Are Income Disparities and Environmental Impact Connected?

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Author Note

First Section : Abstract and Data Set Explanation

Second Section : Climate Change - Georgette

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Fourth Section: Air Pollution - Antonia

Fifth Section: Data Visualization to Depict Findings

Abstract

In this paper, we will explore Environmental factors and how they are influenced by income disparities. We will present data that comes from The World Bank, which is a "unique global partnership: five institutions working for sustainable solutions that reduce poverty and build shared prosperity in developing countries" (Peters et al., *World Bank Open Data* 2024). Through modeling subsets of our data set we will construct answers to the following environmental questions: How do levels of 'greenhouse gases' affect different economic statuses'? How does climate change relate to the economic status of a country? How does wastewater treatment affect the quantity of unsafe drinking water? Does Ocean plastic impact the quantity of unsafe drinking water? And how does the economic status impact Unsafe drinking water, Wastewater treatment, and Ocean plastics? Does land losses (trees, wetlands, and grassland) or emissions affect air quality? And lastly, how does the economic group impact the air quality of different regions/countries? Through the exploration of these questions, we have determined that economic status does have a significant impact on environmental degradation!! Due to this, we call for more environmental initiatives to be put in place to prevent low-income groups from being equitably impacted by environmental degradation.

Economic Disparities and Environmental Impact: Exploring the Interconnection

The data we used in this case study comes from The World Bank, whose goal is to create a world free of poverty on a livable planet. We used two data sets, Economic Data and Environmental Data. Our Economic data set contains 267 countries and classifies each of these countries into 4 income groups: low, lower-middle, upper-middle, and high income. It does this by looking at the gross national income (GNI) per capita data in U.S. dollars, converted from local currencies using the World Bank Atlas method, which is applied to smooth exchange rate fluctuations. Our second data set is an Environmental data set. This data set contains 180 countries and provides a quantitative basis for comparing and analyzing environmental performance in these countries. The World Bank has scored and ranked each country on their environmental performance using the most recent year of data available and calculated how these scores have changed over the last decade. We combined these data sets by ordering the countries alphabetically and matching each country. To get rid of missing values, we create a for loop that calculates the average value of the column and inputs the average for each missing value.

Climate Change-Georgette

Our aims for the climate change section of our data set were summarized into two questions: How do levels of 'greenhouse gasses' affect different economic statuses and how does climate change relate to the economic status of a country? What other factors could play into it? Our first target was to look at greenhouse gas emissions for each country because we can infer a lot from their emissions. We start by selecting only the relevant columns from the cleaned_df data frame, which likely contains various information about countries. We specifically focus on the country name (country), the income group of each country (Income group), and their greenhouse gas emissions per capita (GHP.new). This step ensures that we're working with the data we're interested in.

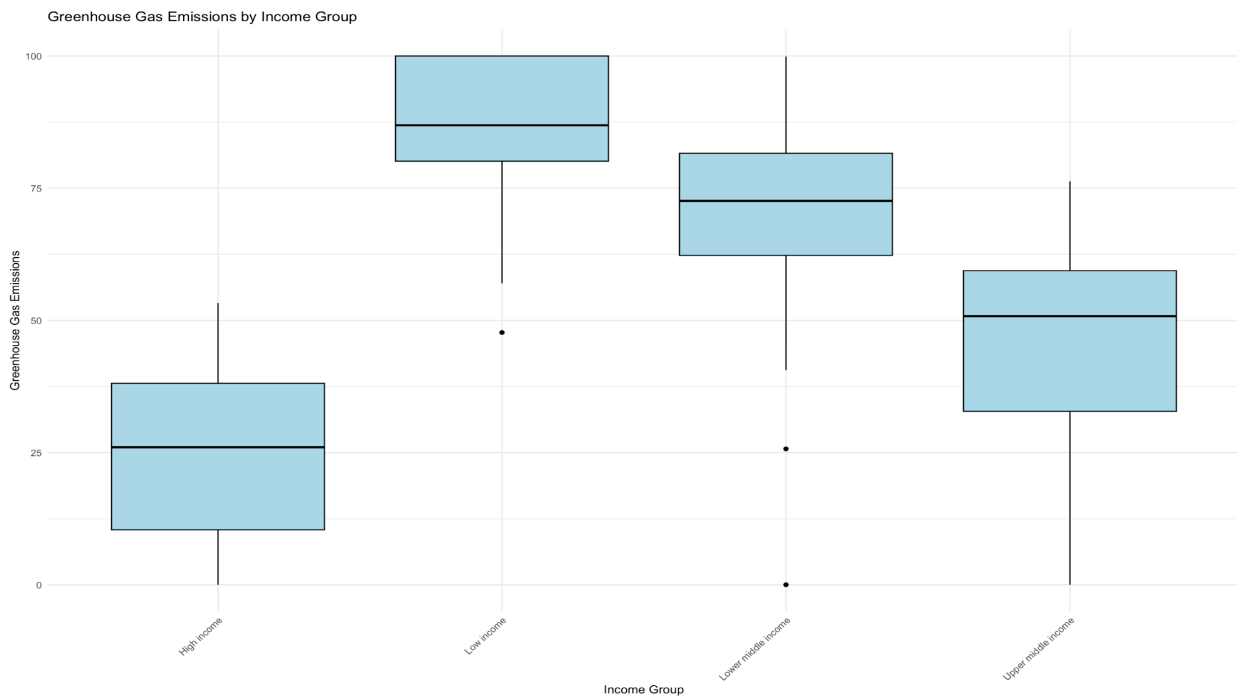
Next, we want to ensure that each country appears only once in our dataset. We remove any duplicate rows based on the greenhouse gas emissions per capita. Although all the data in our data frame is valuable, the bar plot would not have shown variability efficiently. Instead, we chose to exclude them from visualizations but have put them into their own data frame to keep, as their data is still very valuable and telling.

We then select the top 20 and bottom 20 greenhouse gas emitters based on their emissions per capita. This allows us to focus our analysis on the countries that contribute the most and least to greenhouse gas emissions.

We create bar plots to visually represent the greenhouse gas emissions per capita for the top 10 and bottom 10 emitting countries. The bars are colored differently to distinguish between the top and bottom emitters. This visualization helps us understand how economic statuses correlate with greenhouse gas emissions visually.

For this particular data set, I wanted to explore the context of what it means to be a generally low-income country or a high-income country, so I also decided to put them into a boxplot to compare the four groups.

The boxplot visualizes the distribution of greenhouse gas emissions (GHP.new) across different income groups (Income group). Our broad hypothesis was that income would be correlated negatively with the rate of greenhouse gas emissions. We can explore the potential reasons for that as well.



The boxplot shows that the median greenhouse gas emissions for countries in the low-income group are the highest among all income groups. At a mean of 70 overall, the low-income group takes the lead in the rate of greenhouse gas emissions. The box plot indicates a wide range of emissions, with the upper whisker capping past the measurable emission rate. This suggests significant variability in emissions within this income group, with some countries emitting substantially more than others. One can imagine the different factors that could play into their contribution towards climate change.

One of the more obvious reasons is that environmental consideration is a privilege that many people around the world do not get to have, as when one is struggling with more basic needs (i.e. food, water, finances, community, etc.) their priority is likely not going to be the global warming we are experiencing.

We decided to look more closely at the situation of some of the countries to understand what factors might play into their position in these visualizations, rather than keeping them as numbers on a screen. For example, the Democratic Republic of Congo was one of the countries whose emissions were capped at 100 on the barplot (and was removed because it was part of the duplicate rows, for visual ease), meaning they had one of the highest greenhouse gas emissions. They also have one of the largest carbon dioxide sinks in the world and is also a low-income country (Biggar, 2022) (World Bank Group, 2022). Gas emissions typically indicate production and mining is happening so one can infer that the DR. of Congo is not in control of their own production and finances and is likely influenced by richer, surrounding economies. Although this seems like a bit of a stretch to infer from one data set, it is really important to look at contexts to see why your data set is the way it is, as well as explore other factors that you can research and add to your data set that may add credibility and thoroughness.

Following the low-income group, countries in the low-middle-income group exhibit the second-highest median greenhouse gas emissions. The box plot shows a narrower interquartile range compared to the low-income group, indicating relatively less variability in emissions within this income group. However, the upper whisker extends beyond the upper quartile, suggesting that some countries in this group emit greenhouse gasses at levels comparable to those in the low-income group.

For the high-middle-income group, the box plot displays a lower median greenhouse gas emission level compared to the low-income and low-middle-income groups. The interquartile range appears narrower, indicating less variability in emissions within this income group compared to the previous two. The upper whisker also extends beyond the upper quartile but to a lesser extent than in the low and low-middle-income groups.

Finally, the high-income group exhibits the lowest median greenhouse gas emissions among all income groups. The box plot indicates a relatively narrow interquartile range, suggesting less variability in emissions within this income group compared to the others. The upper whisker is relatively short, indicating that emissions among countries in this group tend to be more consistent and generally lower compared to the other income groups. As we mentioned with the low-income group, it is a privilege for a country's government to consider climate change and set goals for gas emissions, as it shows that most basic needs are already generally met (e.i. food, water, healthcare, etc.). This is shown in our "Income Groups of Top and Bottom 10 Greenhouse Gas Emitting Countries" figure, which shows a stark amount of high-income countries in the bottom 10 emitters. Reasons for this could be having a good democracy that represents the civilian global opinions, investing in clean energy, and setting political goals of net zero emissions. As a matter of fact, the two countries that caught our interest in the bottom ten emitting countries were Saudi Arabia and Australia. For context, both countries have been notorious for advancing in clean energy and both have announced a plan to have net zero emissions by some year within the next 30 years (APNews, 2023) (Shine, 2024).

Overall, the boxplot provides a visual representation of how greenhouse gas emissions vary across different income groups, with lower-income groups generally exhibiting higher emissions compared to higher-income groups. This indicates that our hypothesis is true and income level correlates to greenhouse gas emissions, for various reasons that can only be explored moderately in this study.

Unsafe Drinking Water, Waste Management, & Ocean Plastics - Freya

In order to explore questions relating to Water Waste Treatment, Unsafe Drinking Water, Ocean Plastics, and income impacts I created a subset of our original data frame. This new data frame had only the columns: Country, Region, Income group, Wastewater treatment, Unsafe drinking water, and Ocean plastics. To understand our units of measurement for these columns, I consulted the World Bank Data Index which explains that, “we measure wastewater treatment as the proportion of wastewater that undergoes at least primary treatment in each country, multiplied by the proportion of the population connected to a wastewater collection system. A score of 100 indicates that a country has 100% of its population connected to a sewer system and 100% of household wastewater is treated; a score of 0 indicates that no wastewater is reported as treated within a country” (Peters et al., *World Bank Open Data* 2024). This means that higher scores have more access to water waste treatment. For Unsafe Drinking Water, “we measure unsafe drinking water using the number of age-standardized disability-adjusted life-years lost per 100,000 persons (DALY rate) due to exposure to unsafe drinking water. A score of 100 indicates a country has among the lowest DALY rates in the world (≤5th-percentile), while a score of 0 indicates a country is among the highest (≥95th-percentile)” (Peters et al., *World Bank Open Data* 2024). We can interpret this as, the lower the score the more that country is impacted by unsafe drinking water. And lastly for Ocean Plastics, “we measure ocean plastic pollution as the absolute quantity, in millions of metric tons, of plastics a country releases into the oceans in a given year. A score of 100 indicates a country emits zero tons of plastic each year, while a score of 0 indicates a country is among the highest (≥99th-percentile) ocean plastic polluters” (Peters et al., *World Bank Open Data* 2024). Therefore, in this case, a high score means that the country has a low rate of ocean plastics emissions. Now with our new subset data, we can begin to explore the following questions: How does wastewater treatment affect the quantity of unsafe drinking water? Does Ocean plastic impact the quantity of unsafe drinking water? And does economic status impact the quantity of Unsafe drinking water, Wastewater treatment, and Ocean plastics?

Initially, I tried to make several predictions surrounding my questions. For my question, how does wastewater treatment affect the quantity of unsafe drinking water? I predicted that the more unsafe drinking water there is, the more need there will be for wastewater treatment. For my second question, Does Ocean plastic impact the quantity of unsafe drinking water? I predicted that either ocean plastics would not have any correlation with the quantity of unsafe drinking water or that the increase in Ocean Plastics would create more unsafe drinking water. And lastly, for my final question, how does the economic group impact Unsafe drinking water, Wastewater treatment, and Ocean plastics, I predicted that economic status will have a large impact on these factors. I predicted that if you are of a higher income you have more access to clean water and wastewater treatment, as you can afford it. But lower-income groups, without the ability to afford these life-sustaining measures, will be impacted greatly by environmental degradation.

I started my research by modeling wastewater treatment vs. unsafe drinking water on a scatter plot (figure 1). I went ahead and added a linear regression line, and it was very apparent that wastewater and unsafe drinking water have a positive direct relationship. When wastewater increases, so does the value associated with unsafe drinking water. But remember, high numbers for unsafe drinking water actually mean that the associated country is less impacted by unsafe drinking water. I went ahead and switched the axes of my graph (figure 2) to see if I could interpret the data in another way. I observed that as unsafe drinking water increased, meaning more people have access to sewers and such, that wastewater treatment also increased. Both of these observations matched my overall predictions relating to the relationship between wastewater treatment and unsafe drinking water. Lastly, I plotted a linear regression line on my plot and found it's formula to be given by :

$$f(x)=0.6311x+29.7952$$

This demonstrates a positive slope which means our variables have a positive direct relationship.

I next took a look at Ocean Plastics and their impacts on Unsafe drinking water. I plotted Ocean plastics on the x-axis of my plot, and unsafe drinking water on the y-axis (figure 3). I observe that my data points are all spread out and there seems to be no direct trend in the data. I went ahead and tried to plot a linear regression line (figure 4), but this didn't help as there are no trends in the data. Thus, I conclude that Ocean plastics and unsafe drinking water do in fact have no correlation. This makes sense as we do not drink ocean water (which is salt water). Thus even if ocean plastics increase they will not impact the quantity of drinking water available to us. Therefore my first prediction, that ocean plastics have no correlation with unsafe drinking water is correct.

Lastly, I explored how economic status impacts Unsafe Drinking water, Wastewater treatment, and Ocean Plastics. I started by looking at how economic status impacts the quantity of unsafe drinking water (figure 5). I found a positive relationship between these variables, as income increases, unsafe drinking water also increases. It is important to note that the value of unsafe drinking water represents the amount of people impacted by unsafe drinking water, high values mean less impact while lower values mean more impact. Thus higher economic status countries are less likely to be impacted by unsafe drinking, while lower income countries are more likely to be impacted by unsafe drinking water.

Next, I decided to investigate how income groups impact wastewater treatment by calculating the averages for each income group. I determined that the low-income had the smallest average at 7.36 while our high-income group averaged the highest rate at 46.7 (figure 6). Therefore, it is apparent from the data that those of higher income status have more access to wastewater treatment than low-income groups. This makes sense as high-income countries have more access to resources, as they can afford them.

Lastly, I looked at how income groups impacted the quantity of ocean plastics (figure 7). When looking at each group's average, it became clear that ocean plastics are not at all impacted by income group. All of the income groups had an average ocean plastic associated value of 32.78-38.32 (figure 8). But, there was no specific increasing order within the income groups. For example, low income had a higher average than the lower middle-income group. Therefore, I conclude that income status does not impact ocean plastics. I believe this is the case because ocean plastic is evenly distributed throughout the ocean and does not just rest near the country it originated from.

From these observations, we can conclude that lower-income countries are more likely to be impacted by environmental degradation as they have less access to safe drinking water and fewer overall resources, including wastewater treatment.

Air Pollution - Antonia

When determining the relationship between Air Pollution and Economic Status, I wanted to use the best indicators to reflect the nature of their dynamic to see if they supported my hypothesis that Air Quality is affected by Economic Status. I created two sub-data frames from the original data frame, the first with land losses which contain columns Grasslands (GRL.new), Trees (TCL.new), and Wetlands (WTL.new), and the second with emissions which contain columns, Overall Air Quality (AIR.new), Acidification (ACD.new), Sulfur Dioxide Adjusted Emissions (SDA.new), and Nitrous Oxide Adjusted Emissions (NXA.new). Will these indicators given their descriptions play a role in the Air Quality (figure 9, 10)?

I ran each of these data frames through a linear regression model to determine how well the data fits in relation to air quality. The land losses had very weak coefficients within the linear model that told us little information. I then ran a correlation matrix to better visualize the strength of the indicators and the highest correlation was 0.24 for Grassland losses to Air Quality. The colors themselves ranged from white, with little to no correlation, to faint blue (slight correlation), and the same for faint pink (figure 9). This was alluding that the land losses would not be very helpful when describing the relationship to air quality. The emissions data had slightly stronger coefficients but not strong enough to create an analysis behind, there would be too much interference. The correlation matrix had more dense saturation and darker blues meaning there was a more moderate correlation, from this model the strongest correlation was 0.63 for Acidification to Air Quality. I could have used these indicators but there’s not enough strength to tell us about how they affect Air Quality, in my own judgment (figure 10).

It was prevalent to use other data points to see the direct factors making up for the Air Quality. I primarily sourced a third sub-data frame with solely just air pollutants consisting of the columns, Particular Matter (PMD.new), Household Fossil Fuels (HAD.new), Ozone Exposure (OZD.new), Nitrogen Oxide Exposure (NOE.new), Sulfur Oxide Exposure (SOE.new), and Volatile Organic Compounds (VOE.new). Each of these indicators has extensive data collection behind them which plays into their values averaged scores (figure 12). I ran these columns through a linear regression model and all of the coefficients were immensely stronger overall. However, I did notice that the multiple regression and adjusted R2 were calculated to be the value of 1 (figure 14).

In theory, this is fantastic news, but in actuality that means there is cause for something else. When this is the case, there is suspicion of multicollinearity meaning that one of the indicators in this model is too correlated or is directly predicting the Air Quality highly efficiently. This is not effective in this analysis since I want to determine the individual effects on this dependent variable so I ran a Variation in Inflation (VIF) Test which creates a score that declares a variable suspect of multicollinearity, the cut-off threshold is a score of 5. The results of this procedure showed that the Nitrogen Oxide Exposure indicator was suffering from multicollinearity with a score of 5.8 (figure 14). Once removing this column the regression shows a promising regression with an adjusted R2 of 0.9995. For reference of the correlation matrix for the Air Pollutants see below (figure 15).

Now that the Air Quality indicator can be understood. What goes into the evaluation of its score? I could start analyzing how the Economic Levels played a role as well in adjacent to the Regions of the 180 countries our data set was residing within. Since there were a multitude of regions in the scatterplot showing the disparities of Economic Levels in relation to Air Quality, my diagrams continued to be visually challenging to interpret (figure 16). Using a more scalable graph, ggplot allowed me to plot the regions on a global scale to see if my hypothesis held true (figure 17). I created two global maps, one that displays the economic status of the regions and a second that pinpoints the air quality of regions. When cross referencing the color coordination of the graphs there was a correlation between High Economic Levels and Air Quality (figure 18).

Overall Results

We conclude that economic status does play a large role in how much a country is impacted by environmental degradation. Therefore we call for more policies and initiatives that promote equitable distribution of resources and prioritize environmental sustainability. In addition, we believe raising awareness about this issue is important as many people may not be aware of just how disproportionately lower-income countries are impacted by environmental degradation. With more awareness surrounding this issue, we can take global steps forward in order to make meaningful changes. As a community, we can strive to make a world where every individual no matter their economic status has access to safe and livable environments.

Data Visualization

Figure 1

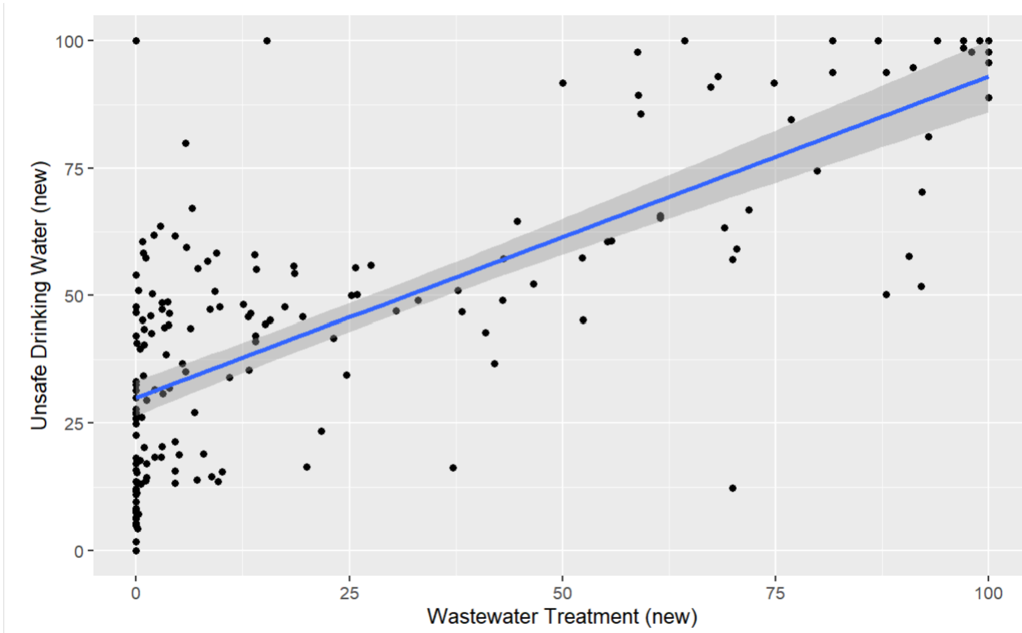


Figure 2

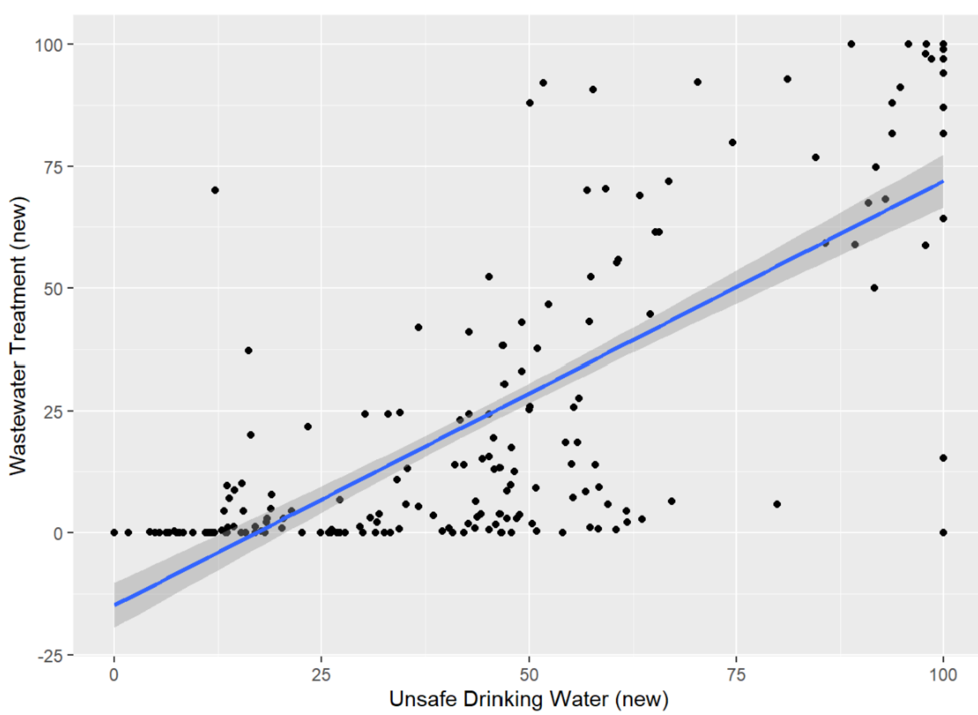


Figure 3

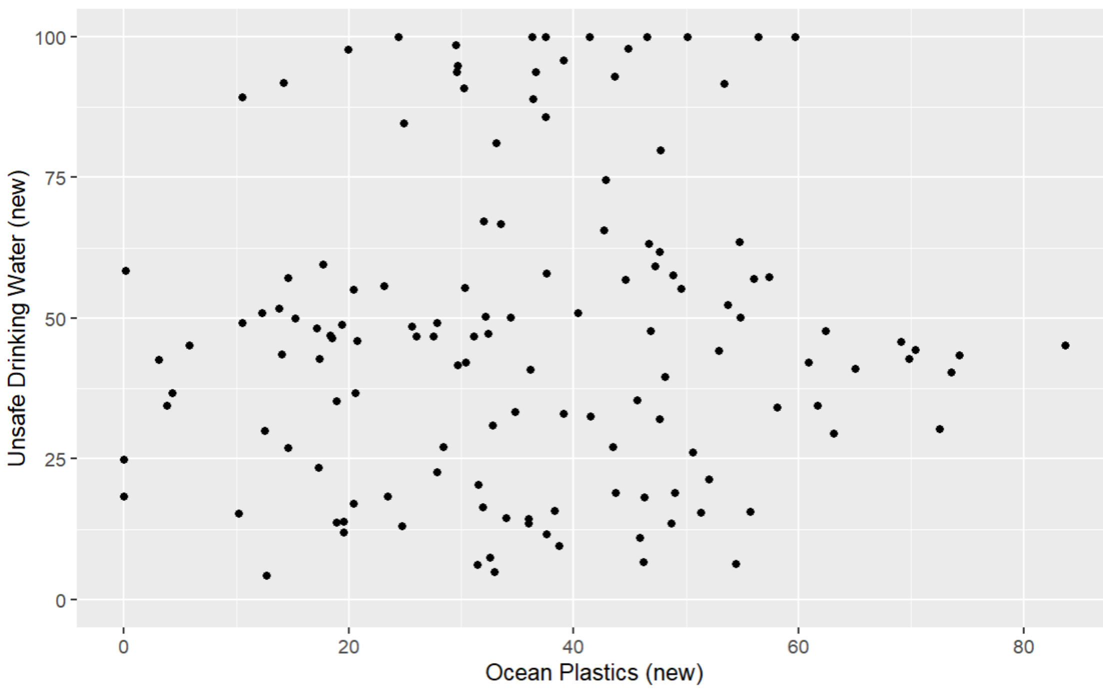


Figure 4

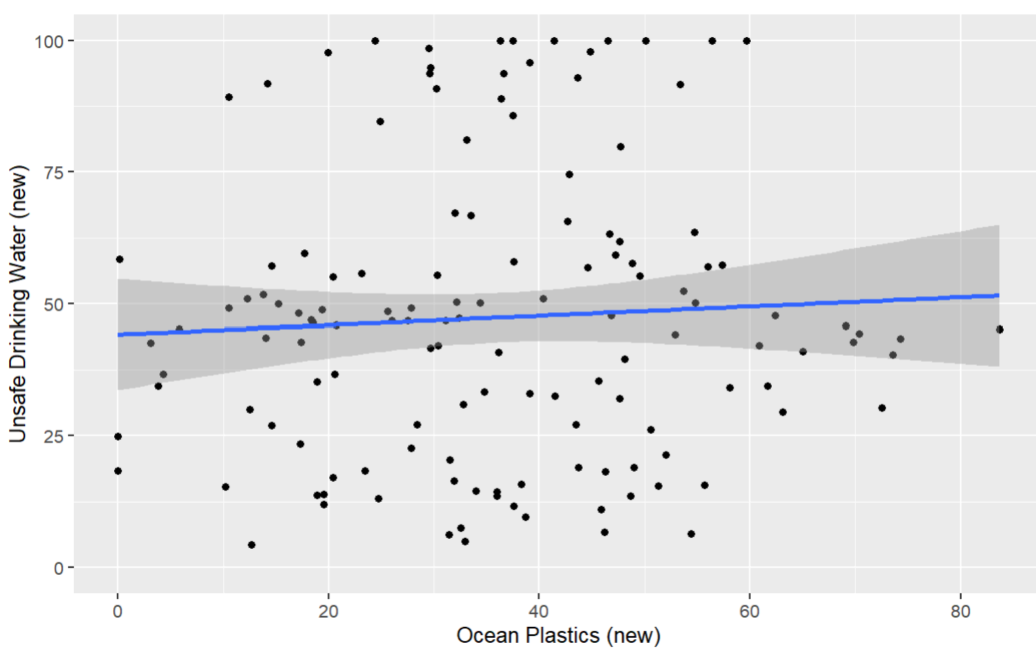


Figure 5

```
ggplot(water_df, aes(x = income_group, y = UWD.new, color = income_group)) +
  geom_violin() +
  labs(x = "Income Group", y = "Unsafe Drinking Water (new)")
```

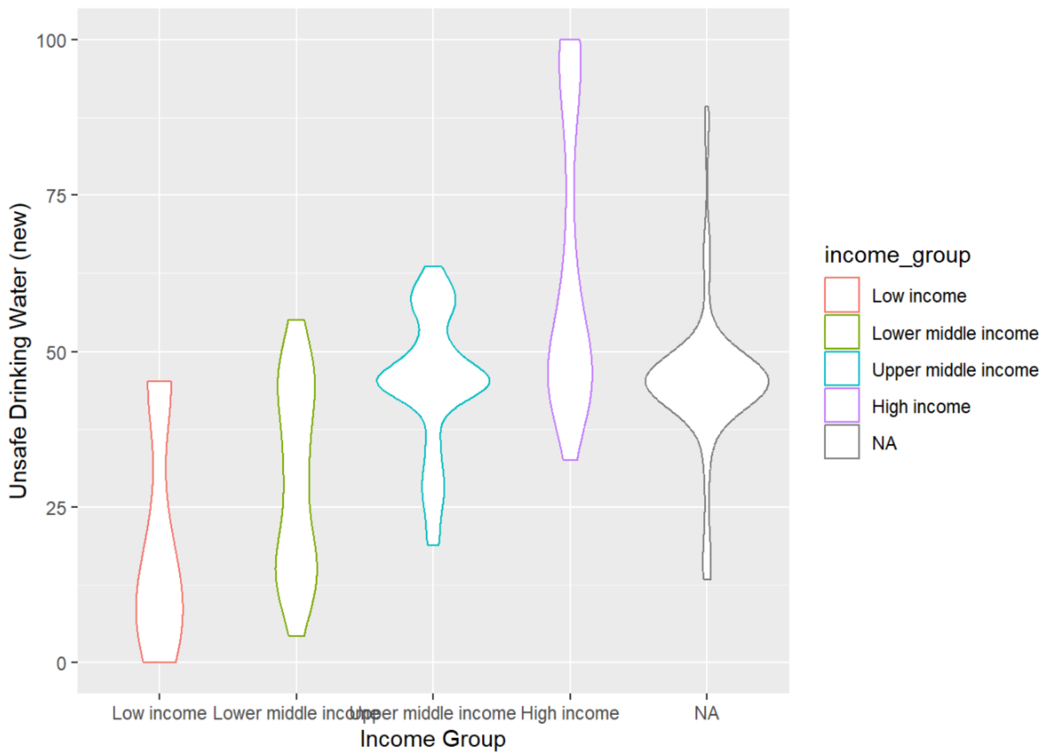


Figure 6

```
summary_data <- water_df %>%
  group_by(income_group) %>%
  summarise(mean_WWT = mean(WWT.new))

summary_data
```

```
## # A tibble: 5 × 2
##   income_group        mean_WWT
##   <fct>                  <dbl>
## 1 Low income              7.36
## 2 Lower middle income    10.6
## 3 Upper middle income    13.6
## 4 High income            46.7
## 5 <NA>                   23.3
```

Figure 7

```r
ggplot(water_df, aes(x = income_group, y =  OCP.new, shape = income_group)) +
  geom_violin() +
  labs(x = "Income Group", y = "Ocean Plastics (new)")
```

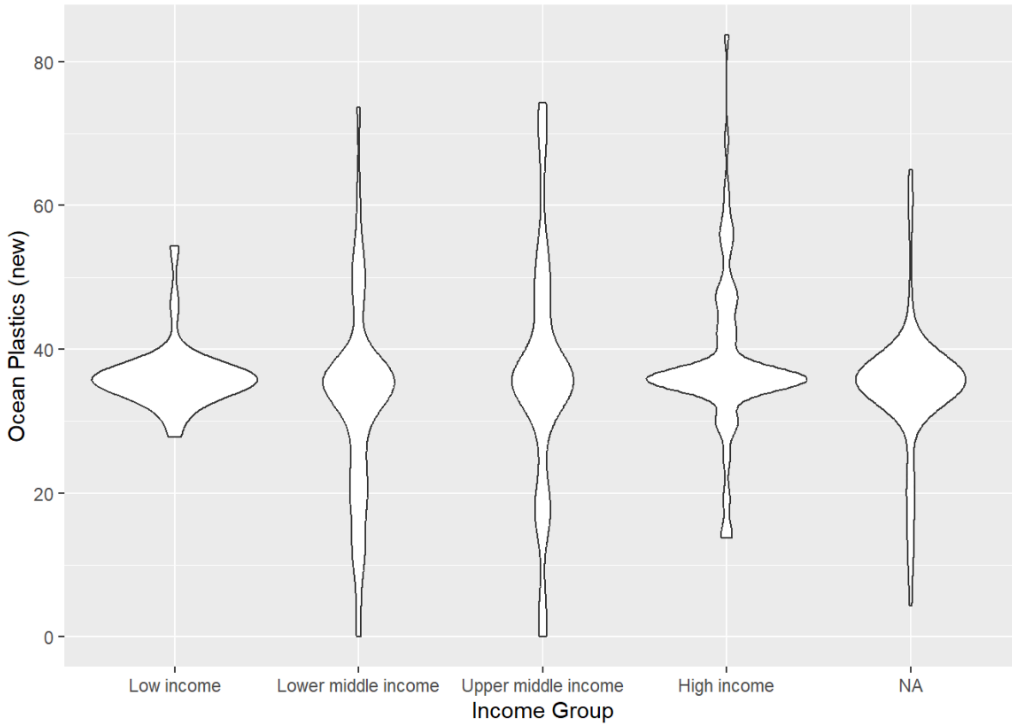


Figure 8

```r
summary_by_status = tapply(water_df$OCP.new, water_df$income_group, summary)

print(summary_by_status)
```

```
## $`Low income`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   27.80   35.79   35.79   36.35   35.79   54.40
##
## $`Lower middle income`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00   25.02   35.79   32.78   35.79   73.60
##
## $`Upper middle income`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00   32.17   35.79   36.16   44.33   74.30
##
## $`High income`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   13.80   35.79   35.79   38.32   41.45   83.70
```

Figure 9

```
- **AIR: Overall Air Quality** - This indicator likely provides an assessment or measurement of the overall quality of the air in a specific area. It may include data on various pollutants and their concentrations, such as particulate matter, ozone, nitrogen dioxide, sulfur dioxide, carbon monoxide, and volatile organic compounds.

- **TCL: Tree Loss** - This indicator likely measures the extent or rate of deforestation or loss of tree cover in a particular region or ecosystem. It's important for monitoring changes in forest ecosystems, biodiversity loss, carbon sequestration, and impacts on climate.

- **GRL: Grassland Loss** - This indicator likely measures the extent or rate of conversion or degradation of grassland ecosystems. Grasslands are important habitats for biodiversity, grazing animals, and carbon storage, so monitoring their loss is crucial for conservation and land management.

- **WTL: Wetlands Loss** - This indicator likely measures the extent or rate of degradation or conversion of wetland ecosystems. Wetlands provide valuable ecosystem services such as flood control, water filtration, habitat for wildlife, and carbon storage, so monitoring their loss is essential for ecosystem management and conservation efforts.
```

Figure 10

```
2. **ACD** = Acidification: Acidification typically refers to the process by which air pollutants, particularly sulfur dioxide (SO2) and nitrogen oxides (NOx), combine with water vapor in the atmosphere to form acidic compounds. These compounds can then be deposited onto land or water bodies, leading to environmental damage.

3. **SDA** = Adjusted Emissions Growth Rate for Sulfur Dioxide: This indicator measures the rate at which emissions of sulfur dioxide (SO2) are increasing or decreasing over time. Adjusted emissions growth rate likely takes into account factors such as changes in population, industrial activity, or emission control measures.

4. **NXA** = Adjusted Emissions Growth Rate for Nitrous Oxides: Similar to SDA, this indicator measures the rate at which emissions of nitrous oxides (NOx) are changing over time. Nitrous oxides are another group of pollutants that contribute to air pollution and can have significant environmental and health impacts.
```

Figure 11

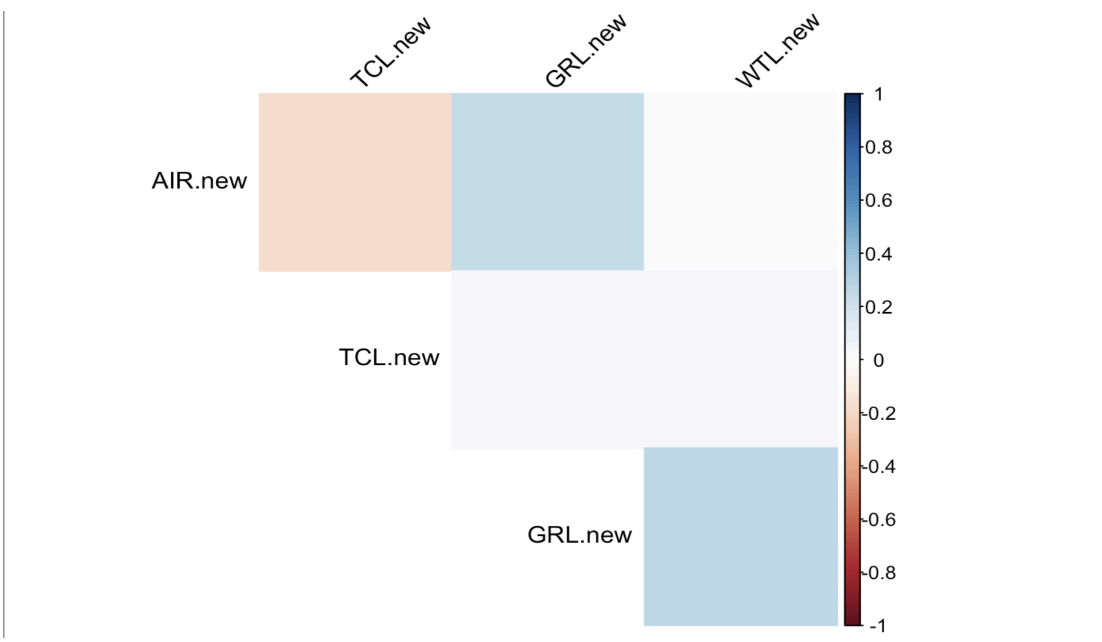


Figure 12

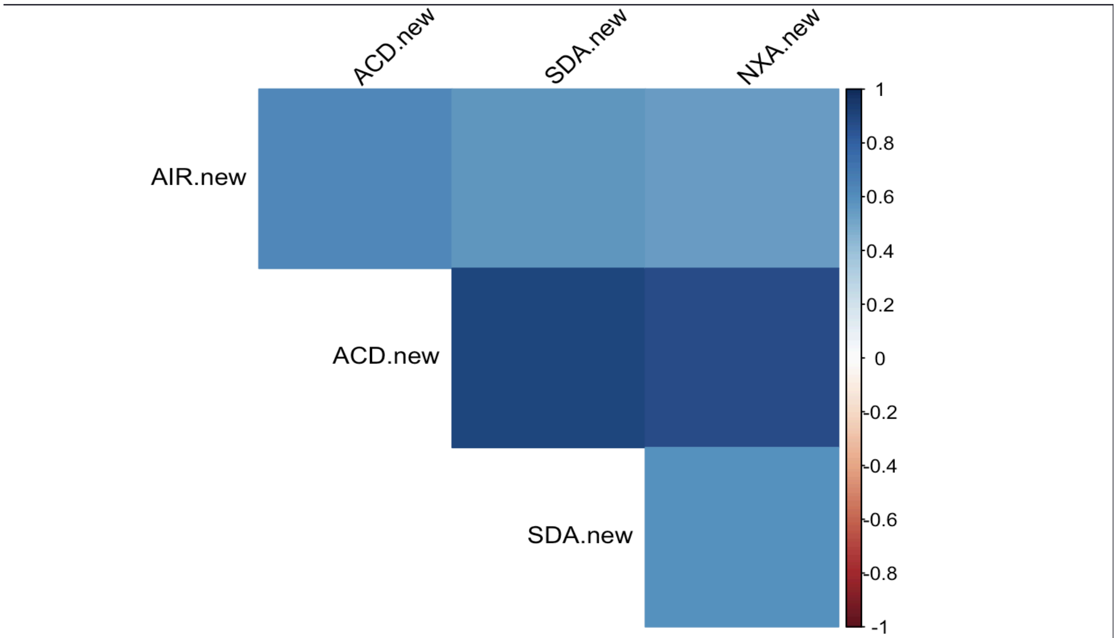


Figure 13

Particulate Matter (PM): PM refers to tiny particles or droplets in the air that can be inhaled into the lungs. It is categorized based on size, such as PM10 (particles with a diameter of 10 micrometers or smaller) and PM2.5 (particles with a diameter of 2.5 micrometers or smaller). PM pollution can come from various sources, including vehicle emissions, industrial processes, and natural sources like dust and wildfires.

2. **Nitrogen Dioxide (NO2)**: NO2 is a common air pollutant primarily emitted from vehicle exhaust and industrial activities. It can irritate the airways in the human respiratory system and aggravate respiratory diseases like asthma.

3. **Sulfur Dioxide (SO2)**: SO2 is produced by burning fossil fuels containing sulfur, such as coal and oil. It can lead to respiratory issues and contribute to the formation of fine particulate matter and acid rain.

4. **Ozone (O3)**: Ground-level ozone is a secondary pollutant formed by the reaction of nitrogen oxides (NOx) and volatile organic compounds (VOCs) in the presence of sunlight. It can cause respiratory problems and aggravate existing lung conditions.

5. **Carbon Monoxide (CO)**: CO is a colorless, odorless gas produced by incomplete combustion of carbon-containing fuels. It can be harmful when inhaled, especially in enclosed or poorly ventilated spaces.

Figure 14

```
Call:
lm(formula = "AIR.new ~ .", data = airpol_columns)

Residuals:
      Min        1Q    Median        3Q       Max
-0.068500 -0.023087 -0.001017  0.024054  0.080608

Coefficients:
              Estimate Std. Error  t value Pr(>|t|)
(Intercept) -0.0101953  0.0074243   -1.373    0.171
PMD.new      0.4727196  0.0001275 3706.416   <2e-16 ***
HAD.new      0.3818940  0.0001208 3162.583   <2e-16 ***
OZD.new      0.0452108  0.0001602  282.171   <2e-16 ***
SOE.new      0.0180286  0.0001748  103.118   <2e-16 ***
NOE.new      0.0456789  0.0002372  192.566   <2e-16 ***
COE.new      0.0185229  0.0001912   96.884   <2e-16 ***
VOE.new      0.0180667  0.0001378  131.062   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.03271 on 172 degrees of freedom
Multiple R-squared:      1,	Adjusted R-squared:      1
F-statistic: 1.051e+07 on 7 and 172 DF,  p-value: < 2.2e-16

 PMD.new  HAD.new  OZD.new  SOE.new  NOE.new  COE.new  VOE.new
1.588891 2.594851 2.018138 3.553973 5.804745 3.976949 2.482032
```

Figure 15

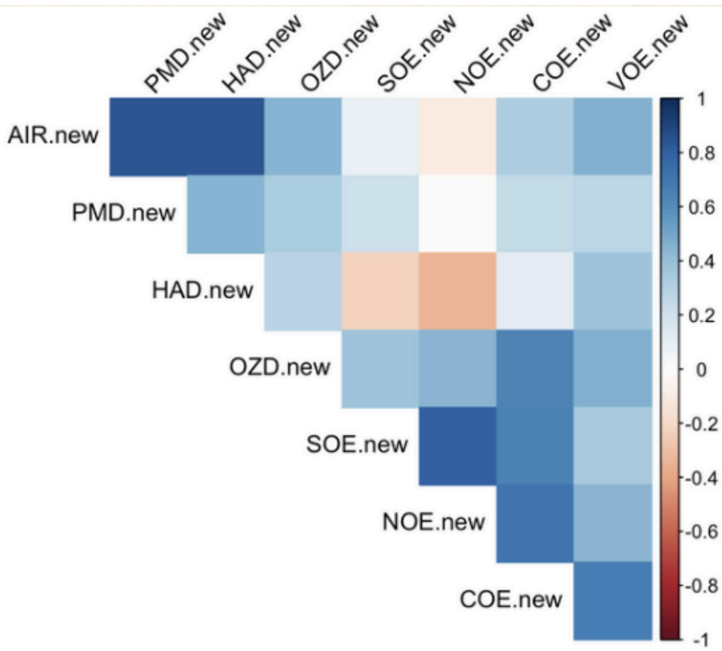


Figure 16

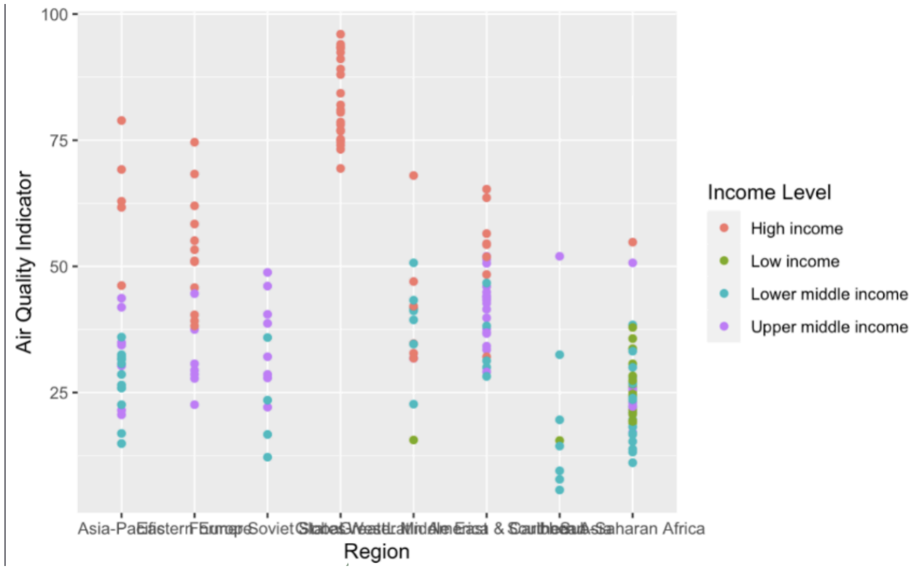


Figure 17

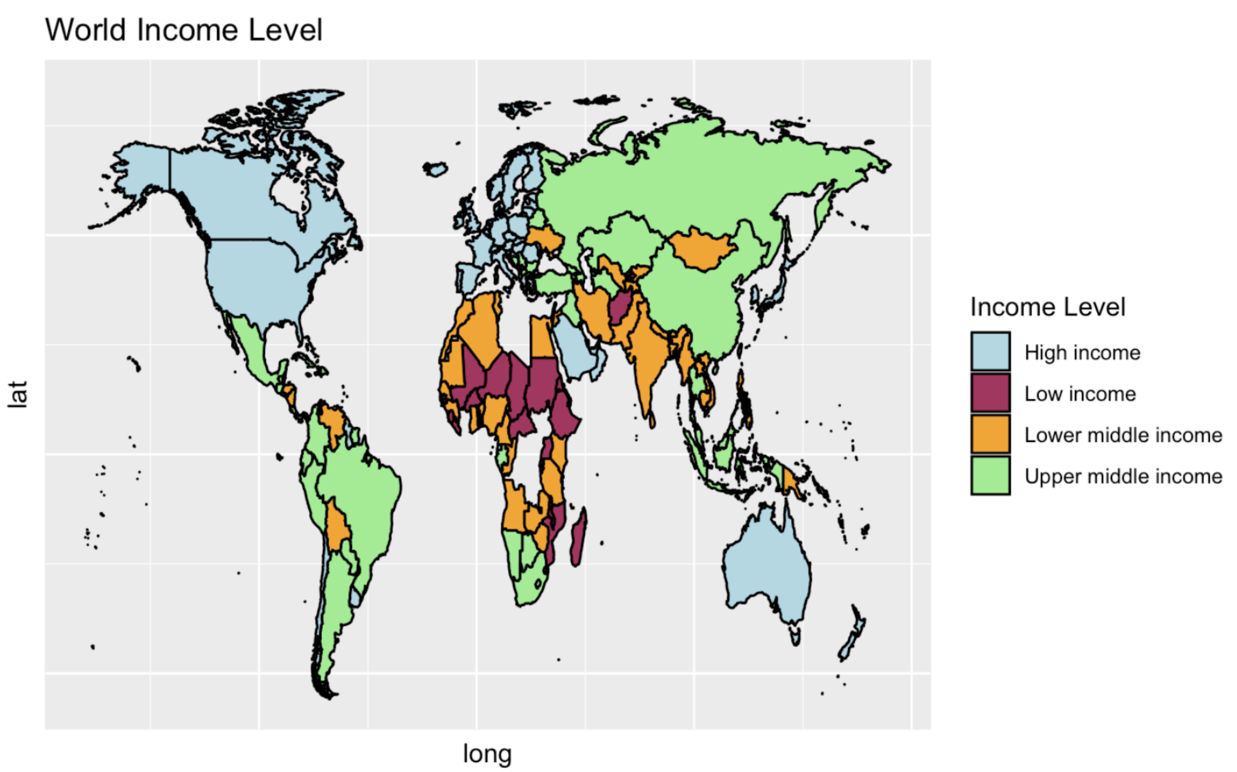
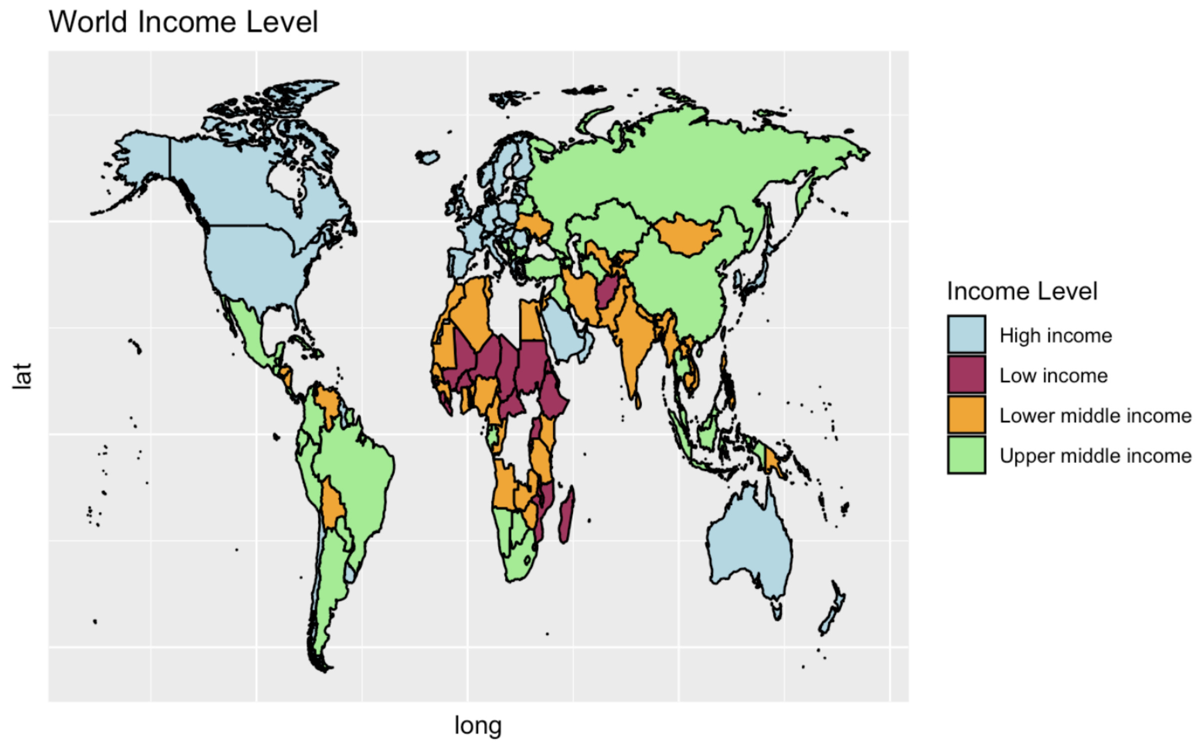


Figure 18


World Income Level
lat
long
Income Level
High income
Low income
Lower middle income
Upper middle income

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