somewhere between 296.1 and 742.1Mt.

Land Cover - Artificial Surfaces

Slope Confidence Interval: $10.3 < \beta 1 < 24.4$

We are 95% confident that the population slope is somewhere between 10.3 and 24.4. This means that for every increase in total artificial surface cover of 1000km2, annual CO_2e emissions would be expected to increase by somewhere between 10.3Mt and 24.4Mt, on average.

Confidence Interval: 180.9 < Y < 246.9

We are 95% confident that for a given total area of 12,000km2 of artificial surface cover, the average annual CO_2e emissions for that country would be somewhere between 180.9 and 246.9Mt.

Prediction Interval: 5.1 < Y < 422.7

We are 95% confident that for a given total area of 12,000km2 of tree cover, the annual CO_2e emissions for that country would be somewhere between 5.1 and 422.7Mt.

Discussion

The test shows that total population, total GNI, amount of tree cover, and amount of artificial surface cover are strong predictors of a country's annual CO_2e emissions. Our original research question, "can the total population, urban population, the density of the country's total population, GDP, GNI, land cover, and median household incomes be used to predict carbon dioxide equivalent emissions?", was answered by the research; however, our hypothesis was not entirely correct. We learned that urban population, population density, GDP, household income, and cropland area are not significant predictors of CO_2e emissions. The majority of the final model makes sense, although, it was unexpected that tree cover and CO_2e emissions would have a positive relationship. Determining GNI as one of the strongest predictors was also surprising. The preliminary research indicated that economic growth contributes to emissions, but emissions and climate change are often attributed more heavily to population distribution.

The final model, with population, GNI, tree cover, and artificial surface cover as the strong predictor variables, could be useful for further climate action taken by governments. It shows which characteristics of a country have the most drastic impact on emissions and climate change. With this, governments could target these characteristics when creating policies to target climate change. For example, since population is such a significant contributor to total emissions, this indicates that a carbon tax could make sense, as a larger population would generate the amount of money that the country needs to create climate change action plans. Similarly, with artificial surface cover as the most significant predictor, governments could use this information to pay special attention to the total area of artificial surfaces that exist in the country.

The confidence intervals estimating population slope align with the regression equation. This result further validates the model as it shows that the given sample aligns with the population. Since each of the population slope intervals is above zero, there is further evidence of a positive relationship between the variable and CO_2e emissions. These intervals could be useful for governments or developers when estimating the environmental impacts of developments or economic growth. The point confidence intervals help predict an average annual CO_2e output based on a given value for each predictor variable. The prediction intervals are useful for predicting the actual emissions of a particular country based on its population, GNI, tree cover, or artificial surface cover. Both of these types of intervals could be useful for governments to estimate the costs of carbon emissions, based on estimated future emissions, for carbon pricing purposes in policy.

Conclusion

While all the variables in our test possibly have some impact on emissions, the strongest, most significant predictors are population, GNI, tree cover, and artificial surface cover. Our final regression model showed sufficient evidence to reject the null hypothesis, and conclude that the variables do have an impact on annual CO_2e emissions. These findings are relevant for future policy, development, and climate action.

The positive relationship between tree cover and emissions indicates a need for future analysis. Since higher artificial surface area also showed an increase in emissions, it could be possible that higher emissions could be related to a larger land area occupied by a country. There could also be other variables impacting the relationship between tree cover and emissions. Future analysis could determine the actual implications.

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Appendix A

Limitations of the Study

When collecting data, we found that to be able to represent all the variables, 2017 was the most reliable year. This limits the study in regard to the relevance and timeliness of the data. For future studies to be more relevant, more recent data would be required. It is possible that if more recent data was used, results might have been different as laws and regulations regarding emissions may have changed.

When we check the regression plots for assumptions of linearity, independence, equal variance, and normality, we run into some problems with the validity of the model. As can be seen in the plots located in Appendix C, we are unable to assume linearity from the line plots generated for each independent variable, due to the concentration of data points in the corner. Similarly, with the residual plots, there is increasing variance along the plot, where the variation of the residuals increases as the value of the independent variable increases. As well, the normal probability plots show strong curvature at the low and high ends of the percentile range. These problems may be able to be addressed by transforming the data, but this is beyond our scope, so at this point, we are unsure whether the assumptions can or cannot be met.

Appendix B

Data

Raw Data

Country	Annual emissions 2017 (MtCO2e	Population (20	Total GDP ($USD)	Population Density (people per sq. km of land area)	Urban Population Density (% of total populatio	Gross National Income ($USD) 201	Median Household Income ($USD)	Land Cover - Cropland (km2 - 000's)	Land Cover - Tree Cover (km2 - 000's)	Land Cover - Artificial Surfaces (km2 - 000's)
Afghanistan	44.416	35530081	$21,992,764,469	57	25	$20,291,074,614.00	$4,121	78.81121	7.92841	0.81071
Albania	8.308	2873457	$13,039,355,905	105	60	$13,059,105,109.00	$7,314	14.41532	10.0817	0.29182
Angola	155.722	29784193	$126,505,710,445	25	66	$118,386,000,000.00	$3,534	72.57779	752.31615	0.93019
Argentina	334.237	44271041	$637,486,214,712	16	92	$626,304,000,000.00	$14,432	653.5261	364.73334	6.8816
Armenia	8.594	2930450	$11,536,591,404	104	63	$11,934,826,625.00	$3,865	17.015	6.01648	0.66781
Australia	580.1	24601860	$1,408,675,702,262	3	86	$1,293,970,000,000.00	$46,555	630.97687	899.01698	12.04471
Austria	78.474	8797566	$416,835,975,862	107	58	$413,575,000,000.00	$34,911	19.36242	45.36223	2.34974
Azerbaijan	69.722	9854033	$40,748,862,281	120	56	$39,106,056,124.00	$11,446	51.51388	10.48187	1.29914
Bahrain	33.406	1492584	$245,633,488,923	2017	89	$33,443,031,915.00	$24,693	0.01801	0.00147	0.22466
Bangladesh	163.63	164669751	$54,441,189,058	1240	37	$260,455,000,000.00	$2,819	105.33485	17.03077	1.09535
Belarus	90.498	9498264	$494,763,551,891	47	79	$52,669,027,791.00	$15,085	109.34102	90.07327	1.83163
Belgium	113.409	11382393	$9,236,440,857	377	98	$508,431,000,000.00	$26,703	15.66214	6.88067	3.44872
Benin	12.169	11175692	$37,508,642,165	102	47	$9,203,118,378.00	$1,502	48.26409	37.6428	0.54176
Bolivia	46.804	11051600	$2,055,512,218,230	10	69	$36,448,198,278.00	$6,399	79.00937	615.23038	1.27171
Botswana	12.925	2291661	$12,324,811,435	4	69	$16,826,458,734.00	$3,603	35.04103	49.93628	0.42452
Brazil	1017.875	209288278	$3,155,456,445	25	87	$2,015,530,000,000.00	$7,522	2122.65628	4374.4367	25.78333
Bulgaria	54.855	7075947	$22,121,368,236	65	75	$58,984,842,869.00	$8,487	62.66249	42.28934	2.28366
Burkina Faso	23.505	19193382	$34,924,030,341	72	29	$11,920,723,914.00	$1,530	197.30729	6.95857	0.37846
Burundi	3.047	10864245	$1,647,120,175,449	435	13	$3,167,492,069.00	$673	15.4364	3.70067	0.11175
Cambodia	27.097	16005373	$277,080,967,210	92	23	$20,803,188,298.00	$2,308	80.4824	84.08476	0.3171
Cameroon	83.276	24053727	$12,237,781,802,039	53	56	$34,263,095,724.00	$2,075	72.53436	359.55902	0.73505
Canada	738.383	36708083	$309,191,382,587	4	81	$1,630,460,000,000.00	$41,280	568.53699	4654.17697	11.70111
Chad	28.441	14899994	$55,201,151,720	12	23	$9,845,129,125.00	$2,394	238.59217	44.7377	0.2657
Chile	103.563	18054726	$22,054,267,383	25	88	$266,381,000,000.00	$8,098	48.68336	237.1203	2.42193
Colombia	159.584	49065615	$37,642,481,749	45	81	$306,040,000,000.00	$6,544	140.32108	752.10994	2.55965
Comoros	0.404	813912	$329,865,537,183	447	29	$1,080,713,350.00	$3,912	0.19367	1.38825	0.02805
Croatia	23.477	4124531	$75,931,730,487	73	57	$54,508,067,106.00	$16,231	23.967	26.13374	0.96219
Cyprus	6.936	1179551	$104,295,862,000	129	67	$21,948,565,296.00	$18,242	4.01251	2.36249	0.36215
Czech Republic	120.986	10594438	$195,135,524,253	138	74	$202,642,000,000.00	$22,913	39.30664	29.12679	3.49563
Democratic Republi	39.559	81339988	$24,805,439,641	37	44	$7,859,167,565.00	$1,988	273.82904	1892.35037	2.11001
Denmark	52.887	5764980	$25,921,079,612	138	88	$337,179,000,000.00	$44,360	31.48967	5.24921	1.72382
Dominican Republic	33.167	10766998	$252,246,619,923	220	81	$76,204,245,976.00	$6,302	15.95466	23.24811	0.78289
Ecuador	58.266	16624858	$2,582,492,292,090	69	64	$101,931,000,000.00	$6,858	36.22858	174.71988	1.47891
Egypt	272.379	97553151	$15,159,029,523	99	43	$230,801,000,000.00	$3,111	48.78614	0.02411	2.99777
El Salvador	11.596	6377853	$3,693,204,332,230	310	72	$23,540,000,000.00	$4,828	4.90042	14.83814	0.32421
Estonia	23.348	1317384	$203,085,551,429	30	69	$26,085,606,572.00	$12,577	11.66502	26.75804	0.2994
Finland	63.532	5508214	$22,978,547,168	18	85	$254,474,000,000.00	$24,615	28.89494	242.69556	0.5624
France	440.849	67105513	$139,761,138,103	122	80	$2,647,900,000,000.00	$31,112	278.28206	147.91887	17.74302
Georgia	14.795	3728004	$460,976,107,833	65	59	$15,424,959,912.00	$2,591	24.5498	33.1679	1.0312
Germany	894.057	82685827	$353,268,413,308	237	77	$3,750,320,000,000.00	$33,333	164.11281	114.32715	24.36455
Ghana	30.892	28833629	$1,943,835,376,342	131	56	$57,430,377,373.00	$2,050	113.92195	84.71061	2.30832
Greece	86.969	10753531	$4,872,415,104,315	83	79	$203,480,000,000.00	$17,777	0.00046	0.00108	0.00518
Guatemala	26.612	16913503	$40,708,450,704	161	51	$74,256,259,054.00	$4,516	54.84405	37.5839	1.98821
Haiti	8.064	10981229	$16,853,104,545	404	55	$8,463,151,298.00	$2,735	5.22409	3.93839	0.42452
Honduras	21.111	9265067	$30,463,302,414	86	57	$21,453,599,844.00	$4,848	25.78364	79.57253	0.50814
Hungary	56.92	9787966	$53,393,799,595	108	71	$135,832,000,000.00	$12,445	63.28099	17.19824	3.76404
Indonesia	744.34	263991379	$25,127,294,467	148	55	$982,443,000,000.00	$2,199	667.0566	1157.85508	16.70069
Iran	716.815	81162788	$47,544,459,559	50	75	$454,858,000,000.00	$12,046	316.65535	19.30786	5.9858
Israel	89.591	8713300	$314,707,268,049	411	92	$349,685,000,000.00	$30,364	6.25483	0.59609	0.93398
Italy	420.824	60536709	$12,553,225,573	205	70	$1,967,670,000,000.00	$20,085	161.57047	87.96805	13.21487
Japan	1353.347	126785797	$1,158,229,075,169	347	92	$5,037,720,000,000.00	$33,822	91.51268	249.41556	24.28379
Jordan	30.822	9702353	$8,128,478,103	112	91	$40,502,605,634.00	$8,276	5.484	0.03261	0.4991
Kazakhstan	313.725	18037776	$11,135,047,196	7	57	$148,657,000,000.00	$7,492	626.13727	53.10817	3.74874
Kenya	60.137	49699862	$4,844,606,146	90	27	$78,082,475,276.00	$1,870	145.75855	86.84449	0.46502
Kyrgyzstan	15.496	6198200	$109,708,752,746	33	36	$7,331,361,334.00	$4,034	50.17849	12.93572	0.64285
Laos	11.492	6858160	$24,870,224,032	31	35	$15,963,624,218.00	$3,379	42.80977	130.40964	0.15573
Latvia	12.644	1942248	$830,572,618,850	31	68	$30,060,092,993.00	$10,461	19.40539	37.28095	0.35574
Lebanon	26.944	6082357	$202,044,224,387	669	89	$53,353,823,748.00	$13,004	5.97568	0.3239	0.32104
Liberia	2.152	4731906	$375,769,719,405	50	51	$2,982,565,100.00	$781	51.70555	43.92483	0.25055
Libya	133.011	6374616	$399,470,173,408	4	80	$39,163,538,384.00	$6,398	21.77198	1.26993	1.09612
Lithuania	19.324	2828403	$302,139,476,734	45	68	$45,857,919,611.00	$12,375	36.93588	22.5633	0.7546
Luxembourg	11.291	596336	$61,838,175,837	250	91	$41,281,165,720.00	$52,493	0.93243	0.85376	0.15047
Madagascar	26.443	25570895	$29,435,069,062	45	37	$12,822,459,004.00	$1,013	0.00649	0.00108	0.0102

Country	Annual emissions 2017 (MtCO2e	Population (20	Total GDP ($USD)	Population Density (people per sq. km of land area)	Urban Population Density (% of total populati	Gross National Income ($USD) 201	Median Household Income ($USD)	Land Cover - Cropland (km2 - 000's)	Land Cover - Tree Cover (km2 - 000's)	Land Cover - Artificial Surfaces (km2 - 000's)
Madagascar	26.443	25570895	$29,435,069,062	45	37	$12,822,459,004.00	$1,013	0.00649	0.00108	0.0102
Malaysia	303.152	31624264	$313,595,085,587	96	76	$309,969,000,000.00	$11,207	62.26764	24.90353	0.36555
Malta	2.979	467999	$167,605,420,589	1511	95	$11,725,406,765.00	$21,141	265.08907	23.0195	0.37413
Mauritania	11.191	4420184	$211,803,717,466	4	54	$4,809,245,711.00	$6,679	0.17976	0.00031	0.07991
Mexico	733.01	129163276	$9,136,162,028	65	80	$1,128,750,000,000.00	$11,680	323.12324	725.90489	14.2058
Moldova	11.464	3549196	$683,827,144,289	124	43	$10,226,329,985.00	$4,158	28.3776	2.54944	2.09671
Mongolia	38.637	3075647	$21,126,148,693	2	68	$9,817,032,347.00	$5,922	102.5367	82.90054	0.61935
Montenegro	3.388	622373	$41,589,720,454	46	67	$4,943,496,281.00	$11,519	2.44094	9.12461	0.09552
Morocco	78.884	35739580	$3,739,578,024	81	62	$107,564,000,000.00	$6,634	94.04906	20.20258	1.9668
Nepal	36.031	29304998	$348,872,149,565	196	20	$25,472,405,094.00	$2,718	43.53616	68.19927	0.35535
Netherlands	186.778	17131296	$1,314,314,164,402	511	91	$838,081,000,000.00	$38,584	13.78275	3.56766	3.921
New Zealand	75.092	4793900	$87,356,647,561	19	87	$194,716,000,000.00	$35,562	6.3505	82.81467	2.73253
Niger	26.611	21477348	$7,145,666,195	18	16	$7,942,047,105.00	$2,708	101.54105	1.20687	0.17466
Nigeria	304.064	190886311	$52,090,320,325	215	50	$364,253,000,000.00	$2,667	584.62401	193.10373	6.5002
Norway	46.593	5276968	$455,302,534,660	15	82	$416,066,000,000.00	$51,489	14.50118	140.96741	3.48891
Pakistan	326.774	197015955	$40,068,818,004	275	37	$321,203,000,000.00	$4,060	283.6494	19.36065	3.87726
Panama	17.089	4098587	$851,541,613,736	56	68	$56,477,556,600.00	$8,356	23.11031	49.50349	0.34963
Paraguay	37.575	6811297	$112,154,158,555	18	62	$37,805,459,967.00	$6,179	92.03381	176.63853	0.72346
Peru	86.21	32165485	$2,631,228,009,993	25	78	$201,299,000,000.00	$5,161	46.98504	826.1322	2.49071
Philippines	171.604	104918090	$19,485,394,000,000	358	47	$377,083,000,000.00	$2,401	182.1951	104.80545	2.32215
Poland	361.191	37974826	$59,180,196,956	124	69	$504,586,000,000.00	$15,338	182.24263	99.42053	7.59462
Portugal	62.031	10300300	$223,779,866,149	112	65	$215,628,000,000.00	$16,186	47.12523	37.51574	2.65671
Qatar	82.846	2639211	$25,868,140,477	240	99	$166,509,000,000.00	$26,555	0.26879	0.02419	0.49647
Romania	109.485	19583986	$206,467,000,000	85	54	$206,467,000,000.00	$7,922	127.75687	77.5065	8.73193
Russia	2199.117	144496740	$1,536,570,000,000	9	74	$1,536,570,000,000.00	$11,724	1866.39832	9829.60555	32.99424
Rwanda	6.631	12208407	$8,939,827,629	499	17	$8,939,827,629.00	$1,101	17.63435	3.79673	0.13509
Saudi Arabia	546.818	32938213	$699,284,000,000	16	84	$699,284,000,000.00	$24,980	27.3304	0.74919	3.65159
Senegal	25.486	15850567	$20,495,918,001	82	47	$20,495,918,001.00	$3,897	63.98729	52.08748	0.55196
Serbia	59.018	7020858	$41,226,657,716	80	56	$41,226,657,716.00	$8,921	50.12918	32.77359	1.55503
Sierra Leone	6.73	7557212	$3,629,620,900	106	42	$3,629,620,900.00	$2,330	48.59664	21.96071	0.27366
Singapore	52.951	5612253	$314,871,000,000	7953	100	$314,871,000,000.00	$32,360	0.21176	0.07953	0.28209
Slovakia	40.32	5439232	$93,716,410,509	113	54	$93,716,410,509.00	$17,415	21.25975	23.5472	1.98434
Slovenia	18.023	2066388	$47,565,306,137	103	55	$47,565,306,137.00	$25,969	5.62535	13.4036	0.40265
South Africa	510.238	56717156	$339,071,000,000	48	66	$339,071,000,000.00	$5,217	171.23151	94.96372	7.35265
Spain	306.612	46593171	$1,309,010,000,000	94	80	$1,309,010,000,000.00	$21,959	268.07973	156.88181	7.27675
Sri Lanka	38.376	21444000	$85,705,080,605	346	18	$85,705,080,605.00	$3,242	32.21182	23.32686	1.17564
Sweden	50.845	10057698	$548,705,000,000	25	87	$548,705,000,000.00	$50,514	38.90152	301.95941	1.92136
Tajikistan	10.244	8921343	$8,256,219,891	66	27	$8,256,219,891.00	$5,137	31.18858	0.94147	0.56286
Tanzania	77.946	57310019	$52,106,608,384	64	34	$52,106,608,384.00	$2,154	267.50249	382.95374	1.01327
Thailand	369.431	69037513	$434,950,000,000	136	50	$434,950,000,000.00	$7,029	350.71085	131.08649	4.17643
Togo	6.582	7797694	$4,813,025,661	145	42	$4,813,025,661.00	$571	28.44105	21.42305	0.29012
Tunisia	35.648	11532127	$38,573,034,637	74	69	$38,573,034,637.00	$8,966	46.72382	3.81188	1.13886
Turkey	408.457	80745020	$841,633,000,000	107	75	$841,633,000,000.00	$8,955	435.96492	192.1543	7.83722
Uganda	33.351	42862958	$25,276,591,105	213	24	$25,276,591,105.00	$1,775	119.05252	52.35782	0.5981
Ukraine	375.667	44831135	$109,177,000,000	77	69	$109,177,000,000.00	$11,074	451.34312	93.36796	25.1394
United Kingdom	546.264	66023290	$2,634,440,000,000	275	83	$2,634,440,000,000.00	$31,617	72.92789	21.21314	13.36573
Uruguay	34.028	3456750	$53,127,324,505	20	95	$53,127,324,505.00	$7,949	35.13485	21.43905	0.59632
Vietnam	256.761	95540800	$206,917,000,000	308	36	$206,917,000,000.00	$4,783	159.36656	115.30649	3.4379
Zambia	50.103	17094130	$24,721,833,710	23	44	$24,721,833,710.00	$1,501	127.9034	468.55604	0.75035

Individual Regression Data

Population

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.65159247							
R Square	0.42457275							
Adjusted R S	0.4192936							
Standard Err	235.146376							
Observations	111							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	4446975.83	4446975.83	80.4244668	9.6068E-15			
Residual	109	6027026.16	55293.818					
Total	110	10474002						
	Coefficients	*Standard Erro*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	36.8892369	27.128459	1.35979847	0.17669982	-16.878487	90.6569606	-16.878487	90.6569606
Population (2	4.145E-06	0.00000046	8.96796893	0.0000	3.229E-06	5.0611E-06	3.229E-06	5.0611E-06

GDP

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.03260827							
R Square	0.0010633							
Adjusted R S	-0.0081013							
Standard Erro	309.821864							
Observations	111							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	11136.9973	11136.9973	0.11602297	0.7340442			
Residual	109	10462865	95989.5871					
Total	110	10474002						
	Coefficients	*Standard Erro*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	172.118618	30.7543401	5.59656352	1.6468E-07	111.164516	233.07272	111.164516	233.07272
Total GDP ($U	4.4542E-12	1.3077E-11	0.34062145	0.7340442	-2.146E-11	3.0372E-11	-2.146E-11	3.0372E-11

Population Density

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.05995673							
R Square	0.00359481							
Adjusted R S	-0.0055465							
Standard Erro	309.429039							
Observations	111							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	37652.0356	37652.0356	0.39324782	0.53190848			
Residual	109	10436350	95746.3299					
Total	110	10474002						
	Coefficients	*Standard Erro*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	180.670901	30.6447447	5.89565691	4.243E-08	119.934013	241.407789	119.934013	241.407789
Population De	-0.0234436	0.03738442	-0.6270947	0.53190848	-0.0975383	0.05065114	-0.0975383	0.05065114

Urban Population Density

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.26577623							
R Square	0.070637							
Adjusted R S	0.06211074							
Standard Err	298.837962							
Observations	111							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	739852.119	739852.119	8.28463522	0.00481254			
Residual	109	9734149.88	89304.1273					
Total	110	10474002						
	Coefficients	*Standard Erro*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-57.199658	85.5743359	-0.6684207	0.50527813	-226.80521	112.405894	-226.80521	112.405894
Urban Popula	3.72756243	1.29505505	2.87830423	0.00481254	1.16080542	6.29431944	1.16080542	6.29431944

<u>Gross National Income</u>

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.73866489							
R Square	0.54562583							
Adjusted R S	0.54145726							
Standard Err	208.953619							
Observations	111							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	5714885.99	5714885.99	130.890395	2.1859E-20			
Residual	109	4759116.01	43661.6147					
Total	110	10474002						
	Coefficients	*Standard Erro*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	65.5437606	22.0270322	2.97560561	0.00360206	21.8868989	109.200622	21.8868989	109.200622
Gross Nationa	3.0142E-10	2.6346E-11	11.440734	2.1859E-20	2.492E-10	3.5363E-10	2.492E-10	3.5363E-10

<u>Median Household Income</u>

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.20846144							
R Square	0.04345617							
Adjusted R S	0.03468054							
Standard Err	303.176486							
Observations	111							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	455160.02	455160.02	4.95191384	0.02812084			
Residual	109	10018842	91915.9814					
Total	110	10474002						
	Coefficients	*Standard Erro*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	111.825795	40.4815289	2.76239061	0.00673627	31.5927212	192.058869	31.5927212	192.058869
Median Hous	0.00505494	0.00227159	2.22528961	0.02812084	0.00055273	0.00955714	0.00055273	0.00955714

Land Cover - Cropland

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.73778762							
R Square	0.54433057							
Adjusted R S	0.54015012							
Standard Err	209.251232							
Observations	111							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	5701319.48	5701319.48	130.208499	2.5557E-20			
Residual	109	4772682.51	43786.0781					
Total	110	10474002						
	Coefficients	*Standard Erro*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	61.8562121	22.2060131	2.78556136	0.00630322	17.8446161	105.867808	17.8446161	105.867808
Land Cover -	0.76971574	0.06745446	11.4108939	2.5557E-20	0.63602318	0.90340829	0.63602318	0.90340829

Land Cover - Tree Cover

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.72223948							
R Square	0.52162987							
Adjusted R S	0.51724115							
Standard Erro	214.40016							
Observations	111							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	5463552.27	5463552.27	118.857035	3.6912E-19			
Residual	109	5010449.73	45967.4287					
Total	110	10474002						
	Coefficients	*Standard Erro*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	115.579602	21.0716088	5.48508672	2.7056E-07	73.816358	157.342845	73.816358	157.342845
Land Cover -	0.19950632	0.01829971	10.9021573	3.6912E-19	0.16323689	0.23577575	0.16323689	0.23577575

<u>Land Cover - Artificial Surfaces</u>

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.88932556							
R Square	0.79089995							
Adjusted R S	0.7889816							
Standard Erro	141.749047							
Observations	111							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	8283887.64	8283887.64	412.281556	7.7883E-39			
Residual	109	2190114.35	20092.7922					
Total	110	10474002						
	Coefficients	*Standard Erro*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	14.8339202	15.6007268	0.95084803	0.34378515	-16.086213	45.7540535	-16.086213	45.7540535
Land Cover -	44.2553601	2.17956048	20.3047176	7.7883E-39	39.9355421	48.5751781	39.9355421	48.5751781

Original Multiple Regression:

SUMMARY OUTPUT	
Regression Statistics	
Multiple R	0.94520924
R Square	0.89342052
Adjusted R S	0.88392333
Standard Erro	105.1314
Observations	111

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	9	9357688.27	1039743.14	94.0721721	4.9161E-45
Residual	101	1116313.73	11052.6112		
Total	110	10474002			

	Coefficients	*Standard Erro*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-39.087128	34.3948596	-1.1364235	0.258469	-107.31728	29.1430213	-107.31728	29.1430213
Population (2	1.1458E-06	3.1782E-07	3.60535228	0.000486	5.1538E-07	1.7763E-06	5.1538E-07	1.7763E-06
Total GDP ($	-9.858E-13	4.5184E-12	-0.2181716	0.827736	-9.949E-12	7.9775E-12	-9.949E-12	7.9775E-12
Population De	-0.0040877	0.01318027	-0.3101395	0.757094	-0.0302338	0.02205839	-0.0302338	0.02205839
Urban Popula	0.97657938	0.61667499	1.58362086	0.116406	-0.2467379	2.19989668	-0.2467379	2.19989668
Gross Nationa	1.1302E-10	2.6817E-11	4.21443078	0.000055	5.9821E-11	1.6622E-10	5.9821E-11	1.6622E-10
Median Hous	-0.001036	0.00116266	-0.8910833	0.375002	-0.0033424	0.00127038	-0.0033424	0.00127038
Land Cover -	-0.043003	0.07557631	-0.5690013	0.570618	-0.1929261	0.10692006	-0.1929261	0.10692006
Land Cover -	0.10807256	0.01545073	6.99465867	0.000000	0.07742247	0.13872265	0.07742247	0.13872265
Land Cover -	17.3079436	4.03349591	4.29105271	0.000041	9.30657267	25.3093144	9.30657267	25.3093144

Second Regression Model: We removed GDP because it had the highest p-value.

SUMMARY OUTPUT	
Regression Statistics	
Multiple R	0.94518267
R Square	0.89337029
Adjusted R S	0.88500717
Standard Erro	104.639429
Observations	111

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	8	9357162.17	1169645.27	106.822675	4.7033E-46
Residual	102	1116839.82	10949.41		
Total	110	10474002			

	Coefficients	*Standard Erro*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-39.375602	34.2086003	-1.151044	0.2524	-107.2282	28.4769941	-107.2282	28.4769941
Population (2	1.138E-06	3.1428E-07	3.62085208	**0.0005**	5.1459E-07	1.7613E-06	5.1459E-07	1.7613E-06
Population De	-0.0040554	0.01311776	-0.3091529	**0.7578**	-0.0300744	0.02196362	-0.0300744	0.02196362
Urban Popula	0.96708135	0.61225781	1.57953291	**0.1173**	-0.2473291	2.18149181	-0.2473291	2.18149181
Gross Nationa	1.125E-10	2.6587E-11	4.23143909	**0.0001**	5.9767E-11	1.6524E-10	5.9767E-11	1.6524E-10
Median Hous	-0.0010138	0.00115276	-0.8794276	**0.3812**	-0.0033003	0.00127272	-0.0033003	0.00127272
Land Cover -	-0.0420281	0.07509104	-0.5596949	**0.5769**	-0.1909708	0.10691464	-0.1909708	0.10691464
Land Cover -	0.10777734	0.01531933	7.03538014	**0.0000**	0.07739151	0.13816317	0.07739151	0.13816317
Land Cover -	17.393791	3.99547182	4.35337596	**0.0000**	9.46879155	25.3187904	9.46879155	25.3187904

Third Regression Model: We removed population density because it had the highest p-value

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.94512982
R Square	0.89327037
Adjusted R S	0.8860169
Standard Err	104.179006
Observations	111

ANOVA

	df	SS	MS	F	Significance F
Regression	7	9356115.68	1336587.95	123.150769	4.2731E-47
Residual	103	1117886.32	10853.2652		
Total	110	10474002			

	Coefficients	Standard Erro	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-38.49727	33.9404158	-1.1342604	0.2593	-105.81008	28.81554	-105.81008	28.81554
Population (2	1.1268E-06	3.1084E-07	3.62515545	0.0005	5.1036E-07	1.7433E-06	5.1036E-07	1.7433E-06
Urban Popula	0.94318021	0.60468457	1.55978879	0.1219	-0.256069	2.14242943	-0.256069	2.14242943
Gross Nationa	1.125E-10	2.647E-11	4.25008838	0.0000	6.0003E-11	1.65E-10	6.0003E-11	1.65E-10
Median Hous	-0.0010513	0.0011413	-0.9211573	0.3591	-0.0033148	0.00121218	-0.0033148	0.00121218
Land Cover -	-0.0416	0.07474792	-0.5565371	**0.5791**	-0.1898448	0.10664488	-0.1898448	0.10664488
Land Cover -	0.10773855	0.01525142	7.06416658	0.0000	0.07749096	0.13798613	0.07749096	0.13798613
Land Cover -	17.51911	3.95736576	4.42696254	0.0000	9.67060838	25.3676116	9.67060838	25.3676116

Fourth Regression Model: We removed land cover - cropland because it had the highest p-value

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.94496001
R Square	0.89294943
Adjusted R S	0.88677343
Standard Err	103.832703
Observations	111

ANOVA

	df	SS	MS	F	Significance F
Regression	6	9352754.06	1558792.34	144.583904	3.9617E-48
Residual	104	1121247.94	10781.2301		
Total	110	10474002			

	Coefficients	Standard Erro	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-37.433047	33.7738625	-1.1083437	0.2703	-104.40788	29.5417903	-104.40788	29.5417903
Population (2	1.0563E-06	2.8289E-07	3.7339565	0.0003	4.9532E-07	1.6173E-06	4.9532E-07	1.6173E-06
Urban Popula	0.90985011	0.59971141	1.51714657	0.1323	-0.2794001	2.09910034	-0.2794001	2.09910034
Gross Nationa	1.1711E-10	2.5059E-11	4.67338062	0.0000	6.7416E-11	1.668E-10	6.7416E-11	1.668E-10
Median Hous	-0.0010088	0.00113495	-0.8888324	**0.3761**	-0.0032594	0.00124187	-0.0032594	0.00124187
Land Cover -	0.10240161	0.01182002	8.6634073	0.0000	0.07896207	0.12584114	0.07896207	0.12584114
Land Cover -	16.5881591	3.57452914	4.64065573	0.0000	9.49973372	23.6765846	9.49973372	23.6765846

Fifth Regression Model: We removed median household income because it had the highest p-value

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.94452963
R Square	0.89213623
Adjusted R S	0.88699986
Standard Err	103.728829
Observations	111

ANOVA

	df	SS	MS	F	Significance F
Regression	5	9344236.64	1868847.33	173.690022	4.217E-49
Residual	105	1129765.36	10759.6701		
Total	110	10474002			

	Coefficients	Standard Erro	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-32.216937	33.2268313	-0.9696061	0.3345	-98.099606	33.6657314	-98.099606	33.6657314
Population (2	1.1234E-06	2.7237E-07	4.12435808	0.0001	5.833E-07	1.6634E-06	5.833E-07	1.6634E-06
Urban Popula	0.62130783	0.50374617	1.23337479	**0.2202**	-0.3775278	1.62014343	-0.3775278	1.62014343
Gross Nation	1.09E-10	2.3315E-11	4.67500208	0.0000	6.2769E-11	1.5523E-10	6.2769E-11	1.5523E-10
Land Cover -	0.10209277	0.01180309	8.64966626	0.0000	0.07868943	0.12549611	0.07868943	0.12549611
Land Cover -	16.8456131	3.55920991	4.7329642	0.0000	9.7883573	23.9028688	9.7883573	23.9028688

Final Regression Model: We removed urban population density because it had the highest p-value

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.94370203
R Square	0.89057353
Adjusted R S	0.88644422
Standard Err	103.98354
Observations	111

ANOVA

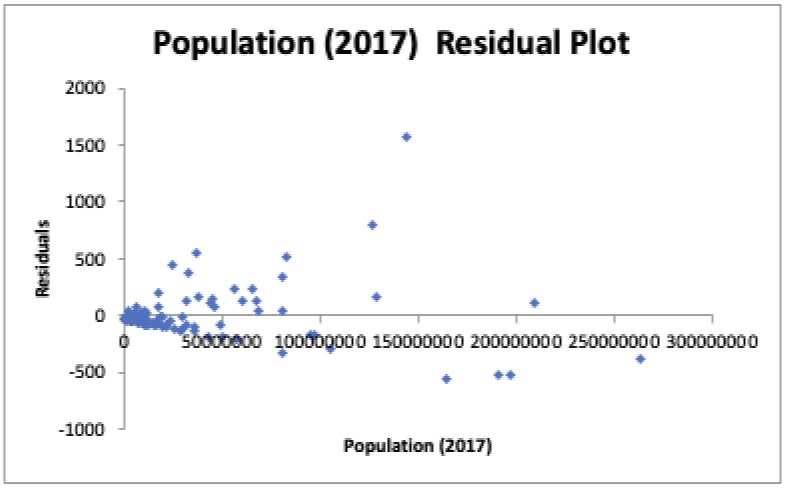
	df	SS	MS	F	Significance F
Regression	4	9327868.88	2331967.22	215.671743	0.0000
Residual	106	1146133.11	10812.5765		
Total	110	10474002			

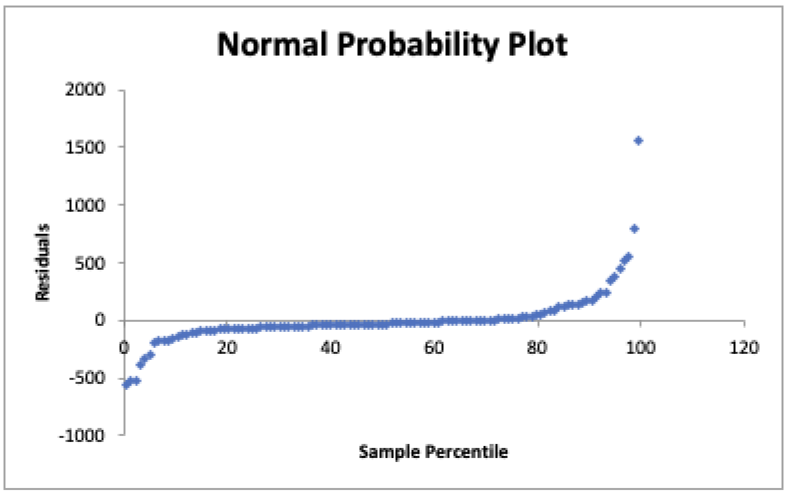
	Coefficients	Standard Erro	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	5.90617116	12.2208993	0.4832845	0.6299	-18.32295	30.1352927	-18.32295	30.1352927
Population (2	1.0189E-06	2.5952E-07	3.92631253	0.0002	5.0443E-07	1.5335E-06	5.0443E-07	1.5335E-06
Gross Nation	1.1494E-10	2.2868E-11	5.02609891	0.0000	6.96E-11	1.6028E-10	6.96E-11	1.6028E-10
Land Cover -	0.10263226	0.01182394	8.68003709	0.0000	0.07919014	0.12607438	0.07919014	0.12607438
Land Cover -	17.3348549	3.54572204	4.8889492	0.0000	10.3051161	24.3645937	10.3051161	24.3645937

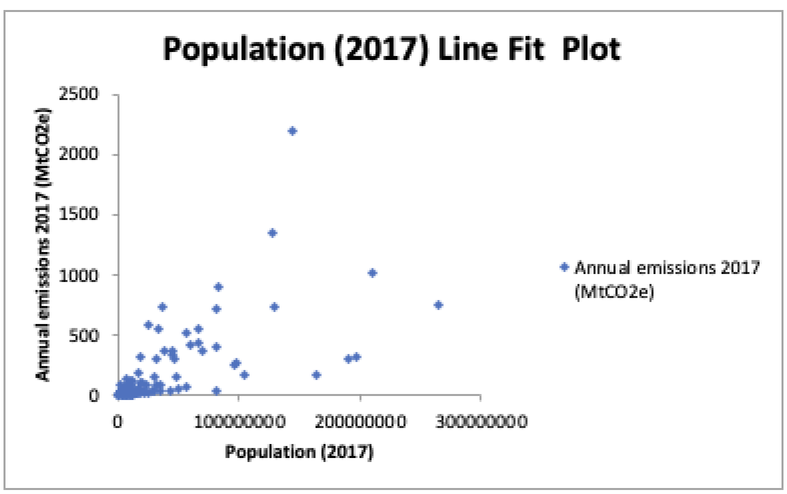
Appendix C

Checking Assumptions

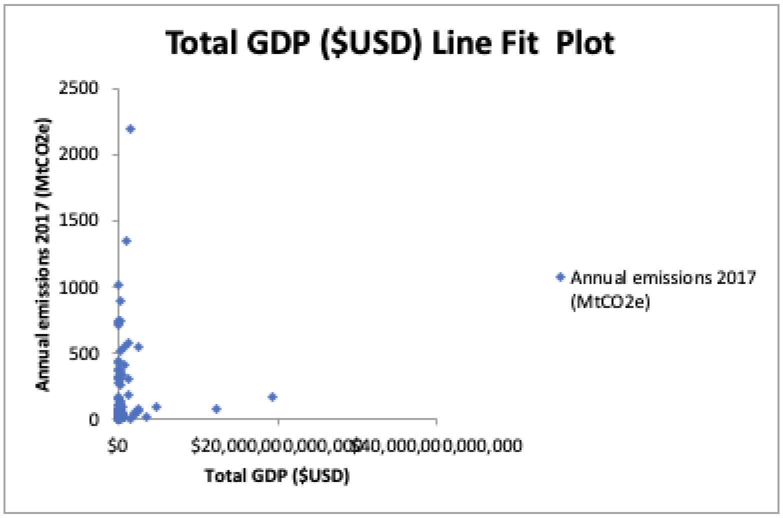
Population

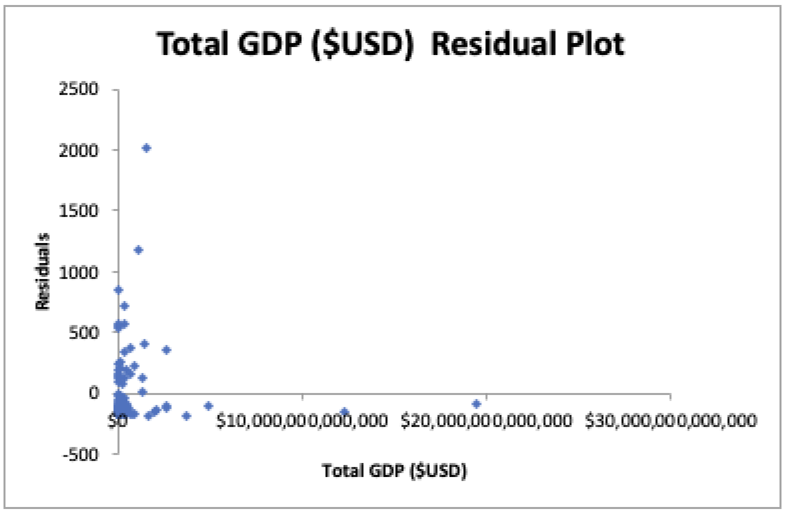


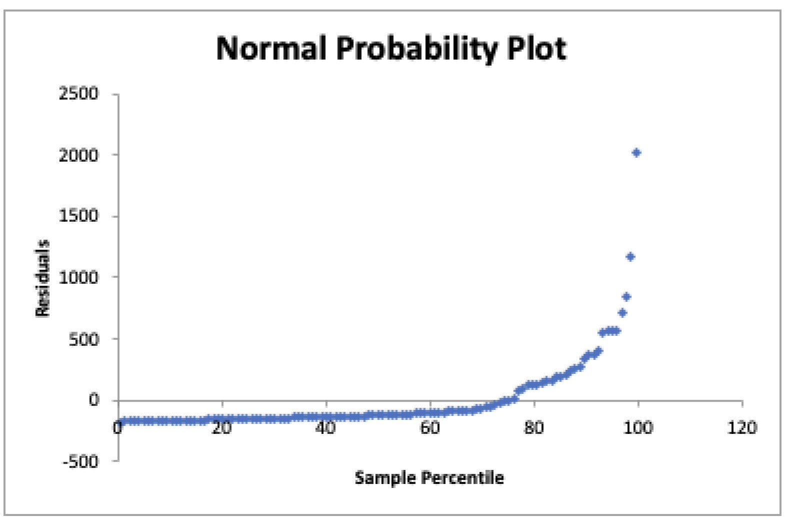




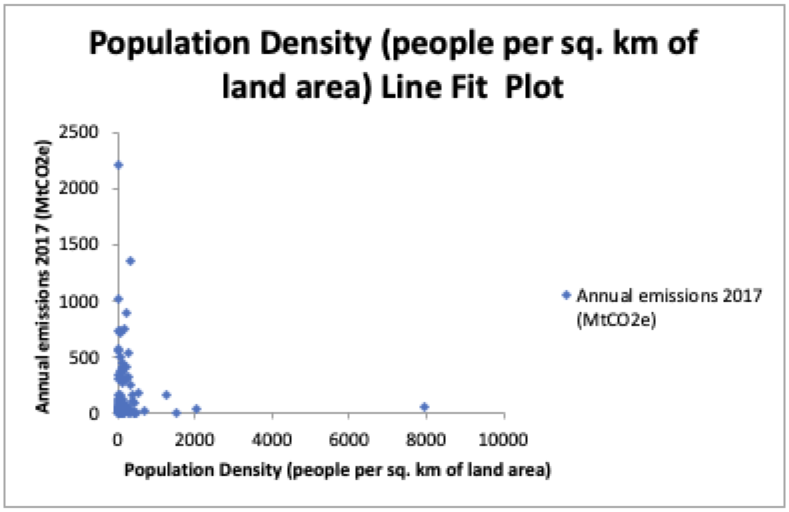
Total GDP

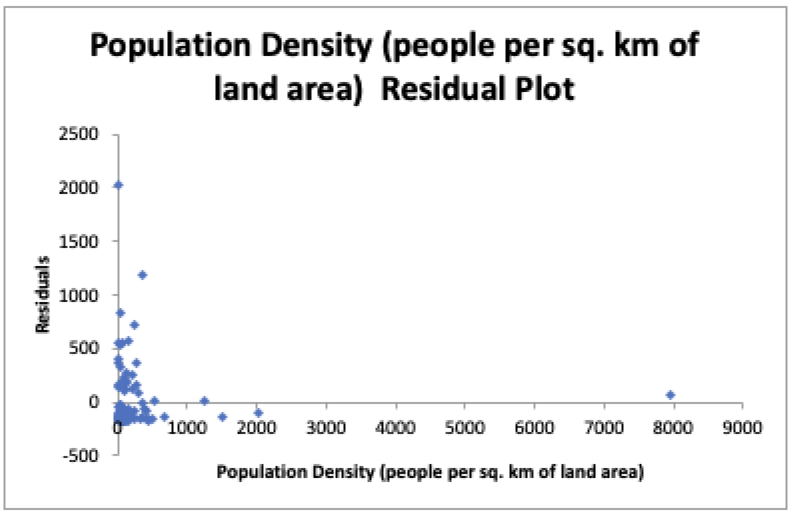


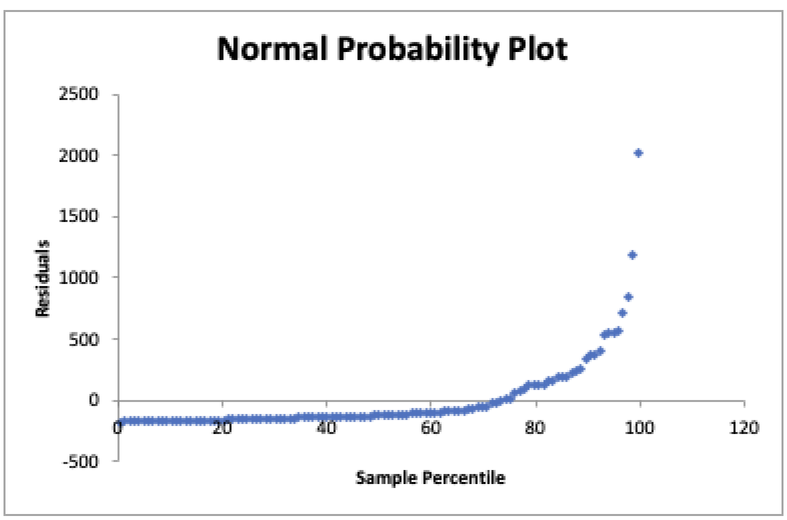




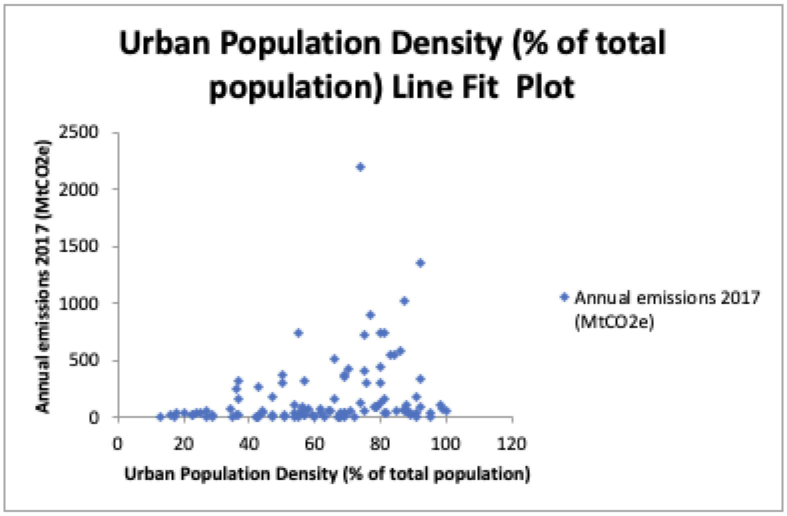
<u>Population Density</u>

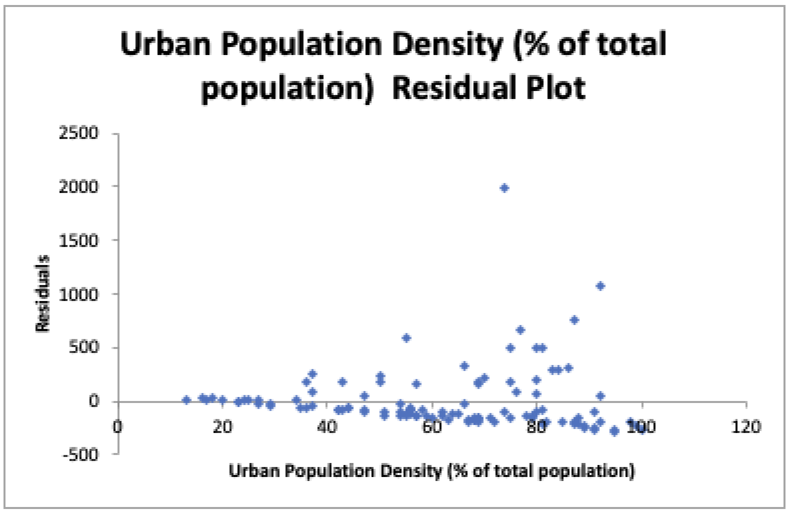


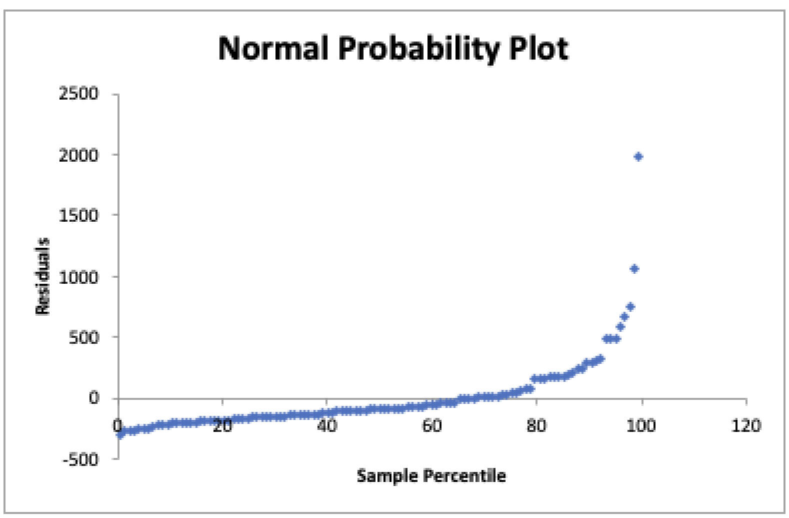




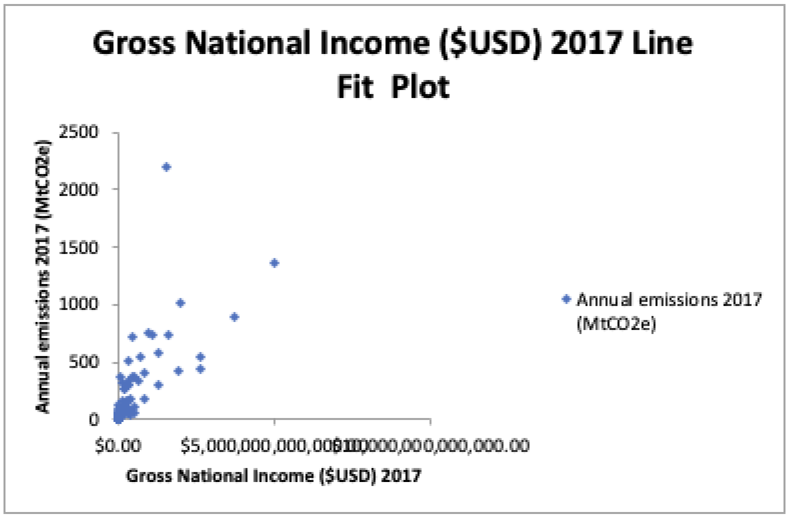
Urban Population Density

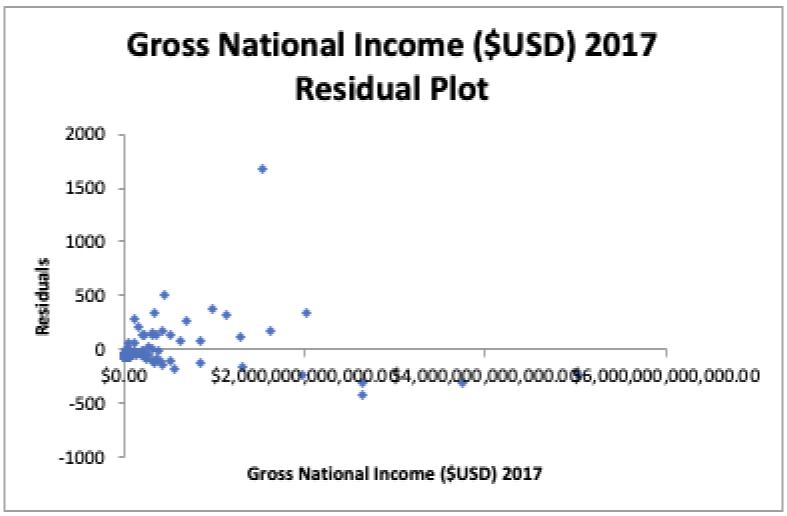


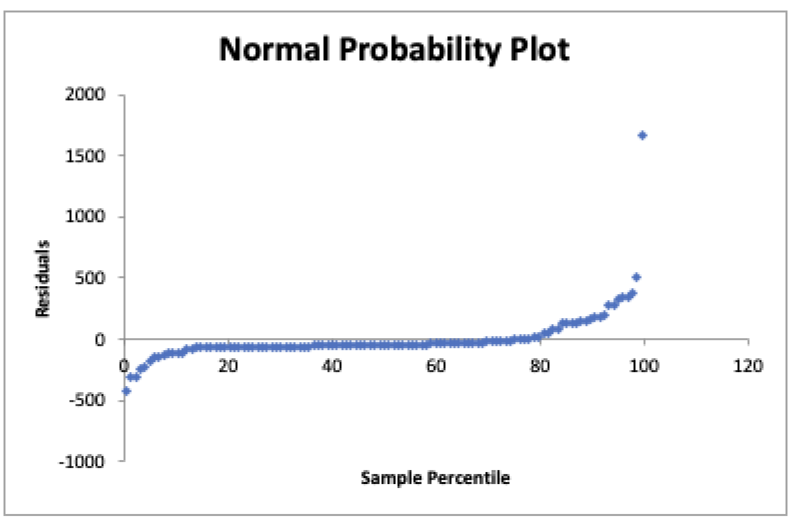




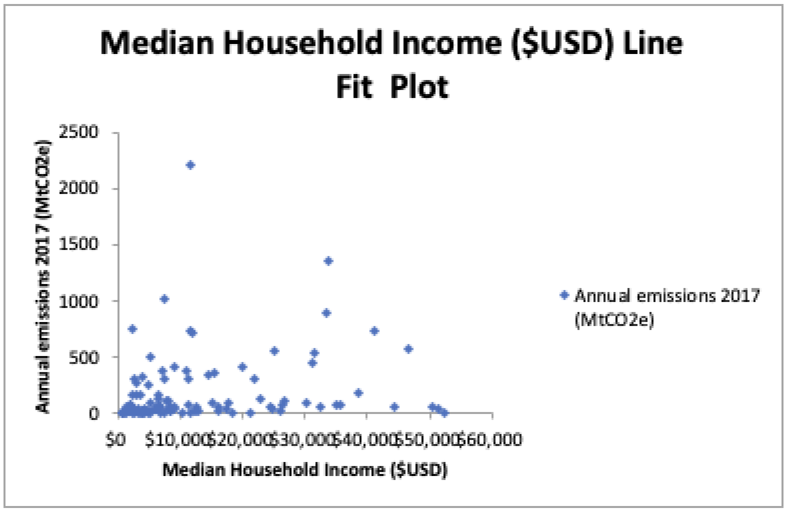
<u>Gross National Income</u>

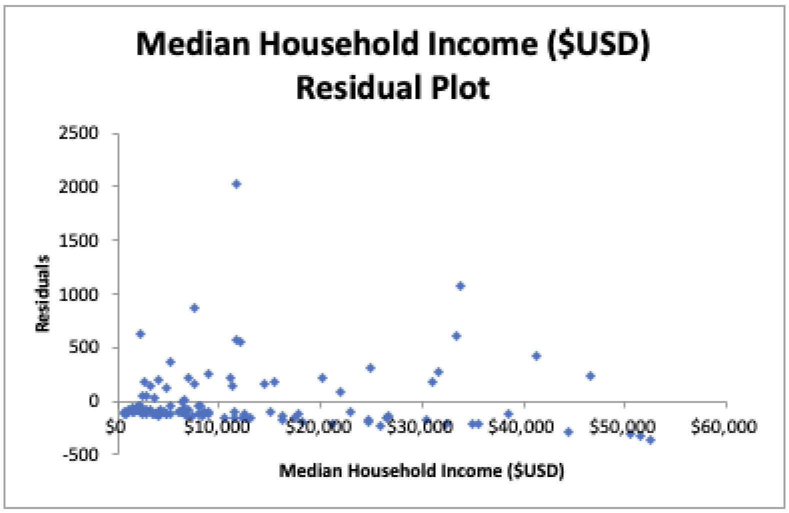


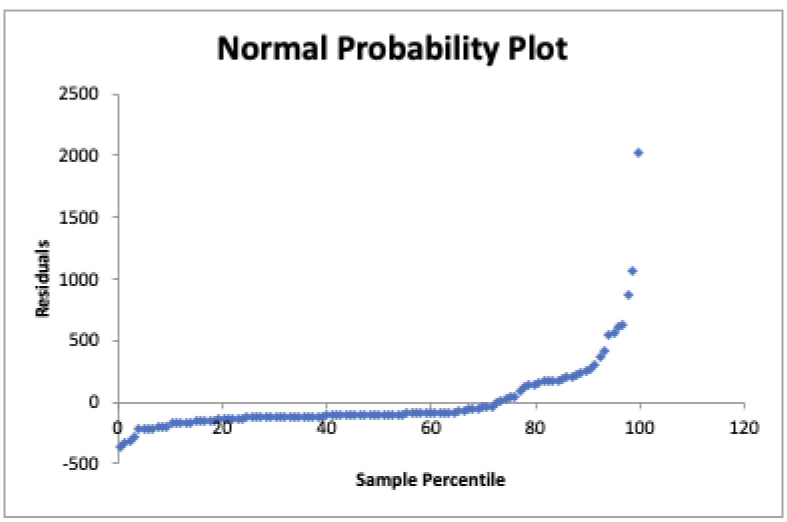




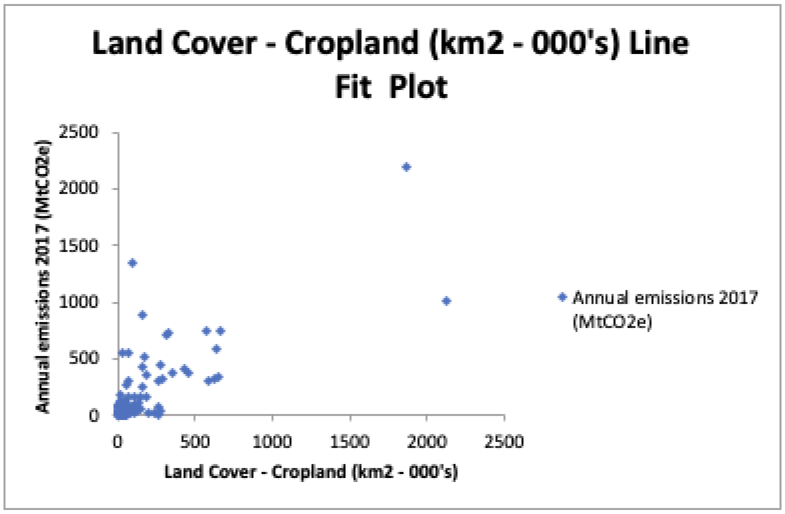
<u>Median Household Income</u>

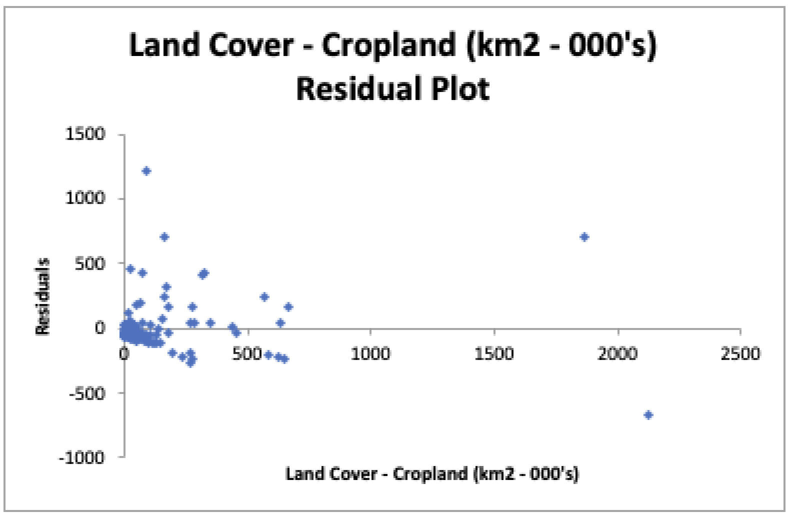


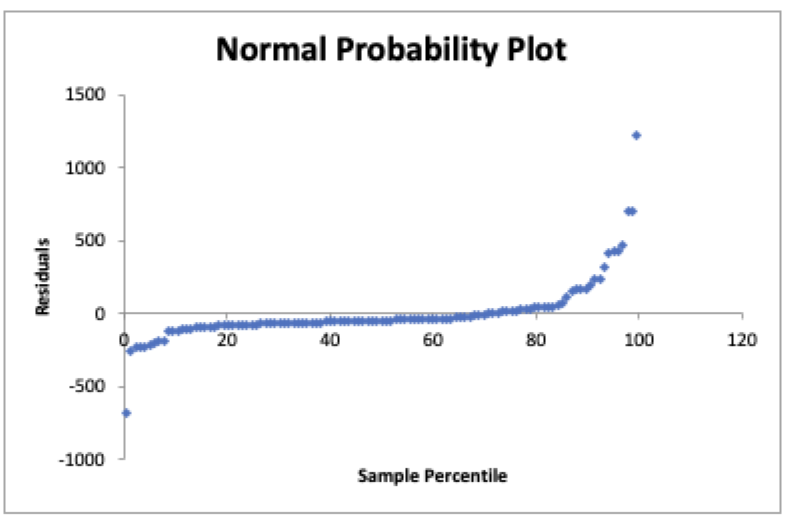




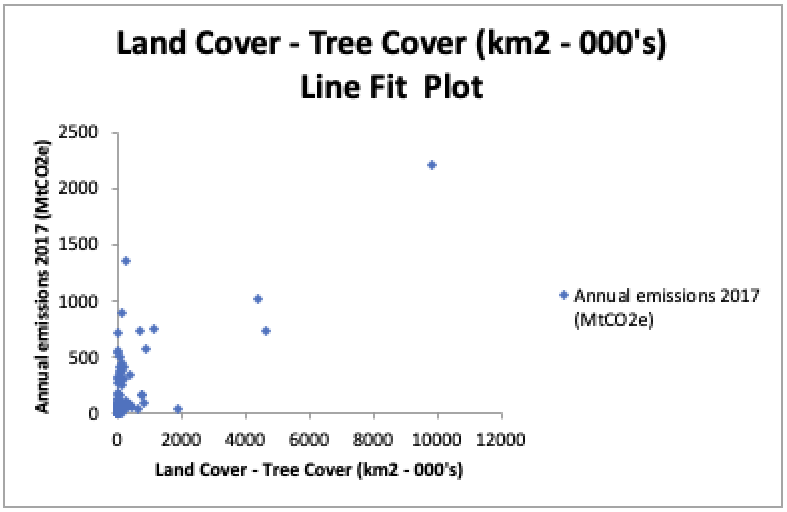
Land Cover - Cropland

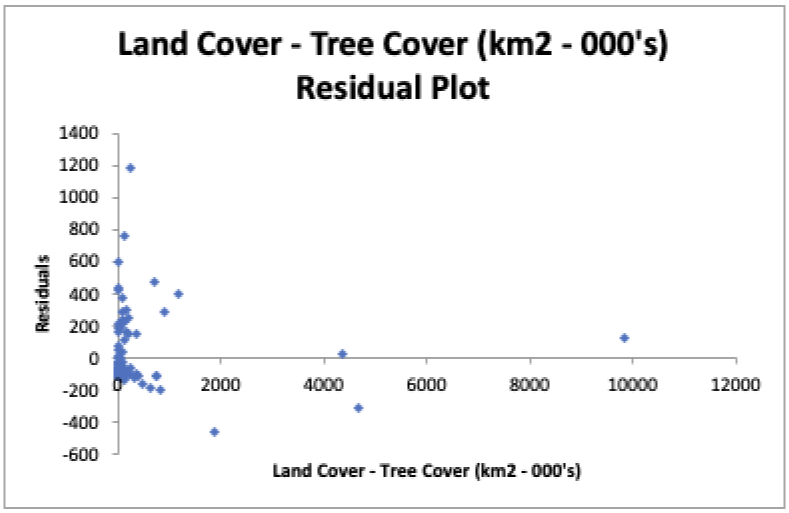


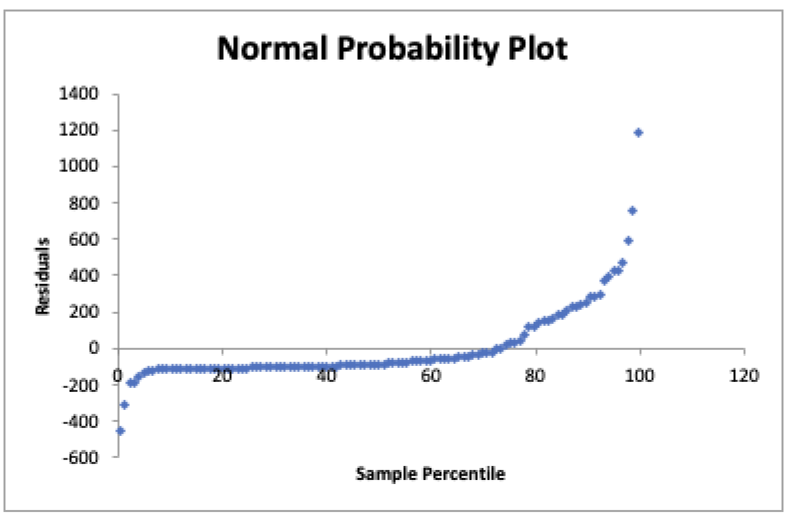




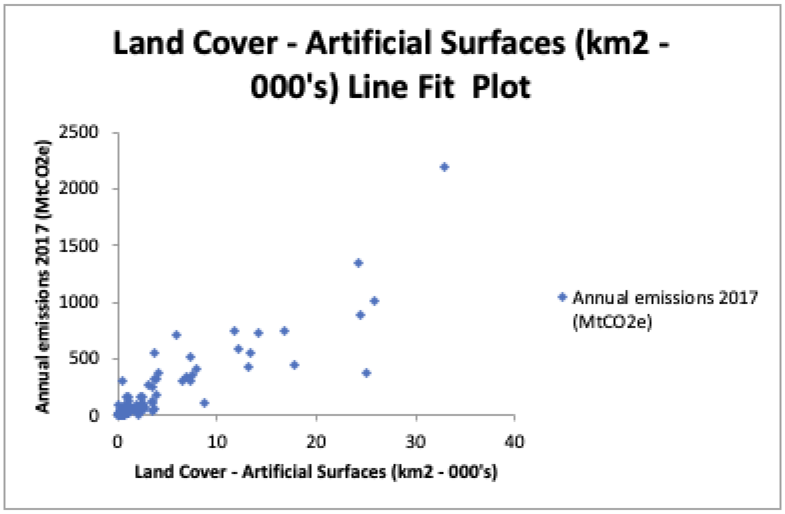
Land Cover - Tree Cover

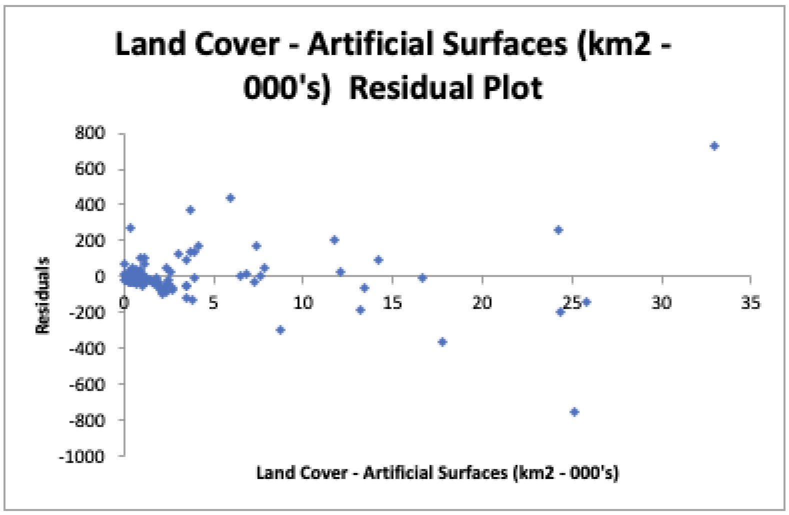


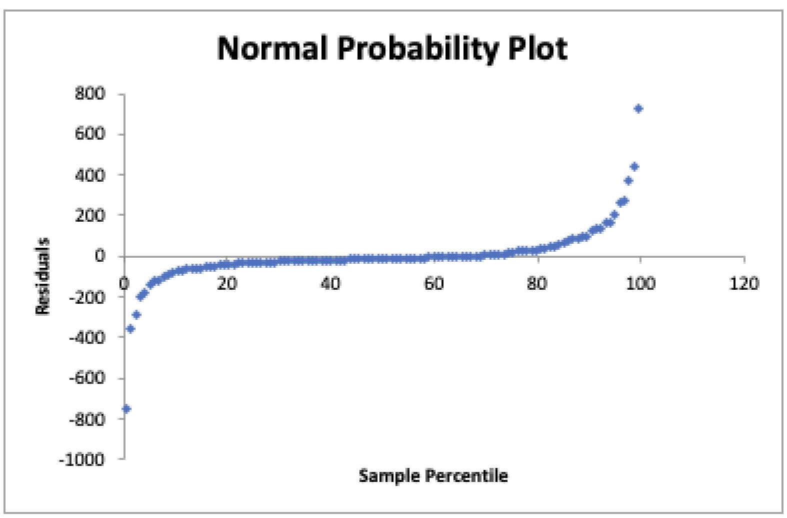




Land Cover - Artificial Surfaces


Land Cover - Artificial Surfaces (km2 - 000's) Line Fit Plot
Annual emissions 2017 (MtCO2e)
2500
2000
1500
1000
500
0
0
10
20
30
40
Land Cover - Artificial Surfaces (km2 - 000's)
Annual emissions 2017 (MtCO2e)


Land Cover - Artificial Surfaces (km2 - 000's) Residual Plot
Residuals
800
600
400
200
0
-200
-400
-600
-800
-1000
0
5
10
15
20
25
30
35
Land Cover - Artificial Surfaces (km2 - 000's)


Normal Probability Plot
Residuals
800
600
400
200
0
-200
-400
-600
-800
-1000
0
20
40
60
80
100
120
Sample Percentile