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

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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.

Keywords: Environmental friendliness, machine learning, countries, regression

I. 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.

II. 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.

III. MATERIALS AND METHODS

To use machine learning, we constructed a dataset of 180 countries with 10 feature variables and 1 target variable.

3.1. Feature Variables and Target

We chose 10 different target variables to predict EPI with. These 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, including: Rule of Law, Security and Safety, Movement, Religion, Association, Assembly, and Civil Society, Expression and Information, Identity and Relationships, Size of Government, Legal System and Property Rights, Access to Sound Money, Freedom to Trade Internationally, and Regulation. 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. To be published in CPI, a country's corruption must be evaluated by at least 3 of any of the following institutions: African Development Bank, Bertelsmann Foundation, Economist Intelligence Unit, Freedom House, Global Insight, International Institute for Management Development, Political and Economic Risk, Consultancy, The PRS Group, Inc. , World Economic Forum, World Bank World Justice Project. CPI was added in order to test whether the effect of corruption reducing government effectiveness had a relationship with environmental friendliness.

GDP per capita ($) data was taken from *UNdata*. GDP per capita ($) 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*. 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.

3.2. Data Exploration

Statistical descriptions of each variable are shown below in Table 1.

	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	6.2375	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	20555.26 91	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+0 7	1.517e+0 8	5.452e+0 4	2.468e+0 6	9.428e+0 6	3.115e+0 7	1.413e+0 9
EPI	180	43.10333 3	12.29765 3	18.9	33.975	41.95	50.675	77.9

Table 1: Presents a variety of statistical characteristics in the features. As can be observed, 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.

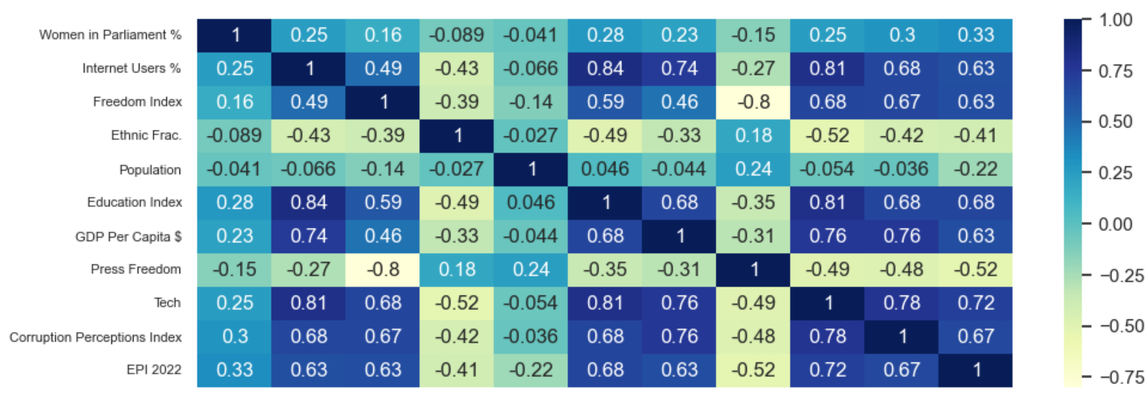


Figure 1: Table of correlation coefficients. The closer the $|correlation\ coefficient|$ to 1, the stronger the correlation. Negative values signify inverse proportionality.

Based on the correlation table, we hypothesize that the Education Index will be the most significant variable for the MLR, and Population will be the least significant variable.

3.3. 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 library because of its robustness. In each of these models, various hyperparameters were varied and measured. All models were sourced from sci-kit learn and XGBoost. The data was split 80% train (n = 144), and 20% test (n = 36).

IV. RESULTS

4.1. Accuracy

For each trial, the Root Mean Square Error (RMSE) was calculated for a variety of configurations. 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. 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.

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

Table 2: The Root Mean Square Error for each of several configurations. 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.

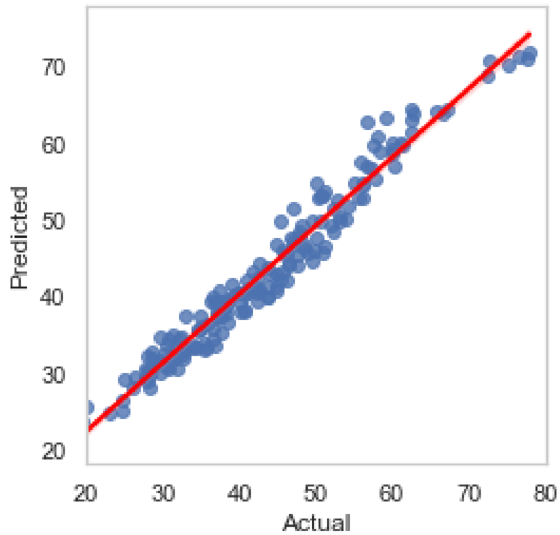


Fig 2: Actual vs Predicted EPI values over the entire dataset. Performed on Random Forest.

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 and 4.

	Predicted	Observed	Error
Denmark	72.409	77.9	-5.491
UK	71.648	77.7	-6.052
Finland	71.729	76.5	-4.771
Malta	68.281	75.2	-6.919
Sweden	70.917	72.7	-1.783

Table 3: Displays the predicted vs actual EPIs for highest EPI countries.

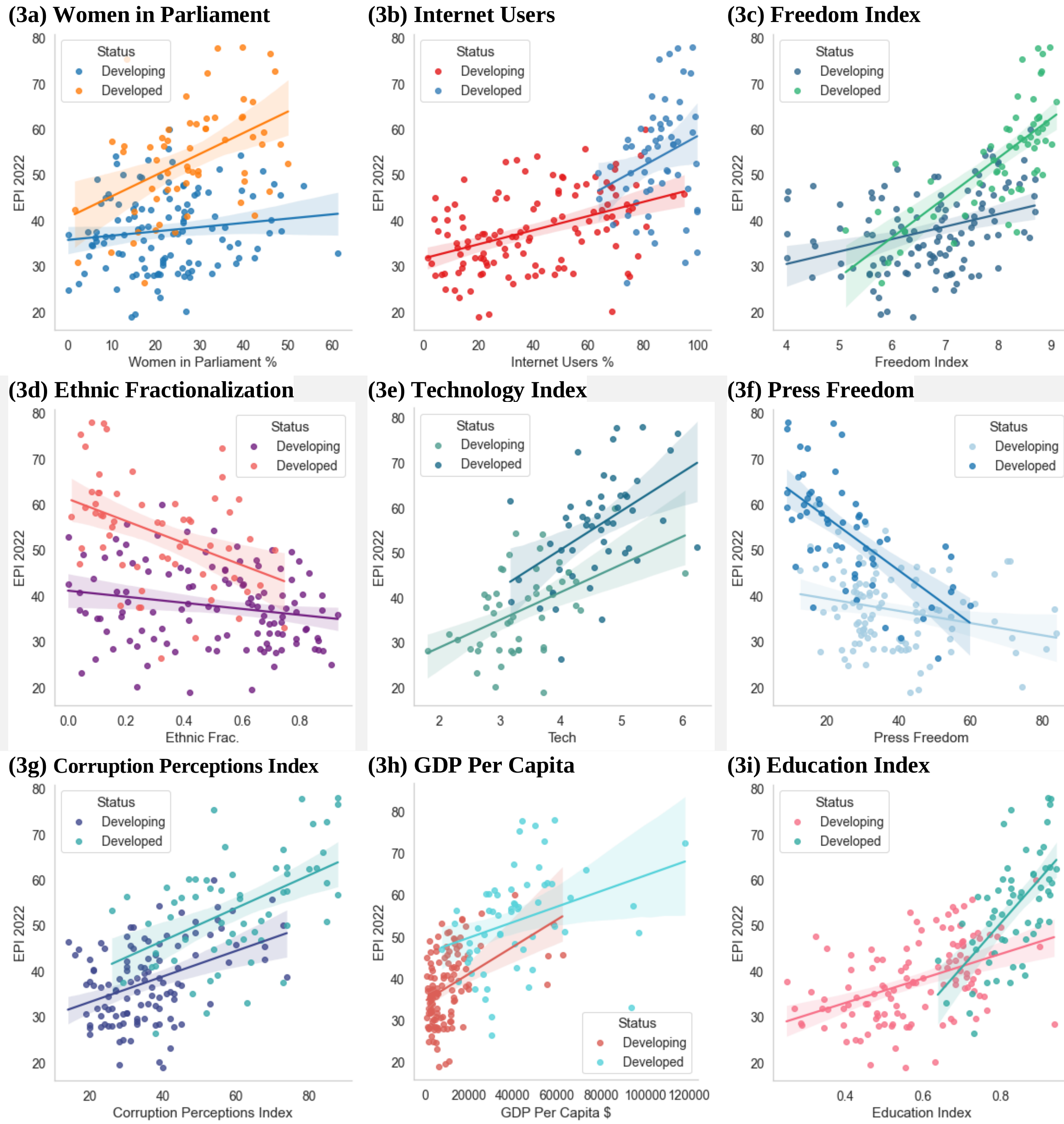
	Predicted	Observed	Error
India	21.317	18.9	2.417
Myanmar	23.436	19.4	4.036
Vietnam	25.93	20.10	5.83
Bangladesh	24.963	23.10	1.863
Pakistan	25.255	24.60	0.655

Table 4: Displays the predicted vs actual EPIs for the lowest EPI countries.

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, although this hypothesis is not verified by the tight nature of the Figure 2 plot. The algorithm predictions also tend towards the median, reflecting a more conservative prediction style. This is also observed in the graph, there the ends skew towards the median instead of intersecting with the origin.

4.2. 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*, and did not include median filled values.



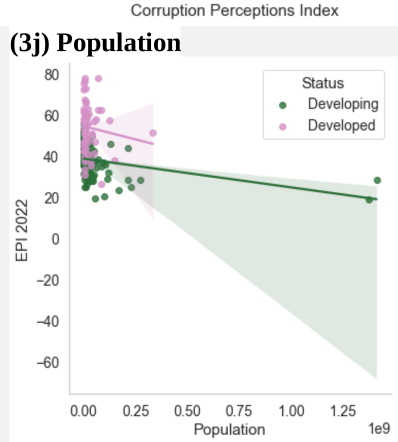


Fig. 3: Linear correlations with developed and developing country hues. The translucent shading represents the general error margin. NOTES: Press Freedom appears inversely proportional because the measurement index is lower-is-better. CPI appears directly proportional because the measurement index is higher-is-better.

V. DISCUSSIONS

5.1. Empirical Analysis

It is clear from the data that MLRs are an effective way of predicting EPI with the features. Of the 5 individual countries tested, the error was relatively low and 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.

There are several considerations that can be made from the plots. Despite a large spread of data, there was an apparent correlation in all tested variables except for GDP per capita and Population (further described below). Additionally, the Technology Index would have likely been a more significant factor if more data points were available. 80/180 of the points had to be filled in with median due to an absence of the data point.

GDP per capita and Population had weak correlations as the majority of data points were concentrated near the left-hand side of the graph. Despite the existence of a line-of-best-fit, any observed correlation in these two variables can likely be attributed to chance variances found in the data.

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; that 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.

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.

5.2. Feature Importance

In order to test the feature importance hypothesis, the *feature_importance_* function was used to determine feature importance after training. The feature importance and the correlation coefficients were then ranked and compared. The results are displayed below in Table 5.

	Women in Parliament %	**Internet Users %**	**Freedom Index**	**Ethnic Frac.**	**Population**	**Education Index**	**GDP Per Capita $**	**Press Freedom**	**Tech**	**CPI**
Value	0.03229290191537431	0.04783453061560474	0.39182974605446735	0.02786959500505293	0.07417124048314039	0.12168026134226591	0.12686962078291245	0.04577283021860488	0.0826409009950742	0.04903837258750286
F.I. Ranking	9	7	1	10	5	3	2	8	4	6
Corr Ranking	10	5	4	8	9	1	3	7	6	2

Table 5: Shows each of the variables' feature importance and ranking in comparison to one another. A higher number indicates a more important feature.

As shown, most variables had similar rankings, except Population and CFI, which increased 4 rankings and decreased 4 rankings, respectively. In the end, the three most important features in order were Freedom Index, GDP per Capita, and Education Index. The strong correlation can also be observed in Fig. 3c and Fig. 3i for Freedom Index and Education Index, respectively.

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.

VI. 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.

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