HIGH SCHOOL EDITION
Journal of Student Research

Volume 12 Issue 1 (2023)

A Machine Learning Approach to Finding Factors that Lead to Environmental Friendliness

Sucheer Maddury[1] and Anjana Manian[#]

[1]Leland High School, San Jose, CA, USA
[#]Advisor

ABSTRACT

To maintain a sustainable society, environmental friendliness is necessary, an effort that all countries must take part in. The effort must be pioneered by developed nations with the resources to enact sustainable policies, reduce emissions and conserve energy, from which developing nations will follow the eroded path. Recognizing the factors that promote environmental friendliness is necessary for researchers, policymakers, and activists alike.

Several past studies have examined the relationship between environmental performance and various nationwide factors such as economic strength, education, and corruption. In this paper, however, we introduce the machine learning approach Multiple-Linear Regression, allowing several variables to be used in tandem.

We constructed a dataset using a variety of variables from a variety of sources, either examined in past literature or justified logically. We measured environmental friendliness through the Environmental Performance Index (EPI), and chose feature variables of Women in Parliament (%), Internet users (%), Freedom Index, Ethnic fractionalization, Technological development, Press Freedom Index, Corruption Perceptions Index, GDP per capita ($), and Education Index, and Population.

We found that Multiple-Linear Regression is an effective way of measuring EPI, where several metrics indicate that EPI is almost completely determined by the feature variables. We end the study by presenting the correlations of each of the variables with EPI, and find that almost all exhibit strong linear relationships. These correlations should bring light to the characteristics of environmentally friendly countries, mainly Nordic nations.

Introduction

Despite agreements made at the UN Framework Convention on Climate Change Conference in 2010, developed and developing nations have consistently failed to meet the reduction of warming to +2°C. (Wei, Yang, & Moore et al. 2012). While developments in renewable energy and energy conservation efforts have helped, emissions still far exceed those agreed upon. (Wandana, Arachchige, Preethika, & Wadanambi et al. 2020). Runaway climate change leads to several side effects, such as deforestation and sea contamination. (Wandana, Arachchige, Preethika, & Wadanambi et al. 2020).

While developing nations are comparatively under-industrialized, they make up a substantial portion of global greenhouse gas emissions. (Wei, Yang, & Moore et al. 2012). To address this, developed nations must swiftly reduce CO 2 emissions in order to assist and encourage developed nations to pursue sustainability (Dong, Hochman, & Timilsina 2020). One of the reasons for this is that while developed nations' CO 2 emissions have slightly decreased since 1997, developing countries' CO 2 emissions have increased by over one-third, now making up the majority of global CO 2 emissions. (Kessel & Tabuchi 2019).

Developed nations have the monetary legroom to improve their sustainability. Previous literature suggests that one's attitude towards climate change is positively correlated with their environmental friendliness

(Seif & Nematolahi 2019). Recognizing the factors that promote environmental friendliness can provide vital information to policymakers for their nations.

Multiple linear regression (MLR) is a powerful method for correlating several variables to a single target, making it the ideal tool to analyze relevant nationwide factors. In this paper, we identify several previously correlated and uncorrelated factors and utilize them in tandem with MLR to accurately predict environmental friendliness.

Background Review

Several previous studies have examined the relationship between environmental friendliness and other nationwide variables. However, none of them made use of machine learning or attempted to estimate environmental friendliness with those factors.

Lester, Ma, Li, & Lambert 2007 investigated the effects of quality elementary school science education on climate change advocacy in fifth-graders. They found that fifth-graders with better scientific knowledge were more likely to express environmental concerns.

McCright 2010 looked into the differences between men and women in climate change knowledge and advocacy. The study found that women had greater climate change knowledge than men on average. Women also expressed greater concern for climate change than men, a change not accounted for by values, beliefs, or social roles of men and women. Both McCright 2010 and Selm et al. 2019 found that women from undereducated backgrounds were less confident about their scientific knowledge than men from undereducated backgrounds.

Fredriksson & Neumayer 2016 examined the relationship between historical corruption rates and climate change policies in various nations. They found that historical corruption rates were negatively and significantly correlated to today's climate change policies, but did not test today's corruption rates.

Shahabadi, Samari, & Nemati 2017 examined the relationship between Environmental Performance Index (EPI) and various country characteristics in petrol states (OPEC). They found that World Governance Index (WGI), internet users and natural resource abundance were positively correlated with EPI and CO 2 emissions per GDP was negatively correlated with EPI. They additionally saw that Human Development Index (HDI) and industry sector value were positively and negatively correlated respectively, but they were both insignificant.

Dong, Hochman, & Timilsina 2020 measured the relationship between economic development and related variables with CO 2 emissions. They found that economic development was strongly correlated to the increase in CO 2 emissions since 1997 in all countries. Additionally, they found that population growth was also a main driver of CO 2 emissions in low-income nations primarily.

Wang, Cardon, Liu, & Madni 2020 tested the effects of various nationwide factors on environmental performance. They found that ethnic diversity; institutional quality and political freedom are positively and significantly correlated with environmental performance, while foreign direct investment (FDI) was positively and insignificantly correlated with environmental performance. They additionally saw that GDP growth and financial development was negatively correlated with environmental performance.

Leitão 2021 plotted economic growth, corruption, renewable energies, international trade against CO 2 emissions in European countries. They found that corruption index and economic growth have a positive and significant effect on CO 2 emissions, while renewable energies and international trade have a negative effect on CO 2 emissions and improve environmental quality.

Materials and Methods

Feature Variables and Target

To use machine learning, we constructed a dataset of 180 countries with 10 feature variables and 1 target variable. These features consisted of Women in Parliament (%), Internet users (%), Freedom index, Ethnic fractionalization, Technological development, Press Freedom index, Corruption perceptions index, GDP per capita ($), and Education Index, and Population. All variables are proportional; country size/population had minimal effect on the scores.

Women in Parliament (%) data was taken from UNdata 2021. Women in Parliament (%) is calculated by taking the percentage of a country's parliament that happen to be women. The rationale behind this variable is that women are generally more knowledgeable about the climate and concerned about the climate than men (outlined in the Background Review), raising the possibility that women in Parliament may lead to more environmentally friendly policy.

Internet Users (%) data was also taken from UNdata 2021. Internet Users (%) is calculated with the percentage of a country's population that regularly use the internet. The reason we test this feature is because widespread internet usage enables more effective communication and distribution of information, and can also indicate a technologically advanced society.

Freedom Index data was taken from the annual report from the Vásquez, McMahon, , Murphy, & Schneider 2021. Human Freedom Index (HFI) is calculated through 82 different indicators in 12 different categories. Each of the 82 indicators are scored from 0-10, and a weighted average is calculated to determine personal freedom and economic freedom, both of which are used to determine HFI. This variable was chosen because human freedom allows citizens to participate in civil discussion and decision-making about the environment (Wang, Cardon, Liu, & Madni 2020).

Ethnic Frac. data was taken from Alesina et al. 2003 & Fearon 2003. Ethnic Frac. is calculated via the measure of similarity between languages; 1 = the population speaks two or more unrelated languages and 0 = the entire population speaks the same language. This variable was chosen because ethnic diversity leads to more innovative solutions to environmental degradation (Wang, Cardon, Liu, & Madni 2020).

Technology Index data was taken from Nation Master 2005. Technology Index is calculated through indicators such as company spending on R & D, scientific creativity, and computer/internet penetration rates. Technology Index indicates a country's technological readiness and development. We chose this variable to test if the degree of technological development is correlated with better environmental solutions.

Press Freedom Index (PFI) data was taken from Misachi 2017 (uses data from Reporters Without Borders). PFI is calculated through a series of questions for reporters and the tallies of crime and abuse against reporters. The questions mainly pertain to the evaluation of pluralism, independence of the media, legislative framework of the country, and the safety of journalists. High press freedom promotes public exposure to various climate issues, putting pressure on policymakers to provide sustainable bills.

Corruption Perceptions Index (CPI) data was taken from Transparency International 2021. CPI is calculated through the perception of corruption due to difficulties calculating absolute corruption. CPI was added in order to test whether the effect of corruption reducing government effectiveness had a relationship with environmental friendliness.

GDP per capita ($) data was taken from UNdata 2021. GDP per capita ($) is simply calculated by dividing the Gross Domestic Product by the population. GDP per capita is considered a good metric for standard of living (Hall et al. 2021), and was included in this study to test the effects of citizen welfare on environmental friendliness.

Education Index data was taken from Marindi, Diab, & McBride 2018. Education Index is calculated by averaging the expected years of schooling / 18 (As 18 represents a master's degree) and the mean years of actual schooling / 15 (Representing the projected maximum in 2025). Education Index was included because environmental friendliness in minors improves with better scientific education (Lester, Ma, Li, & Lambert 2007).

Population data was taken from UNdata 2021. Population is simply the amount of people within the borders of a country. It was included to test if larger countries are more/less environmentally friendly.

Data Exploration

Table 1. Variety of statistical characteristics in the features.

	Count	Mean	SD	Min	25%	50%	75%	Max
Women in Parliament %	180	24.375	12.308	0	15.375	23	31.75	61.3
Internet Users %	180	55.036	29.507	1.3	27.4	60.95	81.3	99.7
HFI	180	7.143	1.242	4	6.238	7.215	8.2	9.11
Ethnic Frac.	178	0.437	0.257	0	0.201	0.426	0.659	0.930
Technology Index	100	3.977	0.921	1.81	3.203	3.99	4.67	6.24
Press Freedom Index	165	33.778	15.831	8.59	23.84	30.35	42.64	83.92
CPI	173	44.179	18.194	14	30	39	56	88
GDP per capita ($)	180	20555.2691	21299.93	760	5081	12846	30196.75	118001
Education Index	180	0.664	0.173	0.249	0.531	0.692	0.78	0.943
Population	180	4.245e+07	1.517e+08	5.452e+04	2.468e+06	9.428e+06	3.115e+07	1.413e+09
EPI	180	43.103333	12.297653	18.9	33.975	41.95	50.675	77.9

[1] As can be observed in "Count", there are missing values in Ethnic Fractionalization, Technology Index, Press Freedom Index, and Corruption Perceptions Index. The missing values were filled in using the median to avoid omission of rows.

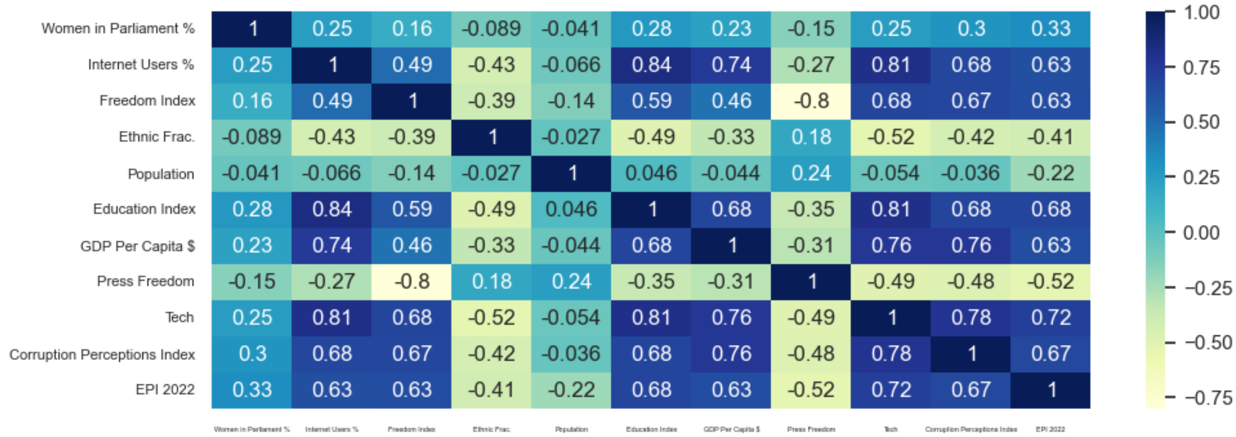

Figure 1. Correlation coefficients heatmap.

[1] The closer the $|correlation\ coefficient|$ to 1, the stronger the correlation.

Models

To run multiple-linear regression on the dataset, we chose to test several different MLR algorithms. These include Linear Regression, Decision Tree Regressor, Random Forest Regressor, Support-Vector Regressor (SVR), and Gradient-Boosted Decision Trees. For the GBDT, we chose the XGBoost (https://xgboost.readthedocs.io/) library because of its robustness. In each of these models, various hyperparameters were varied and measured. All other models were sourced from scikit-learn (https://scikit-learn.org/). The data was split 80% train (n = 144), and 20% test (n = 36). For each trial, the Root Mean Square Error (RMSE) was calculated (and also used for loss).

Equation 1: Root Mean Square Error Loss.

$$\boldsymbol{RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}}$$

All trials were run 10,000 times each on random testing allocations in order to simulate real-world performance. The median and standard deviation of those runs was then calculated for each trial.

Results

Accuracy

The RMSE for a variety of configurations is shown below in **Table 2**. Criterion and max_features values were varied on RandomForest because they historically produce significant result changes, and kernels and boosters were varied on SVR and GBDT because they each represent differing approaches to MLR.

Table 2. Root Mean Square Error for several configurations.

Configuration	Root Mean Square Error
LinearRegression	7.607 ± 1.019
DecisionTree, default parameters	9.364 ± 0.906

RandomForest, default parameters	6.978 ± 0.666
RandomForest, criterion = absolute error	7.051 ± 0.645
RandomForest, max_features = sqrt	7.009 ± 0.663
GBDT, gblinear booster	8.046 ± 1.505e+18
GBDT, gbtree booster	7.484 ± 0.81
SVR, Sigmoid	11.963 ± 1.378
SVR, Radial Basis Function	12.089 ± 1.416
SVR, Polynomial	12.247 ± 80.635
SVR, Linear	12.006 ± 1.545

[1] RMSE represents the average error for each prediction. The SD of the gblinear GBDT likely signifies a few extreme predictions.

The best performing model was Random Forest, with an RMSE of 6.978. EPI ranges from 18.9 - 77.9, so this RMSE equates to ~88.17% accuracy over the range of the target variable. Most hyperparameter variations produced negligible changes in performance, the highest differences were seen in the SVR kernel changes and the GBDT booster changes. Overall, the Root Mean Square Error was lower than expected given R^2 tests. Next, the model accuracy was visualized, in **Figure 2**.

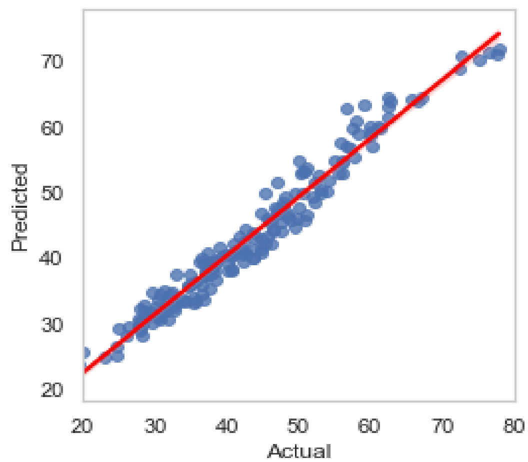

Figure 2. Actual vs Predicted EPI values.

As can be observed, the values are close to the actual value, with low variance across the plot. Further, individual tests were run for the most and least environmentally friendly countries, in order to better observe the performance at the extremes. The results are shown in **Table 3**.

Table 3. Predicted vs actual EPIs for extreme EPI countries.

	Type	Predicted	Observed	Error
Denmark	High	72.409	77.9	-5.491
UK	High	71.648	77.7	-6.052
Finland	High	71.729	76.5	-4.771
Malta	High	68.281	75.2	-6.919
Sweden	High	70.917	72.7	-1.783
India	Low	21.317	18.9	2.417
Myanmar	Low	23.436	19.4	4.036
Vietnam	Low	25.93	20.10	5.83
Bangladesh	Low	24.963	23.10	1.863
Pakistan	Low	25.255	24.60	0.655

Based on these tests, the algorithm seems to do a good job of estimated EPI at the extremes, confirmed by the better accuracy at the ends of the **Figure 2** plot. The high accuracy of these select countries may suggest that the existence of outliers. The algorithm also has a slight median skew, as seen in **Figure 2**.

Statistical Significance

P-values for the data were calculated to examine the probability of the null hypothesis (the feature variable's observed correlation with the target variable is due to chance variation), and standard error was found to see how different the population was likely to be from the sample, through the equation $\boldsymbol{SE = \frac{SD}{\sqrt{n}}}$. The values were calculated with the statsmodels library (https://www.statsmodels.org/), shown in **Table 4**. The adjusted R^2 coefficient was also found to quantify statistical significance, which was calculated to be 0.974, meaning 97.4% of variable variation was explained by the linear model.

Equation 2: R^2 Coefficient of Determination.

$$\boldsymbol{R^2 = 1 - \frac{RSS}{TSS}}$$

[1] RSS is the sum of squares of residuals and TSS is total sum of squares.

Table 4: P-values and standard errors.

Feature Variable	P-value	Standard error
Women in Parliament %	0.0034	0.0468
Internet Users %	0.7279	0.0389
Freedom Index	0.0016	0.5961
Ethnic Fractionalization	0.295	2.2824
Population	0.0004	0.0000
Education Index	0.0031	6.7297
GDP per capita $	0.0418	0.0000
Press Freedom Index	0.1312	0.0391
Technology Index	0.0004	0.9781
Corruption Perceptions Index	0.7007	0.0574

[1] The standard error is measured in the units of the specific feature variable.

The F-statistic was found to be 667.3, which represents the overall statistical significance of the entire dataset. In more interpretable terms, the probability F-statistic was found to be 8.6e-131, representing the probability that that a model with no independent variables would perform better than our model.

Single Variable Correlations

To observe the effects of each variable visually, we also plotted the correlation between each of the features and EPI with the line-of-best-fit calculated through linear regression. We split the data by the status of the country as developed or developing to see if certain variables have a greater or lesser effect based on their level of development. This was performed using seaborn (https://seaborn.pydata.org/), and did not include median filled values.

A **B** **C** **D**

HIGH SCHOOL EDITION
Journal of Student Research

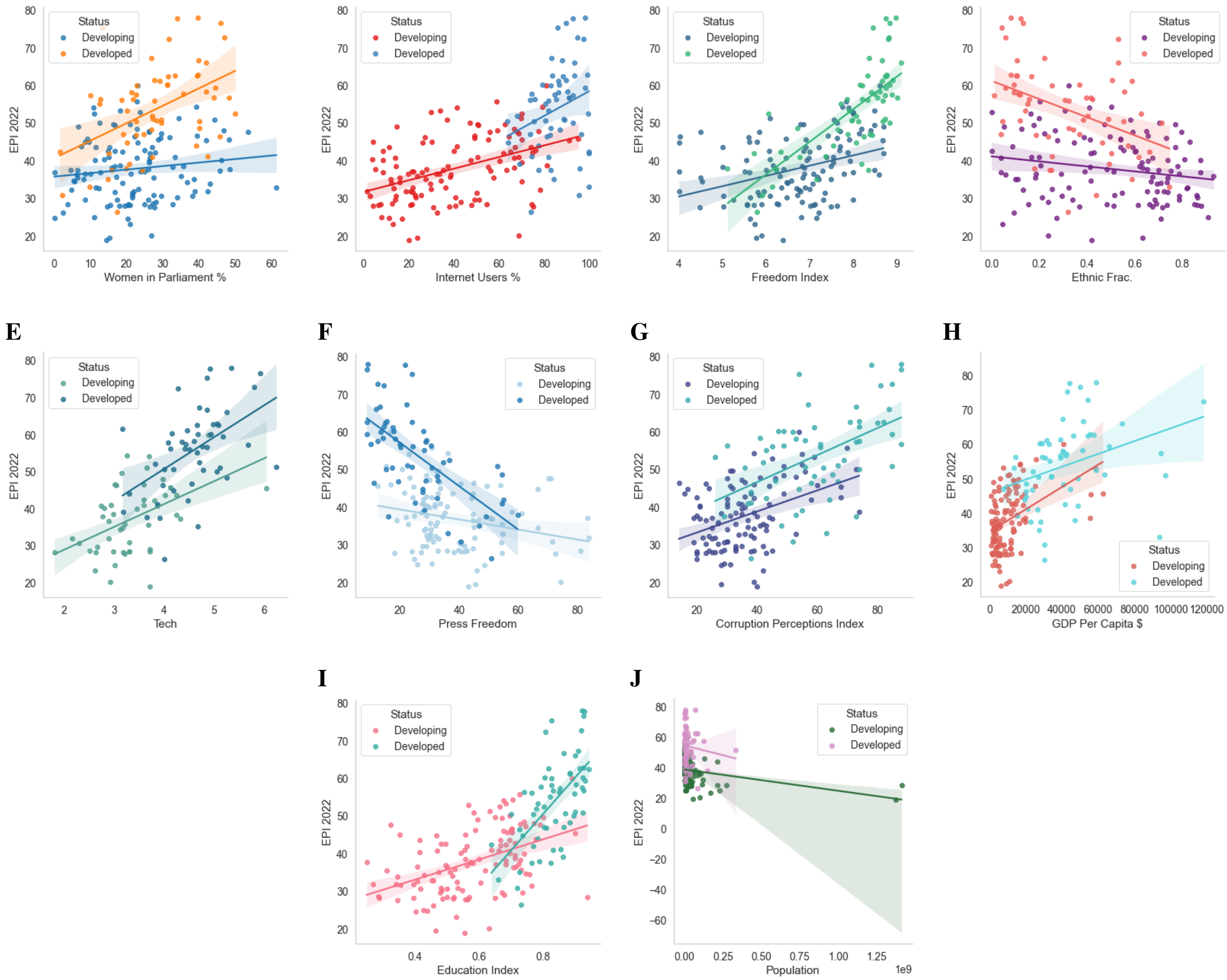

Figure 3. Linear correlations of each feature variable against EPI.

[1] The translucent shading represents the general error margin. NOTES: Press Freedom Index is lower-is-better. CPI appears directly proportional because the measurement index is higher-is-better.

Discussions

The 5 individual countries tested, the error was relatively low which indicates that the feature variables generally provide enough information for an accurate prediction. Despite this, a low sample size could have caused some noise in the dataset and worsened the accuracy.

The p-values in **Table 4** for Women in Parliament %, Freedom Index, Population, Education Index, GDP per capita $, and Technology Index were all found to be less than 0.05, thus we reject the null hypothesis for only those variables at 95% confidence. The p-values for Population and Technology Index were close to zero. One possibility is that Technology Index would have been a more significant predictor had cases been filled in due to a lack of data. Interestingly, Internet Users % and Corruption Perceptions Index were found to have very high p-values, despite the plots for each in **Figure 3** showing a reasonable level of correlation. The F-statistic instills high confidence that the model is statistically significant overall.

Additionally, the single-variable correlations in all variables except GDP per capita were stronger and more significant with developed nations than developing nations. This somewhat suggests that one of the primary limiters of environmental performance is the economic prosperity of the nation, although the correlation is weak, and this finding contradicts previous literature.

The results indicate that the factors commonly associated with autocratic governments (Freedom, Press freedom, CPI) are strongly correlated with environmental performance, giving rise to the possibility that democratic values may be linked to EPI; this is outside of this study's scope. GDP per capita also had a surprising direct proportionality, contradicting previous literature (Dong, Hochman, & Timilsina 2020, Wang, Cardon, Liu, & Madni 2020, & Leitão 2021), although the relationship is not significant. Based on these factors, we suggest that countries invest in more accessible and higher quality educational facilities. This will foster environmental awareness in citizens from a young age and has shown to be a common trend in the most environmentally friendly countries, namely Denmark, Sweden, and Finland.

This study has a few limitations. First, the use of Random Forest strays the algorithm from a simple correlation and into a more complex and interconnected one. Additionally, the sample size is generally limited by the number of different countries, and thus poses a serious barrier for the diversity of the dataset. The spread of the data is a testament to this. Furthermore, the size and influence of a nation was not controlled, effectively giving very small nations the same effect on the algorithm as the largest nations. Finally, it is impossible to determine exactly why performance is high, a problem inherent to machine learning.

Conclusions

Environmental performance has emerged as a forefront of modern nations, and developed nations must funnel their efforts to become the most environmentally friendly possible, in order to assist and encourage developing nations to follow the effort. In this paper, we determined the relationship between Environmental Performance and Women in Parliament (%), Internet users (%), Freedom index, Ethnic fractionalization, Technological development, Press Freedom index, Corruption perceptions index, GDP per capita ($), and Education Index, and Population. We find significant, consistent correlations in all variables except Population and GDP per capita. Moreover, we built a Multiple-Linear Regression that was capable of accurately estimating EPI based on the factors presented in tandem. At the very least, this study indicates that the general attributes of a nation have a strong tendency of predicting environmental friendliness, and should be considered by policymakers and environmental activists.

The empirical findings are by no means homogenous and are with exceptions, but present general trends that link a country's level of development, education, and governmental legitimacy to their environmental performance. A more rigorous investigation into specific countries or tracking the trends over the years may be topics for future research. The application of deep neural networks may also be a subject of follow-up studies, geared more towards prediction than correlation.

Acknowledgments

The author would firstly like to thank Brianna Hajek (B.S.) for her mentorship and support throughout the project. Additionally, the author would like to thank Nicholas Bodony for his contributions in data collection and processing. Lastly, the author would like to thank the DIYA Research mentors, including Suma Bhat (Ph.D.), Mahe Krishnan (M.S.), and Anjana Manian (M.S.) for their consultancy.

References

Wei T, Yang S, Moore JC, Shi P, Cui X, Duan Q, Xu B, Dai Y, Yuan W, Wei X, Yang Z, Wen T, Teng F, Gao Y, Chou J, Yan X, Wei Z, Guo Y, Jiang Y, Gao X, Wang K, Zheng X, Ren F, Lv S, Yu Y, Liu B, Luo Y, Li W, Ji D, Feng J, Wu Q, Cheng H, He J, Fu C, Ye D, Xu G, Dong W. Developed and developing world responsibilities for historical climate change and CO 2 mitigation. Proc Natl Acad Sci U S A. 2012 Aug 7;109(32):12911-5. doi: 10.1073/pnas.1203282109. Epub 2012 Jul 23. PMID: 22826257; PMCID: PMC3420160.

Shahabadi, Abolfazl & Samari, Haneih & Nemati, Morteza. (2017). Factors affecting environmental performance index (EPI) in selected OPEC countries. Iranian Economic Review. 21. 457-467. DOI: 10.22059/ier.2017.62925.

Seif, Mohammad Hassan and Nematolahi, Sareh M.A, "The Effective Factors on Environmentally Friendly Behavior: A Case Study" (2019). Library Philosophy and Practice (e-journal). 2842. https://digitalcommons.unl.edu/libphilprac/2842

Hsu, Angel & de Sherbinin, Alex & Esty, Daniel & Levy, Marc. (2016). Global Metrics for the Environment: 2016 Environmental Performance Index Report. 10.13140/RG.2.2.11856.30723.

Wandana, Samadhi & Arachchige, Udara & Preethika, Prabodhi & Wadanambi, Rushini & Chathumini, Limasha & Dassanayake, Nadeesha. (2020). The effects of industrialization on climate change. https://www.researchgate.net/publication/344479407_The_effects_of_industrialization_on_climate_change

Kangyin Dong, Gal Hochman, Govinda R. Timilsina, Do drivers of CO 2 emission growth alter overtime and by the stage of economic development?, Energy Policy, Volume 140, 2020, 111420, ISSN 0301-4215, https://doi.org/10.1016/j.enpol.2020.111420.

Benjamin T. Lester, Li Ma, Okhee Lee & Julie Lambert (2006) Social Activism in Elementary Science Education: A science, technology, and society approach to teach global warming, International Journal of Science Education, 28:4, 315-339, DOI: 10.1080/09500690500240100

McCright, A.M. The effects of gender on climate change knowledge and concern in the American public. Popul Environ 32, 66–87 (2010). https://doi.org/10.1007/s11111-010-0113-1

Selm KR, Peterson MN, Hess GR, Beck SM, McHale MR (2019) Educational attainment predicts negative perceptions women have of their own climate change knowledge. PLOS ONE 14(1): e0210149. https://doi.org/10.1371/journal.pone.0210149

Fredriksson, P.G., Neumayer, E. Corruption and Climate Change Policies: Do the Bad Old Days Matter?. Environ Resource Econ 63, 451–469 (2016). https://doi.org/10.1007/s10640-014-9869-6

Leitão NC. The Effects of Corruption, Renewable Energy, Trade and CO 2 Emissions. Economies. 2021; 9(2):62. https://doi.org/10.3390/economies9020062

Kessel, J., Tabuchi, H., 2019. It's a Vast, Invisible Climate Menace. We Made it Visible. The New York Times. https://www.nytimes.com/interactive/2019/12/12/climate/t exas-methane-super-emitters.html.

Wang C, Cardon PW, Liu J, Madni GR (2020) Social and economic factors responsible for environmental performance: A global analysis. PLOS ONE 15(8): e0237597. https://doi.org/10.1371/journal.pone.0237597

Wolf, M. J., Emerson, J. W., Esty, D. C., de Sherbinin, A., Wendling, Z. A., et al. (2022). 2022 Environmental Performance Index. New Haven, CT: Yale Center for Environmental Law & Policy. Epi.yale.edu

Alberto Alesina; et al. (2003). "Fractionalization" (PDF). Journal of Economic Growth. **8**: 155–194. doi:10.1023/a:1024471506938. Retrieved September 13, 2012.

James Fearon (2003). "Ethnic and Cultural Diversity by Country". Journal of Economic Growth. **8**: 195–222. doi:10.1023/A:1024419522867.

Hall, M. (2022, July 27). *How does GDP affect the standard of living?* Investopedia. Retrieved August 4, 2022, from https://www.investopedia.com/ask/answers/060115/how-does-gross-domestic-product-gdp-affect-standard-living.asp

Vásquez, I., McMahon, F., Murphy, R., & Sutter Schneider, G. (2021). *The Human Freedom Index 2021*. Cato Institute. Retrieved August 4, 2022, from https://www.cato.org/human-freedom-index/2021

Vásquez, I., McMahon, F., Murphy, R., & Sutter Schneider, G. (2021). *The Human Freedom Index 2021*. Fraser Institute. Retrieved August 4, 2022, from https://www.fraserinstitute.org/studies/human-freedom-index-2021

NationMaster. (2005). *Countries compared by Economy > Technology Index. international statistics*. NationMaster.com. Retrieved August 4, 2022, from https://www.nationmaster.com/country-info/stats/Economy/Technology-index

Misachi, J. (2017, April 25). *Countries of the world by degree of press freedom*. WorldAtlas. Retrieved August 4, 2022, from https://www.worldatlas.com/articles/countries-of-the-world-by-degree-of-press-freedom.html
2021 Corruption Perceptions Index. Transparency International. (2021). Retrieved August 4, 2022, from https://www.transparency.org/en/cpi/2021

Marindi, J., Diab, O., & McBride, E. (2018, October 30). *UNDP Human Development Reports: Education Inde*. Humanitarian Data Exchange. Retrieved August 4, 2022, from https://data.humdata.org/dataset/education-index