BIOS 611 Project Report

Global Indicator Data Analysis

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1. Introduction

The future existence of humankind is dependent on our ability to live sustainably. As human populations rise along with greenhouse gas emissions, deforestation rates, and generation of waste, we will continue to deplete natural resources, disrupt ecosystems, and increase global temperatures, leading to an unsustainable future. Because of this, it is critical to study environmental indicators to assess the current state and trajectory of the environment.

For my BIOS 611 project, I chose to analyze global environmental indicator data along with global economic and happiness indicator data. My goal was to assess recent environmental trends of countries around the world and to see how these trends might correspond with the state of the economy and measured levels of happiness within the countries.

2. Source data description

There were three types of source data sets used for this analysis: environmental indicator data, economic indicator data, and happiness indicator data. Each data type contains quantitative indicator measures by country and year.

Environmental indicator data

The environmental indicator source data come from the United Nations Statistics Division (UNSD) / United Nations Environment Programme (UNEP) Questionairre on Environment Statistics. The data were downloaded via Kaggle here (last updated June 5, 2021). Multiple types of environmental indicator data were used in this analysis and fall under the categories of air and climate, biodiversity, energy, forest, inland water resources, land and agriculture, natural disasters, and waste. Environmental indicator data are available within the year range 1990-2020.

Economic indicator data

The economic indicator source data come from the UNSD Human Development Report and were downloaded via Kaggle here (last updated August 11, 2020). The primary measure of economic activity used for this analysis was gross domestic product (GDP) by country. Economic indicator data are available within the year range 1990-2018.

Happiness indicator data

The happiness indicator data come from the World Happiness Report published by the Sustainable Development Solutions Network. The data were downloaded via Kaggle here (last updated November 26, 2019). Each country is given a "happiness score" (0 to 10) that is based on life evaluation survey responses. Happiness indicator data are available within the year range 2015-2019.

3. Results

Exploration of indicator trends within countries

The first goal of my analysis was to explore trends of indicator data within individual countries. To achieve this goal, I created an interactive R shiny app that plots many different types indicator data over time for 190 different countries. The country of interest can first be selected via a drop-down menu in the app. For the selected country, thirteen different types of plots are generated:

- Environmental indicator plots
  - Greenhouse gas emissions by type over time
  - Greenhouse gas emissions by sector
  - Energy supply per capita over time
  - Renewable energy production percentage over time
  - Forest area over time
  - Precipitation over time
  - Natural disaster occurrences over time
  - Natural disaster deaths over time
  - Hazardous waste by type over time
  - Municipal waste recycled over time
- Economic indicator plots
  - Gross domestic product per capita over time
  - Gross national income by gender over time
- Happiness indicator plots
  - Happiness score over time

The plots displayed in the shiny app can give insight into the level and ways that a country may be negatively affecting the environment, the status of a country's economy, and the estimated happiness level of a country's citizens over time.

As an example, we can look at all of the indicator plots generated for Sweden in the shiny app. From this data, we can see that Sweden's greenhouse gas emissions have been decreasing over time, and that most of these greenhouse gas emissions come from energy use. Correspondingly, energy supply per capita has been decreasing over time and the total percentage renewable energy production increasing over time. The total forest area by year in Sweden increased from 1990-2000, but decreased from 2000-2020. While the total precipitation fluctuates year by year in Sweden, the indicator plot shows a general trend of increased precipitation since 1990. Additionally, Sweden has had very few recent natural disasters, treats/disposes of approximately half of its hazardous waste, and has been increasing the percentage of municipal waste it recycles. We can also see that Sweden's GDP has been steadily rising over time, and while the national income has been rising as well, it remains higher for men than women. Furthermore, Sweden's happiness score has only fluctuated by less than 0.1 out of 10 from 2015-19.

We can also notice some other notable trends from the indicator plots generated by the shiny app. In Brazil, for example, where the Amazon rainforest is located, forest area has been decreasing over time. From

1990-2020, Brazil has lost approximately 10 million hectares of forest area. Additionally, we can see that the gross national income has been increasing at a higher rate for men than for women over time in India. Furthermore, in Japan, we can see that the number of meteorological natural disasters (hazards caused by short-lived extreme weather and atmospheric conditions such as extreme temperature or storms) has been steadily increasing over time. This could be due to the effects of global warming. We also see a large number (approximately 20,000) of deaths from geophysical natural disasters (hazards originating from solid earth such as earthquakes or wildfires) between 2010-2019 in Japan. This can be explained by the 9.0 magnitude 2011 Tōhoku earthquake and tsunami.

Energy consumption trends across countries

While the R shiny app displayed various indicator trends over time for individual countries, I also wanted to look at the indicator trends over time between countries. I chose to focus on energy consumption trends for this analysis. I was interested in what countries were consuming the greatest amounts of energy (both in total and per capita), as well as how much of this energy was renewable.

First, I looked at energy consumption trends of the ten countries with the highest total levels of energy consumption between 1990-2017 (Figure 1). Countries were ranked by their highest year of energy consumption in petajoules over the 27 year period. For the top ten energy-consuming countries, I then plotted the total energy consumption by year (Figure 1a) along with the percent of total energy consumption that is renewable by year (Figure 1b). From these plots, we can see that there are two countries with a much higher level of energy consumption than any other country: the United States and China. The United States started as the highest energy-consuming country in 1990, and the amount of energy consumed per year has remained approximately steady since then. Meanwhile, we see that China's energy consumption has greatly increased from 1990 to 2017, surpassing the United States in 2009 as the highest energy-consuming country. While the United States and China are by far the most energy-consuming countries, less than 25% of the energy they consume is renewable. We can see that of the ten countries with the highest total energy consumption, only Brazil and Canada source more than 50% of their total energy from renewable sources.

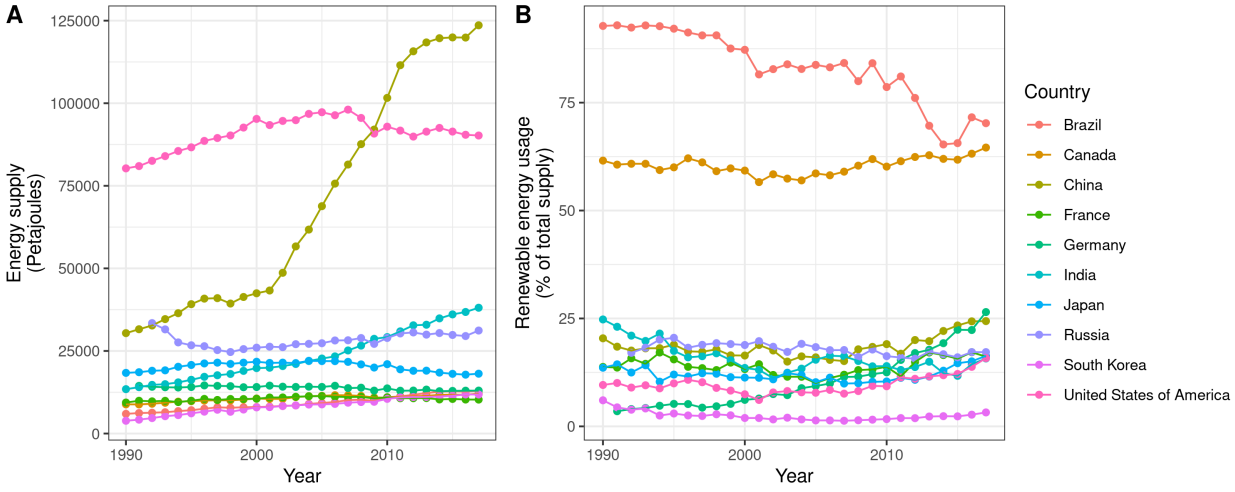

Figure 1: Energy consumption trends for top ten energy-consuming countries. **(a)** Total energy consumption by country over time. **(b)** Percent of total energy consumed that is renewable by country over time.

Next, I looked at energy consumption trends of the ten countries with the highest levels of energy consumption per capita between 1990-2017 (Figure 2). Countries were ranked by their highest year of energy consumption in gigajoules per capita over the 27 year period. Interestingly, none of the top ten energy-consuming countries per capita overlapped with the top ten total energy-consuming countries. For the top ten energy-consuming countires per capita, I then plotted the energy consumption per capita by year (Figure 2a) along with the

percent of total energy consumption that is renewable by year (Figure 2b). We can see from these plots that the two countries with the highest energy consumption per capita as of 2017 are Iceland and Qatar. Iceland's energy consumption per capita has been steadily increasing over time, while Qatar's energy consumption per capita experienced a sharp increase followed by a general decrease over time. We also see that almost all of Iceland's energy comes from renewable sources, which makes sense as it is home to many volcanoes and hot springs that can be used for geothermal energy. On the other hand, we see that almost none of Qatar's energy comes from renewable sources, which also makes sense as it is home to some of the world's largest natural gas and oil reserves.

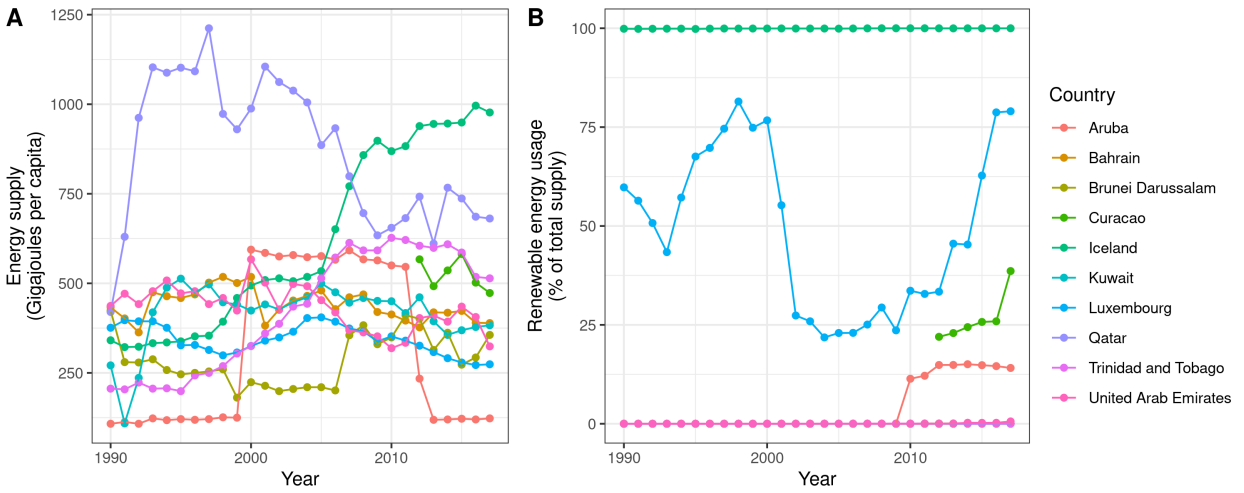

Figure 2: Energy trends for top ten energy-consuming countries per capita. **(a)** Energy consumption per capita by country over time. **(b)** Percent of total energy consumed that is renewable by country over time.

Regional economic and happiness trends

I also wanted to look at trends in the economic and happiness indicator data. To see if there are regional patterns in a country's economic output and estimated happiness level, I plotted the GDP per capita (Figure 3a) and happiness level (Figure 3b) of 142 countries in 2018, grouped by region of the world. From these plots, we can see that the three regions with the highest happiness levels (Australia and New Zealand, North America, and Western Europe) are also the three regions with the highest GDP per capita. While we can generally observe similar patterns between the two plots, we do see that there are some differences. Latin America and Caribbean, for example, had a relatively higher happiness than GDP, while Eastern Asia had a relatively higher GDP than happiness.

Correlations between indicator data

Next, I wanted to look to see if there were any correlations between different types of indicator data. To do this, I combined GDP per capita data with happiness score data and six different measures of environmental indicator data: greenhouse gas (GHG) emissions (kg of CO2 equivalent per capita), energy consumption (gigajoules per capita), renewable energy percentage, agricultural area percentage, forest area percentage, and protected area percentage. These six measures were chosen because they had the largest amounts of countries with non-missing data. Data from 2018 was used for the GDP per capita and the happiness indicators, and data from the most recent year available was used for the environmental indicators. Only countries with non-missing data in all eight types of indicators were kept for analysis (n = 142). I then generated scatterplots and calculated the correlation between each pair of indicator data (Figure 4). From this analysis, we can see that the pairs of indicators with the highest positive Pearson correlations were

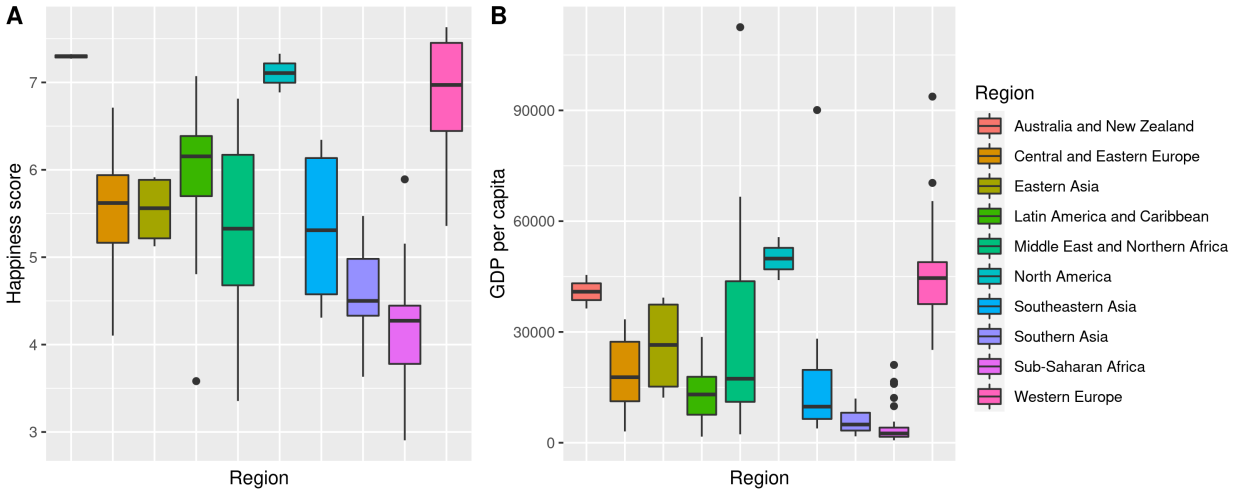

Figure 3: Boxplots displaying **(a)** estimated happiness scores and **(b)** gross domestic product per capita of countries grouped by region of the world.

energy consumption and GHG emissions (0.783), economic activity and GHG emissions (0.770), economic activity and happiness (0.723), and energy consumption and economic activity (0.722). The pair of indicators with the highest negative Pearson correlation was forest area percentage and agricultural area percentage (-0.394).

Principal components analysis of environmental indicator data

I then performed principal components analysis on the six different environmental indicator types used in the correlation analysis in Figure 4 to get a better sense of the variation among these environmental indicators (that will later be used for training predictive models). The environmental indicator data across 142 countries was first scaled and centered, and then principal components analysis was performed, with the following summary:

```
## Importance of components:
##                           PC1    PC2    PC3    PC4     PC5    PC6
## Standard deviation     1.4154 1.2902 0.9436 0.8999 0.66219 0.4395
## Proportion of Variance 0.3339 0.2774 0.1484 0.1350 0.07308 0.0322
## Cumulative Proportion  0.3339 0.6113 0.7597 0.8947 0.96780 1.0000
```

We can see that more than half (61.13%) of the variation in the dataset is accounted for by the first two principal components. I then reduced the dimensionality to these two components and plotted PC2 vs. PC1, coloring countries by region of the world (Figure 5). We can see that most countries have PC1 values < 2, but there are some outlying countries with higer PC1 values. Notably, the two countries with the highest PC1 values (Qatar and Iceland), are the same two countries with the highest energy consumption per capita we noted earlier (Figure 2). Many other countries with PC1 values > 2 are also some of the highest energy consumers in Figures 1 and 2, suggesting that much of the variation in PC1 is driven by energy consumption. While there are not any strong groupings of country by region of the world seen in Figure 5, it can be noted that many of the outliers along PC1 come from the Middle East and Northern Africa. The countries along PC2 are a lot more evenly distributed, with Bhutan being the largest outlier (PC2 $<$ -3). It remains unclear what factors might be driving most of the variation along PC2; this variation could be further explored in future analyses.

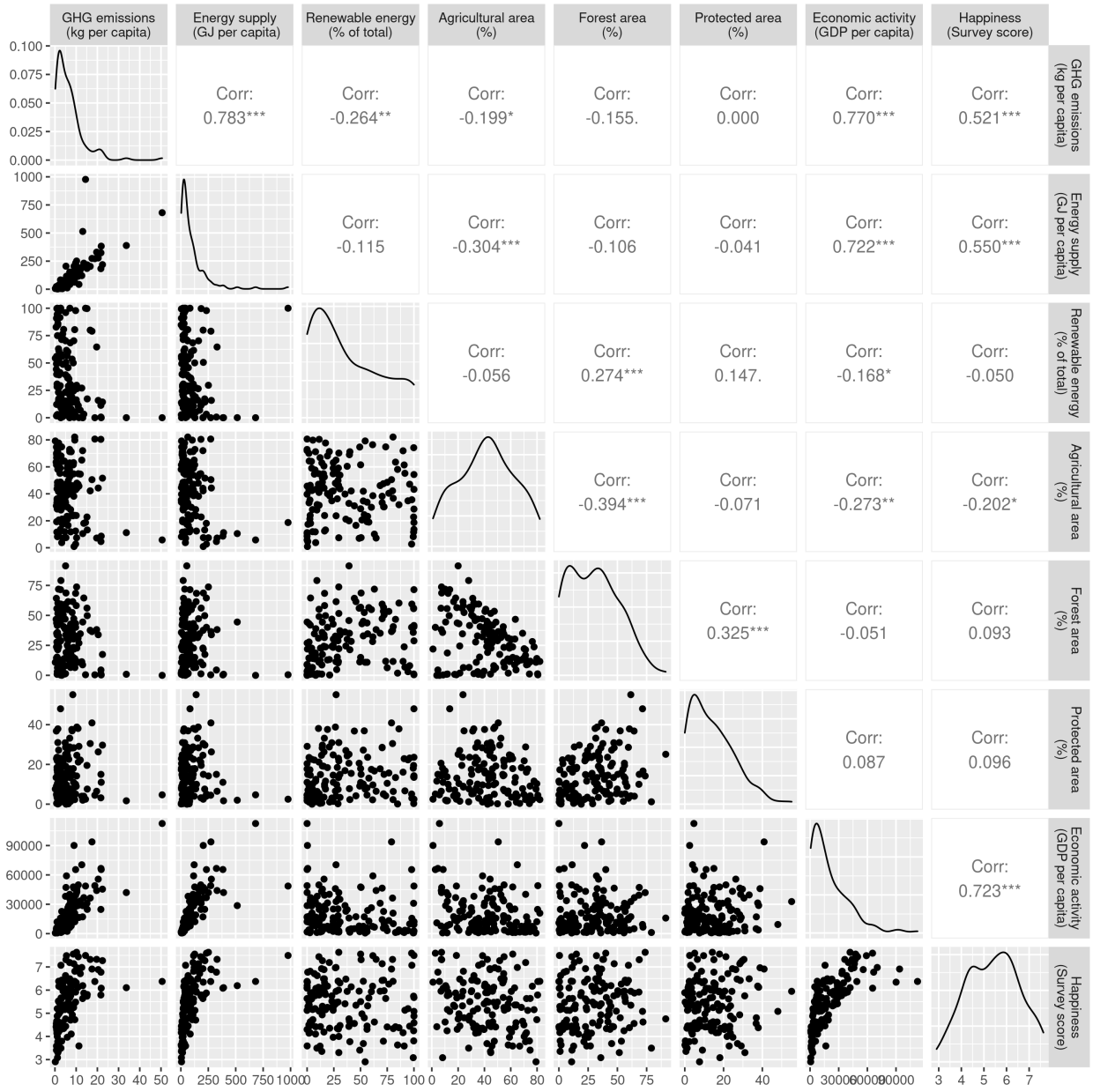

Figure 4: Matrix of correlations between pairs of indicator data. Scatterplots between each pair of indicator data are displayed on the left, variable distribution is displayed on the diagonal, and Pearson correlations between each pair of indicator data are displayed on the right.

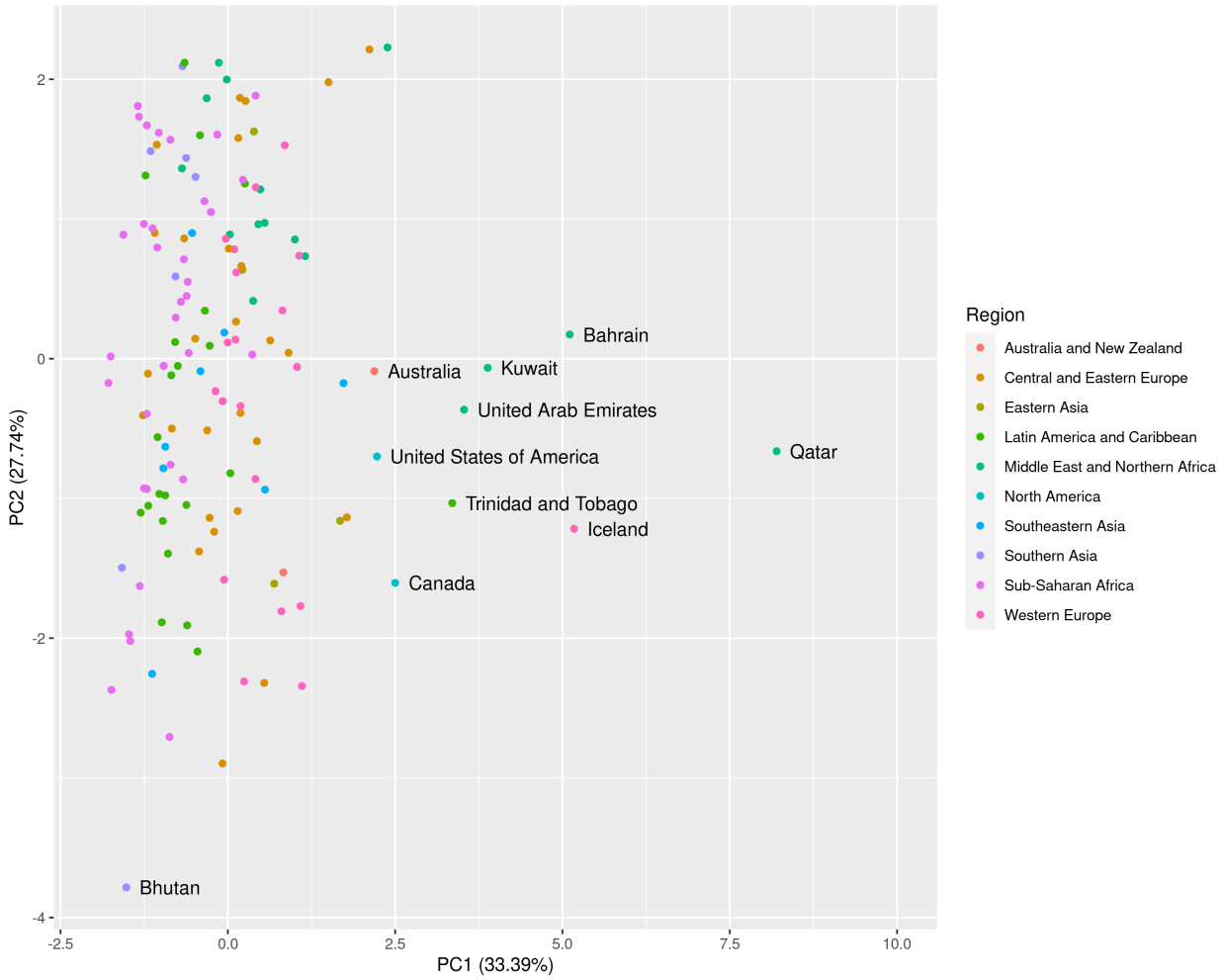

Figure 5: Plot of first two principal components colored by region of the world from principal components analysis of environmental indicator data

Elastic net prediction of happiness level from environmental indicator data

We have seen from the exploratory analysis above that there are correlations between environmental indicators and happiness scores of a country. One question I had was whether I could train a model to predict a country's high vs. low happiness level from environmental indicator data with high performance accuracy. To answer this question, I chose to train an elastic net model for its ease of interpretability and ability to combine the L1 and L2 penalties of lasso and ridge regression models. For the predictors, I used the six environmental indicator types used in the correlation and principal component analyses (Figures 4 and 5). For the outcome to predict, I split countries into "High" and "Low" happiness levels based on whether its happiness score fell above or below the median happiness score. I trained on 60% of the data (n = 86) using 10-fold cross validation and the default tuning grid. The remaining 40% of the data (n = 56) was held out for testing. The trained model summary is printed below:

```
## glmnet
##
## 86 samples
##  6 predictor
##  2 classes: 'Low', 'High'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 77, 77, 78, 77, 78, 78, ...
## Resampling results across tuning parameters:
##
##   alpha  lambda        Accuracy   Kappa
##   0.10   0.0005588992  0.7805556  0.5610976
##   0.10   0.0055889918  0.7594444  0.5202439
##   0.10   0.0558899181  0.7594444  0.5202439
##   0.55   0.0005588992  0.7805556  0.5610976
##   0.55   0.0055889918  0.7594444  0.5202439
##   0.55   0.0558899181  0.7783333  0.5603833
##   1.00   0.0005588992  0.7805556  0.5610976
##   1.00   0.0055889918  0.7694444  0.5402439
##   1.00   0.0558899181  0.7758333  0.5553833
##
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were alpha = 0.1 and lambda = 0.0005588992.
```

We can see that the optimal values chosen for the model were $\alpha = 0.1$, meaning the model is closer to ridge regression than lasso regression, and $\lambda = 0.0005588992$. For these α and λ parameters, we get the following trained coefficients for the model, shown below and plotted in Figure 6b:

```
## 7 x 1 sparse Matrix of class "dgCMatrix"
##                                    s1
## (Intercept)               -4.02755295
## GHG_per_capita_emissions   0.29352022
## Energy_per_capita          0.02136925
## Renewable_energy_percent   0.01427311
## Agricultural_area_percent  0.01430855
## Forest_area_percent        0.01609668
## Protected_area_percent    -0.03236558
```

We see that the highest model coefficient is greenhouse gas emissions per capita, meaning that this variable contributes the most to the classification of a country's happiness level. This makes sense, as we saw that

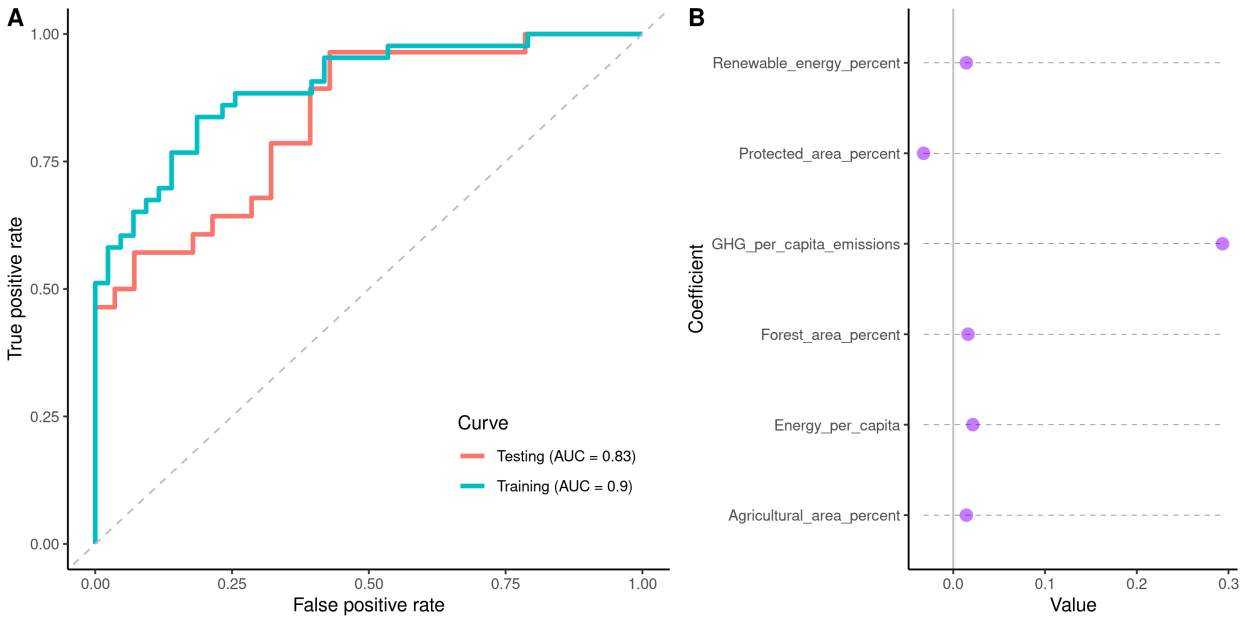

Figure 6: Happiness predictor

happiness and greenhouse gas emissions were strongly correlated in Figure 4. Because the coefficient is positive, this suggests that countries with higher greenhouse gas emissions per capita tend to be happier. The only negative coefficient was protected area percent, suggesting that countries with less protected areas tend to be happier. It is important to keep in mind that correlation does not equal causation, and there may be confounding variables at play (e.g. a country's economy, which we will explore later). We can see that this model performs very well on the testing data, with an area under the receiver operating characteristic curve (AUC) of 0.83 (Figure 6a). This suggests that a country's happiness level can be accurately predicted from environmental indicator data.

Prediction of GDP level from environmental indicator data

After predicting happiness level from environmental indicator data, I was also interested in whether I could train a model to predict a country's high vs. low GDP level from environmental indicator data with high performance accuracy. I again chose to train an elastic net model to answer this question. For the predictors, I used the six environmental indicator types used in the correlation and principal component analyses (Figures 4 and 5). For the outcome to predict, I split countries into "High" and "Low" GDP levels based on whether its happiness score fell above or below the median GDP score. As before, I trained on 60% of the data (n = 86) using 10-fold cross validation and the default tuning grid. The remaining 40% of the data (n = 56) was held out for testing. The trained model summary is printed below:

```
## glmnet
##
## 86 samples
##  6 predictor
##  2 classes: 'Low', 'High'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 77, 77, 78, 77, 78, 78, ...
## Resampling results across tuning parameters:
```

```
##
##   alpha  lambda        Accuracy   Kappa
##   0.10   0.0006950761  0.9305556  0.8599719
##   0.10   0.0069507607  0.8844444  0.7680206
##   0.10   0.0695076065  0.9094444  0.8180206
##   0.55   0.0006950761  0.9305556  0.8599719
##   0.55   0.0069507607  0.8944444  0.7880206
##   0.55   0.0695076065  0.9094444  0.8180206
##   1.00   0.0006950761  0.9208333  0.8399719
##   1.00   0.0069507607  0.9319444  0.8630206
##   1.00   0.0695076065  0.8969444  0.7930206
##
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were alpha = 1 and lambda = 0.006950761.
```

We can see that the optimal values chosen for the model were $\alpha = 1$, meaning the model used lasso regression, and $\lambda = 0.006950761$. For these α and λ parameters, we get the following trained coefficients for the model, shown below and plotted in Figure 7b:

```
## 7 x 1 sparse Matrix of class "dgCMatrix"
##                                       s1
## (Intercept)                -4.746593788
## GHG_per_capita_emissions    0.240806557
## Energy_per_capita           0.066914612
## Renewable_energy_percent   -0.012684575
## Agricultural_area_percent -0.005305846
## Forest_area_percent         0.011387377
## Protected_area_percent      0.022893270
```

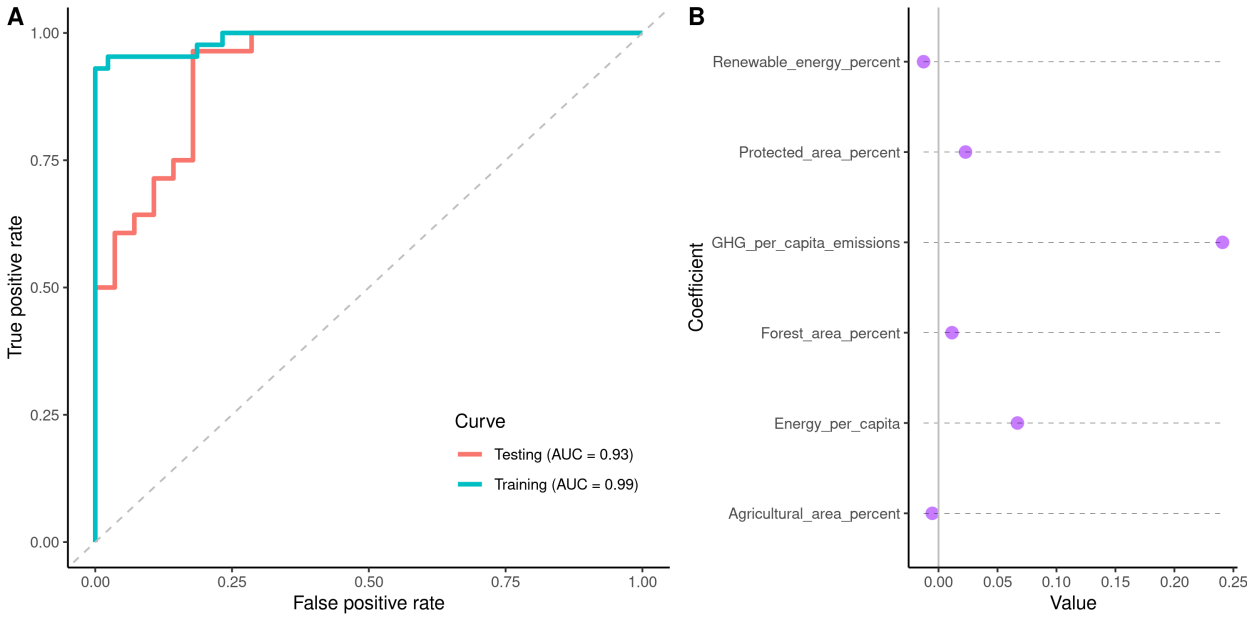

Figure 7: GDP predictor

Just as in the happiness model, we again see that the highest model coefficient is greenhouse gas emissions per capita, meaning that this variable contributes the most to the classification of a country's GDP level. This

corresponds with the strong correlation between GDP and greenhouse gas emissions in Figure 4. Because the coefficient is positive, this suggests that countries with higher greenhouse gas emissions per capita tend to have higher GDP. Logically, this makes sense, because wealthier countries can afford to pollute more. Because a country's GDP and happiness score were also strongly correlated in Figure 4, this may also give additional insight into why high greenhouse gas emissions was a strong predictor for happiness. There were only two negative coefficients in the model: renewable energy percent and agricultural area percent, suggesting that countries with less renewable energy and agricultural area tend to be wealthier. We can see that this model performs very well on the testing data, with an area under the receiver operating characteristic curve (AUC) of 0.93 (Figure 7a). This suggests that a country's GDP level can be accurately predicted from environmental indicator data.

4. Conclusions

In summary, I have shown that there are a variety of interesting trends concerning global indicator data within and between countries. These trends may allow us to better pinpoint countries that are good and poor role models concerning their relationship to the environment, the state of their economy, and the happiness of their citizens. Knowing a country's environmenal strengths and weaknesses may additionally be valuable for a more holistic approach to environmental policy making at a country/regional level. I have also shown that a country's happiness and GDP level can be predicted from environmental indicator data, with high greenhouse gas emissions being the most important contributor to these models.

There is still a lot to learn from global indicator data. One limitation of my analysis was that some of the data was not as recent (e.g. latest data available was 2018). It would be interesting to look at the data for all variables out to 2021 to see how COVID-19 may have impacted the global environmental indicators. Also, because greenhouse gas emissions were by far the strongest contributor to the predictive models, it would be interesting to see how well the models perform without greenhouse gas emissions as a predictive variable.