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Summary Sheet

Examining the Environmental Impact of High-Powered Computing

High-powered computing (HPC) has become an essential tool to unlock the mysteries of the universe, such as DNA sequencing and cures for diseases. However, our drive to know and learn more ultimately comes with consequences–namely with the environment. The global demand for high-powered computing continues to rise in sectors like artificial intelligence and cryptocurrency mining, increasing CO_2 emissions to near life-threatening levels.

We began by collecting data on the current grid, retrieving data from 76 countries that accounted for approximately half of the global energy demand, which was broken down into the amount of electricity produced by renewable and nonrenewable energy sources. We also collected data on the carbon intensity of each country since 2017, and the 2023 carbon emissions breakdown by source of energy.

Using this data, we developed our regression model that accounted for a multitude of different factors. Starting with estimating our energy demand in 2030 using research on the growth rates of energy demand, we used this demand to predict the supply of energy that would be needed to meet these growing demands. Using renewable energy growth rates, we predicted the supply of renewable energy in 2030 and then calculated the amount of nonrenewable energy that would be needed to meet the energy demand in 2030.

With our electricity breakdowns set, we turned to focus on emissions for each source of energy. Combining our data while taking into account technological innovation, we calculated carbon dioxide emissions for each country in 2030, and our summation multiplied by a constant (from our limited data) was our global emissions estimate in 2030 without intervention.

We then followed the same process but removed data centers energy demands from our calculations to determine the climate impact of data centers and HPC. The difference between our estimate without intervention and our estimate without data centers was the yearly amount of carbon dioxide emissions due to data centers in 2030, or 2,948 megatons of carbon dioxide yearly. Accounting for emissions from lithium consumption as well, and utilizing conversions, this is equivalent to a yearly temperature increase ranging from 0.002637℃ to 0.004356℃.

Finally, we developed an actionable set of recommendations that would lower the yearly emissions from HPC. We discovered that the combination of restricting the location of data centers while simultaneously increasing the rate of our renewable energy growth would slice the carbon footprint of data centers in half (-0.002℃).

Keywords: HPC, Average Capacity, Full Capacity, Regression, Renewables, Non Renewables, Carbon Intensity

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1 Introduction

1.1 Background

The digital age marked the rapid transition from traditional industries to technological performances. Ever since the introduction of the World Wide Web in 1993, the world has never looked back, revolutionizing technology into virtually every aspect of life. However, our reliance on ever-changing technology has come with many costs, one of which is the environment. As global demand for high-powered computing (HPC) continues to rise, more energy will be consumed, correlating to more greenhouse gas emissions and eventually more reliance on non-renewable energy sources. This seemingly never-ending loop concerns many environmentalists and–of course–us, as climate change hinders our present and future with rising temperatures, rising sea levels, intense storms, and more. Therefore, we want to develop a plan that provides realistic bounds and balances between our demands and the environment. Whether it be incorporating energy mixes or accounting for HPC capabilities, our plan will take a step in the right direction for our well-being and the well-being of our world.

1.2 Problem Restatement

Question 1: Describe the scope of this problem in terms of the annual energy consumption of the HPC capabilities worldwide considering both full capacity and average utilization rates.
Question 2: Develop a comprehensive model to determine the environmental impact of total carbon emissions resulting from the energy consumption of HPC. Consideration should be given to how the energy is produced, accounting for energy mixes.
Question 3: Explore how your model may change in the future with the growth of HPC, the increasing demand for energy in other sectors, and the potential for different energy sources and mixes. Use your model to provide realistic bounds that can provide insight into the scope of the problem in the year 2030.
Question 4: Model the impact of increasing the portion of renewable energy and calculate the corresponding reductions in carbon emissions. Investigate the effects of switching to a 100% renewable energy source as well as the potential challenges involved.
Refine your model (or develop a new model) to include the environmental impact of one of the other key areas listed above to further understand the impact of HPC. Describe why your group chose that aspect and how it relates to other key areas, especially energy consumption.
Question 5: Develop a set of actionable recommendations to reduce the environmental impact of HPC, considering both technical and policy-oriented solutions.
Assume one of your recommendations is acted upon. Determine and show how you can incorporate this into your model.
Write a one-to-two-page letter to the United Nations Advisory Board urging them to include a more detailed section on the environmental impacts of HPC in their scheduled developmental goals for 2030.

2 Problem Analysis

Question 1: Question 1 asks us to describe the problem at hand: data centers consume a large quantity of energy to run, and with the emergence of artificial intelligence, data centers are projected to grow 160% by 2030 in the US at average utilization rates. However, at full capacity, data center workloads could triple like they did between 2015 and 2019, or grow even more [2]. Global energy demand is expected to increase, especially as Europe continues electrification and de-industrialization of its economy.
Question 2: Question 2 asks us to construct a model of the environmental consequences of the energy consumption of HPC. Accounting for the energy mixes of electricity given by Electricity Maps, we can include biomass, geothermal, hydroelectric, solar, wind, nuclear, hydro storage, coal, gas, and oil energies [18]. Their impact can be modeled by the amount of electricity produced by each energy source with their respective carbon emissions.
Question 3: Question 3 asks us to explore how our model may change in the future with the growth of HPC and other sources of energy demand. In order to answer this question, we need to account for the growth rate of electricity demand globally and the growth rate of HPC electricity demand until 2030. We must also account for changes in energy sources to power HPC, such as a greater reliance on renewable energy or fossil fuels. Using this model, we then need to generate bounds (worst and best-case scenarios) to determine how much of an impact data centers will have in 2030 globally.
Question 4: Question 4 asks us to expand our model by accounting for the global movement of increasing the renewable energy capacity–which includes solar, wind, hydroelectric, geothermal, and biomass–and finding their corresponding reductions in carbon emissions from unrenewable sources. We must then consider the possibility of switching HPC to rely entirely on renewable energy sources and consider the effects and challenges of implementing this. We will also refine our model by including the environmental impact of electronic waste, which is expected to increase to 74.7 metric tons in 2030 and reach 110 metric tons in 2050 unless practices for its management change [22]. Currently, e-waste poses significant threats to low and middle-income families, as toxic materials–such as lead and mercury–will spread when e-waste is recycled inappropriately [7]. One particular component of e-waste has been making a dangerous mark in the world: lithium. The high energy density and light weight of lithium-ion batteries make them favorable for high-powered computing, especially generative AI, but these batteries are difficult to recycle because of their battery chemistry and structure. Thus, we will specifically consider the ecological impact of lithium-ion batteries through our model.
Question 5: Question five asks us to recommend technical and policy-oriented solutions to reduce the environmental impact of HPC and incorporate one of the recommendations into our model. We will also write a letter to the United Nations Advisory Board, which will incorporate the data we acquire from the previous questions.

3 Methodology

Our methodology started with identifying the necessary inputs and outputs of our model. We determined that our inputs were going to include the predicted growth in demand for electricity until 2030, the share of that electricity demand that can be attributed to data centers, and the individual data for how each country produces and consumes its electricity, and what carbon dioxide emissions impact that electricity production creates. Our primary output is a measurement of temperature change that the carbon dioxide emissions directly tied to data centers will produce: this output allows us to have a quantifiable impact for data centers that is relatable to most of humanity. 3 billion tons of carbon dioxide is difficult to imagine, but a temperature change is better understood.

Then, using this framework, we developed our model. We combined questions 2, 3, and 4 to generate an overall model that would account for all of the different factors asked in these questions so that we could then tweak this model to exclude consideration of certain inputs. For example, our original model accounts for the increasing portion of renewable energy in the global energy supply, which we then removed to show what impact renewable energy growth had. Some factors we included in our model in general include the growth of HPC, the growth of renewable energy, the potential for changes in energy distribution, technological innovation, and even lithium consideration. Our model also considers each country's carbon emissions, allowing us to get an in-depth understanding of how geographic location affects the carbon footprint of HPC.

This last note is one of our recommendations: we discovered that certain countries are more efficient than others in producing energy. Countries with a high disposition towards fossil fuels create a larger carbon footprint given the same quantity of energy produced, so restricting HPC center locations to countries with a set bar of efficiency will drastically reduce the emissions quantity, effectively serving a similar purpose as switching HPC to being 100% renewable energy based.

4 Climate Impact Model

4.1 Assumptions

Assumption 1: From 2024 to 2030, power demand in the US will rise by 2.4% and 50% in Europe.
Justification: Goldman Sachs estimated from 2022 to 2030, the US power demand would rise by 2.4% and up to 50% in Europe from 2023 to 2033 [2]. Our estimate is on the higher end, but considering the unanticipated growth of AI, it is within the relative range of demand growth.
Assumption 2: From 2024 to 2030, renewable energy is set to grow 5% annually.
Justification: Expert research predicts an exponential growth of renewable energy.[3]
Assumption 3: From 2024 to 2030, nuclear energy is set to grow 38%.
Justification: Expert research predicts a large growth in nuclear energy [25].
Assumption 4: Unmet energy demand from renewable sources will be satisfied by nonrenewable sources such as fossil fuels.

Justification: Energy demand is met exclusively from nonrenewable or renewable sources.
Assumption 5: The ratio of gas to oil to coal usage in 2024 will remain by 2030.
Justification: The choice of fossil fuels relies heavily on geographic location, and countries with established energy sources are unlikely to greatly switch from one fossil fuel source to another.
Assumption 6: Lithium-ion batteries will be expected to increase to 38.5% of the data center battery market by 2030.
Justification: Although Frost & Sullivan's analysis predicts this percentage to apply by 2025, we will provide a 5-year margin into 2030 to ensure that the prediction actually plans out [5].

4.2 Defining Variables

Renewable Sources of Energy	Nonrenewable Sources of Energy
Biomass (B); Biomass CO_2 (B_C)	Nuclear (N); Nuclear CO_2 (N_C)
Geothermal (GT); Geothermal CO_2 (GT_C)	Coal (C); Coal CO_2 (C_C)
Hydroelectric (H); Hydroelectric CO_2 (H_C)	Gas (G); Gas CO_2 (G_C)
Solar (S); Solar CO_2 (S_C)	Oil (O); Oil CO_2 (O_C)
Wind (W); Wind CO_2 (W_C)	Unknown (U); Unknown CO_2 (U_C)

(See Appendices A and B)

4.3 Calculating 2030 Energy Demand

To start, we estimated the global energy demand in 2030. From Assumption 1, the power demand rate is 102.4% of the 2024 value in the United States, and up to 150% of the 2024 value in Europe/the rest of the world. We used the following equation to calculate the 2030 electricity demand in each country with data from Electricity Maps [18].

$$ED_{2030} = 2024 \rightarrow 2030 \text{ Power Growth Rate} \times 2024 \text{ Electricity Demand}$$

To calculate the global electricity demand, by numbering each country, i, we can write:

$$\text{Global Electricity Demand: } (GED_{2030}) = \sum_{i=1}^{n} ED_{i,\,2030}$$

$$\text{Or for 2024: } GED_{2024} = \sum_{i=1}^{n} ED_{i,\,2024}$$

One limitation of our data source is that Electricity Maps only has data for $n = 76$ countries, missing statistics on China and the entirety of Africa among others [18]. To account for this, we compared our total electricity demand figure for 2024 with the actual figure (29,471 TWh).

$$GED_{2024} = 14954.975\, TWh = \frac{29471\, TWh}{1.97065}$$

Thus, for the rest of our calculations, we will be working with approximately half of the true figures due to limited data. This will be accounted for by multiplying our final result by our constant (1.97065).

4.4 Calculating 2030 Energy Supply

From assumptions 2 and 3, and using data from Electricity Maps, we were able to estimate the electricity supply from renewable sources and nuclear energy in 2030 [18].

$$N_{2030} = N_{2024} \times 1.38 \ \ ; \ \ GT_{2030} = GT_{2024} \times 1.05^{6} \ \ \ldots$$

$$N_{2030} + RES_{2030} = (B_{2030} + GT_{2030} + H_{2030} + S_{2030} + W_{2030}) + N_{2030}$$

Recalling our equation for the 2030 electricity demand, we can write an equation for the electricity demand unmet by renewable energy.

$$\text{Demand Unmet } (DU_{2030}) = ED_{2030} - RES_{2030} - N_{2030}$$

Using assumption 4, $DU_{2030} = UES_{2030}$, where *UES* is the unrenewable energy supply excluding nuclear energy.

$$UES_{2030} = ED_{2030} - RES_{2030} - N_{2030}$$

Based on our definitions, UES_{2030} must be composed exclusively by $C_{2030} + G_{2030} + O_{2030}$.

Using assumption 5, the ratio of nonrenewable energy sources in each country in 2024 is equal to the ratio in 2030. Using an unknown constant *k*, we can write

$$C_{2030} = k(C_{2024}); \ \ G_{2030} = k(G_{2024}); \ \ O_{2030} = k(O_{2024})$$

However, we know that the total energy produced by these sources is $C_{2030} + G_{2030} + O_{2030}$.

$$C_{2030} = \frac{UES_{2030} \times C_{2024}}{C_{2024} + G_{2024}O_{2024}}; \ \ G_{2030} = \frac{UES_{2030} \times G_{2024}}{C_{2024} + G_{2024}O_{2024}}; \ \ O_{2030} = \frac{UES_{2030} \times O_{2024}}{C_{2024} + G_{2024}O_{2024}}$$

We now have for each country the amount of energy produced from each energy source. Note that the global energy consumption would be the summation of each country's electricity breakdown, multiplied by our constant (1.97065) from the limitations of our data.

4.5 Calculating CO_2 Emissions by Energy Source

Starting with carbon emissions by energy type for each country in 2024 ($B_{C,\,2024}$, $H_{C,\,2024}$, $S_{C,\,2024}$, etc.), we can update these values for 2030 using energy produced and proportionality.

$$\frac{B_{2030}}{B_{2024}} \times B_{C,\,2024} = B_{C,\,2030}; \ \ \frac{GT_{2030}}{GT_{2024}} \times GT_{C,\,2024} = GT_{C,\,2030}; \ \ \ldots$$

This is our base rate. However, we are not going to assume that the proportion $\frac{Amount\ of\ Electricity}{Amount\ of\ Carbon\ Dioxide\ Produced}$ remains constant. A multitude of factors, including technological innovation, can change this ratio. To account not only for the increase in capacity of renewable energy, but also the change in efficiency, we used each country's Yearly Carbon Intensity (*I*, measured in gCO_2eq/kWh) from 2017 to 2023 and created exponential regression curves.

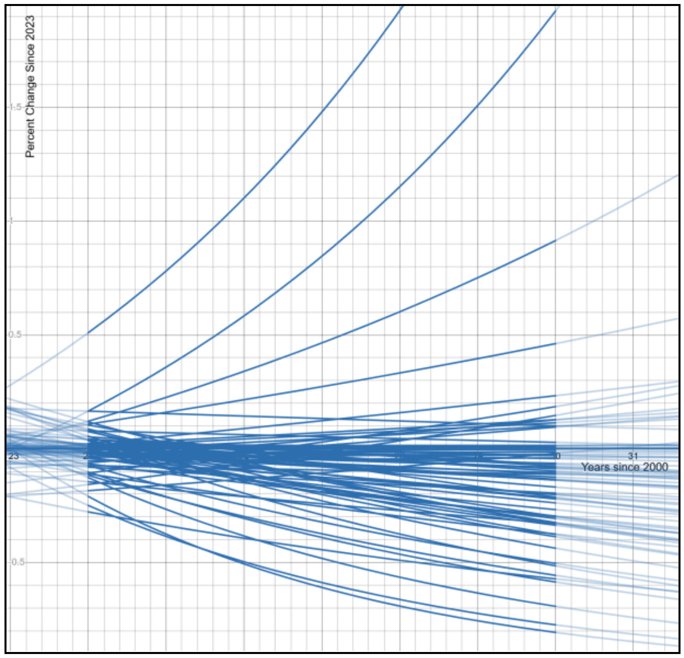

Figure 1: Percent change of projected exponential growth in CO2 emissions compared to 2023

These curves represent the proportional change in efficiency *y* compared to 2023 values *x* years after 2000. A positive correlation signifies a decrease in efficiency (I ↑), while a negative correlation signifies an increase in efficiency (I ↓). For the most part, the majority of countries are becoming more electrically efficient, which matches technological innovation. For other countries such as the UAE, an increase in fossil fuel consumption has resulted in a sharp increase in *I*, showing that our model also accounts for policy changes trending towards using more nonrenewable energy. Thus, our model accounts for the potential for different energy sources and mixes. We used our predicted efficiency values in 2030 and 2023 to model the proportional change in efficiency.

$$\frac{I_{2030}}{I_{2023}} = L, \text{ where } L \text{ represents the proportional change in efficiency}$$

Recall: $\frac{B_{2030}}{B_{2024}} \times B_{C,\,2024} = B_{C,\,2030}$; $\frac{GT_{2030}}{GT_{2024}} \times GT_{C,\,2024} = GT_{C,\,2030}$; … are the equations for the amount of carbon emissions by energy type excluding changes in efficiency. We can now incorporate proportional change in efficiency into these equations.

$$\frac{I_{2030}}{I_{2023}} \times \frac{B_{2030}}{B_{2024}} \times B_{C,\,2024} = B_{C,\,2030}; \quad \frac{I_{2030}}{I_{2023}} \times \frac{GT_{2030}}{GT_{2024}} \times GT_{C,\,2024} = GT_{C,\,2030}; \quad \ldots$$

Since each of these equations is country-specific, global CO_2 emissions are the summation.

$$\sum_{i=1}^{n} B_{C,\,i,\,2030} + GT_{C,\,i,\,2030} + H_{C,\,i,\,2030} + W_{C,\,i,\,2030} + S_{C,\,i,\,2030} + N_{C,\,i,\,2030} + C_{C,\,i,\,2030} + \ldots$$

However, we have one final step: recall our constant (1.97065) due to the limitations of our data. We will multiply this summation by our constant to find our total projected carbon emissions from the electric grid in 2030.

4.6 Applying Our Model

See Appendix A

Some notable values from our calculations include:

- Projected Global Demand for Electricity in 2030: $40,416\ TWh$
- Projected Global CO_2 Emissions in 2030: $14,151\ Mt$

4.7 Supporting Our Model

Utilizing data from the International Energy Agency (the *World electricity final consumption by sector*) between 2000-2019 and the Global Electricity Demand calculated for 2030, we produced an exponential regression model to project the behavior of growing GED between 2024 and 2030.

$$GED = 11420.188(1.04332)^x$$

(where x = years since 2000, and GED is measured in TWh)

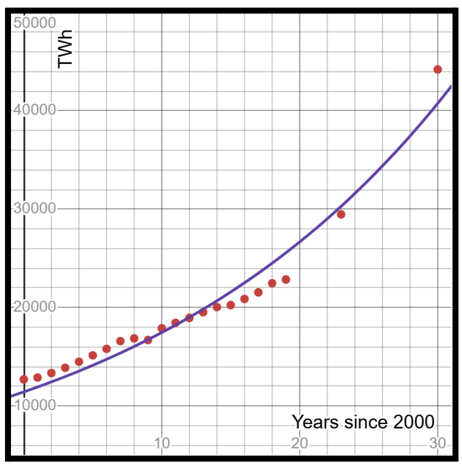

Figure 2: Global Electricity Demand Growth Model

Using this model, we can develop a Carbon Emissions model by using similar parameters. Assuming that Power Usage is directly proportional to Carbon Emissions, we can let:

$R = constant\ of\ proportionality$

Note: R is being used to "scale" our GED model to represent the change in Carbon Emissions.

$c(x) = carbon\ emissions\ as\ function\ of\ years\ after\ 2000$

$= GED \bullet R$

Using the Energy Demanded (from 76 countries) and the Carbon Emissions (from 76 countries) of 2023, we can determine our constant of proportionality.

$$R = \frac{Carbon\ Emissions\ in\ 2023}{Energy\ Demand\ in\ 2023} = \frac{5832.02819\ Mt\ of\ CO2}{14954.975\ TWh} \simeq 0.38997244$$

Thus,

$$c(x) = GED \bullet R = (11420.188[1.04332]^x)(0.38997244)$$

$$c(x) \simeq 4453.559(1.04332)^x$$

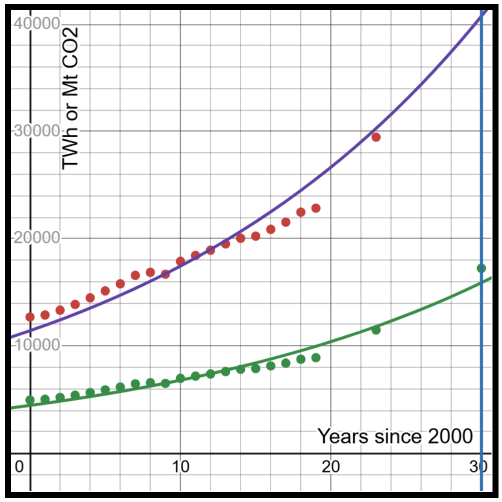

Figure 3: GED Growth Model (Purple) & Carbon Emissions Growth Model (Green)

Let's test the accuracy of the models. At x = 30 years,

$$GED = 11420.188(1.04332)^{30\ years}$$
$$GED \simeq 40756\ TWh$$

Recall Appendix A: Projected Global Demand for Electricity in 2030: 40,416 TWh

Finding the percent difference between these two values gives

$$= \frac{a-b}{\frac{a+b}{2}} \bullet 100\%$$
$$= \frac{40{,}756\ TWh - 40{,}416\ TWh}{\frac{40{,}756\ TWh + 40{,}416\ TWh}{2}} \bullet 100\%$$
$$\simeq 0.83773\%$$

Similarly, we can find the percent difference in carbon emissions.

$$c(30\ years) = 4453.559(1.04332)^{30\ years}$$
$$c(30\ years) \simeq 15893.99936\ Mt$$

Again, finding the percent difference will give

$$= \frac{15893.99936\ Mt - 14151\ Mt}{\frac{15893.99936\ Mt + 14151\ Mt}{2}} \bullet 100\%$$
$$\simeq 7.58849\%$$

Although the Carbon Emissions model deviates from the projected growth by ~7.6% as opposed to the ~0.84% of the GED growth model, both models are relatively accurate representations of future growth. Thus, our model aligns with the research we've done.

4.8 Eliminating Data Centers

To calculate the impact that data centers have on global CO_2 emissions, we can use assumptions X and Y to predict the global CO_2 emissions without data centers and compare that to the global CO_2 emissions with data centers.

$$\text{US: } ED_{2030} = (102.4\% - (0.9\% + 1\%)) \times ED_{2024}$$

$$\text{Non-US: } ED_{2030} = (150\% - (24.5\% + 1\%)) \times ED_{2024}$$

Repeating steps 4.3-4.5 using the new values yields new notable values of:

- Projected Global Demand for Electricity in 2030: 34781 TWh
- Projected Global CO_2 Emissions in 2030: 11203 Mt

The impact the removal of data centers would have on global CO_2 emissions is our old global CO_2 emissions value subtracted from our new CO_2 emissions value without data centers.

$$\text{Final Data Center } CO_2 \text{ Emissions in 2030: } 14151\,Mt - 11203\,Mt = 2948\,Mt$$

Our prediction shows that data centers will emit 2948 megatons of CO_2, or 2.948 billion metric tons of CO_2, through 2030. On the other hand, Morgan Stanley's research report projects that the global data center industry will emit 2.5 billion metric tons of CO_2 through 2030 [9]. Thus, the average CO_2 emissions through 2030 is 2.724 billion metric tons of CO_2. We must consider how dispersed other predictions are in relation to this mean, so we will assume that our prediction is 1 standard deviation away from the mean, which equates to 0.224 billion metric tons. Using 3 standard deviations to identify a range (a low and a high), we get that the low prediction is 2.052 billion metric tons and the high prediction is 3.396 billion metric tons.

4.9 Additional Calculation: E-Waste (Notably Lithium) from Data Centers

Lithium is the building block of our future, a place where data centers and artificial intelligence will be the powerhouses of the world. More specifically, lithium-ion batteries are the ones powering these applications–such as our phone batteries and electric car batteries, to name a few. These batteries are quite high in energy and light in weight design, making them last long without much recharging even though they recharge quite fast [25]. Thus, these batteries are suitable for real-time decisions and large processing. However, this high reliability and long lifespan come with a cost: the environment. In fact, lithium-ion batteries are difficult to recycle because of their battery chemistry and structure. For the battery chemistry, for instance, some batteries use cathodes made of lithium cobalt oxide, while other cathodes are made of lithium nickel manganese oxide cobalt oxide; different materials also mean different proportions and sizes, which makes recycling harder and even more expensive [14]. Adding on to the structure, not all batteries are manufactured so that each part can be taken apart, meaning recycling might not even be possible. With batteries that are unable to be recycled and that can consume a lot of energy, they raise an imminent threat of climate change. Also, mining for lithium not only requires a lot of intensive labor but also emits a lot of carbon dioxide into the atmosphere. It is time to see this in action:

By 2030, the worldwide metric tons of used lithium-ion batteries will hit 2 million metric tons per year [14]. Also by 2030, Li-ion batteries will be expected to increase to 38.5% of the data center battery market [5].

$$2,000,000 \times 0.385 = 0.77 \text{ million metric tons of Li}$$

The batteries are valuable and recyclable, but because of technical, economic, and other factors, less than 5% are recycled today.

$$0.77 \times 0.95 = 0.7315 \text{ million metric tons of Li}$$

For every metric tonne of mined lithium, 15 tonnes of CO_2 are emitted into the air [25].

$$731,500 \times \frac{15 \ tons \ CO_2}{1 \ metric \ ton \ Li} = 10,972,500 \text{ tons of } CO_2$$

4.10 Temperature Change in Regards to CO_2 Emissions

Recall Figure 3 and Figure 4 (page 8).

$\frac{T(x)}{G(x)}$ gives us the temperature increase per ppm increase of CO_2, where

$$\frac{T(x)}{G(x)} = \frac{0.000172137x^2 - 0.670107x + 652.072}{0.0130852x^2 - 50.4644x + 48958.5}$$

Note that $\frac{1}{7.821 \cdot 10^9} \ ppm = 1$ metric ton.

Using our predicted CO_2 emissions due to data centers' energy consumption of 2,948 megatons, or 2,948,000,000 tons of CO_2, our predicted ppm increase of CO_2 due to data centers' energy consumption is 0.3769 ppm. Using our predicted CO_2 emissions due to data centers' lithium consumption of 10,972,500 tons of CO_2, our predicted increase of CO_2 is 1.4×10^{-3} ppm. Thus, our total CO_2 increase is 0.3783 ppm.

Historical data and future data display a proportional relationship between temperature/global warming and parts per million of CO_2 concentration. In fact, for each 10 ppm increase in CO2 concentration, the temperature increases by about 0.1 °C [11].

$$0.3783 \ ppm \times \frac{.1℃}{10 \ ppm} = 0.003783℃$$

$$\text{Low: } 0.2637 \times \frac{.1℃}{10 \ ppm} = 0.002637℃$$

$$\text{High: } 0.4356 \times \frac{.1℃}{10 \ ppm} = 0.004356℃$$

We conclude that data centers in 2030 will raise global temperatures by $\sim 0.003783℃$ yearly, while also consuming over 700,000 metric tons of lithium.

4.11 Expanding our Model to 100% Renewable Energy Source

We will now examine the situation where data centers are completely reliant on renewable energy. We will do this by modifying our model to calculate the amount of carbon emissions data centers would produce in this scenario.

$$\text{For data centers exclusively: } ED_{2030} = ED_{2024} \times (P_I + P_G)$$

Note that P_I represents the initial (2024) percentage of electricity demand that data centers contribute, while P_G represents the percentage of 2024 values that data centers will grow to additionally contribute.

$$\text{In the US: } ED_{2030} = ED_{2024} \times (1\% + 0.9\%)$$

$$\text{Outside the US: } ED_{2030} = ED_{2024} \times (1\% + 24.5\%)$$

Recall our earlier equation:

$$UES_{2030} = ED_{2030} - RES_{2030} - N_{2030}$$

In the scenario, where nuclear and other unrenewable sources of energy powering data centers is 0, this equation becomes:

$$ED_{2030} = RES_{2030}$$

Based on our definitions, RES_{2030} must be composed exclusively by:

$$RES_{2030} = B_{2030} + GT_{2030} + H_{2030} + S_{2030} + W_{2030}$$

Using assumption 5, the ratio of nonrenewable energy sources in each country in 2024 is equal to the ratio in 2030. Using an unknown constant *k*, we can write

$$B_{2030} = k(B_{2024}); \;\; GT_{2030} = k(GT_{2024}); \;\; H_{2030} = k(H_{2024}); \;\; \ldots$$

However, we know that the total energy produced by these sources is:

$$B_{2030} + GT_{2030} + H_{2030} + S_{2030} + W_{2030}$$

So we can write:

$$B_{2030} = \frac{RES_{2030} \times B_{2024}}{B_{2030} + GT_{2030} + H_{2030} + S_{2030} + W_{2030}}; \;\; GT_{2030} = \frac{RES_{2030} \times GT_{2024}}{B_{2030} + GT_{2030} + H_{2030} + S_{2030} + W_{2030}}; \;\; \ldots$$

Following our procedure from sections 4.5-4.6, we find that:

- Projected Global Demand for Electricity from Data Centers in 2030: 5636 *TWh*
- Projected Global CO_2 Emissions from Data Centers in 2030: 175 *Mt*

If we add these values to our values without data centers:

- Projected Global Demand for Electricity in 2030: 34781 *TWh*
- Projected Global CO_2 Emissions in 2030: 11203 *Mt*

We Get:

- Projected Global Demand for Electricity in 2030: 40417 *TWh*
- Projected Global CO_2 Emissions in 2030: 11378 *Mt*

Comparing this to our original scenario:

- Projected Global Demand for Electricity in 2030: 40,416 *TWh*
- Projected Global CO_2 Emissions in 2030: 14151 *Mt*

$$\text{Difference in carbon emissions: } 14151\, Mt - 11378\, Mt = 2773\, Mt = 0.3546\, ppm$$

$$0.3546\, ppm \times \frac{.1°C}{10\, ppm} = 0.003546°C$$

Notice that this value is practically equal to our original calculation of how much data centers contribute to climate change. Thus, we conclude that if data centers relied on entirely renewable energy, it would almost entirely negate (reduce emissions by 93.7%) the greenhouse effect via carbon dioxide emissions that they would've had otherwise.

$$0.003546°C = 93.7\% \times 0.003783°C$$

There are several practical issues with relying solely on renewable energy. One of these issues is funding the project. Renewable energy sources are expensive. Even as the technology becomes more advanced and affordable, it remains out of reach for many countries to implement. In one study, accounting for the 143 countries that make up 99.7% of carbon emissions, it estimates that it would take a collective $73 trillion to turn 100% renewable by 2050 [13]. While the study also predicts it would create 28.6 million more jobs and would cost countries less in the long term, the current price and its timeframe to 2050 make any proposal for 2030 to be near impossible.

Besides the cost, another issue is the accessibility to resources. While renewables like wind and solar are rapidly growing, there are currently not enough raw materials mined to transform to 100% renewable [4]. While there exists enough of these rare-earth metals in the ground, mining them can create environmental harm to the surrounding landscape. A proposed mine in the US for copper and lithium is set to displace an Indigenous heritage site, raising concerns over its morality.

5 Recommendations

5.1 Restricting HPC Locations

After conducting our country-specific research, one question we had was whether restricting data centers to certain locations with high-efficiency rates (low gCO_2eq/kWh) would impact carbon emissions. We started modeling this policy change by sorting the list of countries by their predicted 2030 climate emissions. Selecting the top 41 countries, up to the United States, as the only countries where data centers will operate, we divided our model into three portions:

$$\text{US: } ED_{2030} = (102.4\%) \times ED_{2024}$$

$$\text{Non-US with Data Centers: } ED_{2030} = (150\%) \times ED_{2024}$$

$$\text{Non-US without Data Centers: } ED_{2030} = (150\% - (24.5\% + 1\%)) \times ED_{2024}$$

Calculating the summation of our values, we found a global electricity demand of 36,897 TWh, about 9% lower than our predicted 2030 electricity demand of 40,417 TWh. We also predicted a carbon dioxide emissions amount of 12321 Mt, a 13% carbon dioxide emissions decrease. However, this data relies on the assumption that electricity demand in countries that allow HPC will grow at the same predicted rate, and not grow due to HPCs being limited in other areas. To account for this, we adjusted our *ED* rates in 2030 such that the global ED_{2030} in our scenario equals our original predicted *ED*. Thus, this assumes a worst-case scenario, where the closure of HPC in inefficient areas causes 100% migration rather than discouraging some HPC.

We will start by taking our countries with low-efficiency rates and determining the amount that energy demand decreased without data centers compared to with data centers.

$$\Delta ED_{2030} = 10507.1 - 8720.9 = 1786.2\,TWh$$

We will now redistribute this value to countries with data centers based on the proportion of 2030 energy they will produce.

$$\text{Adjusted Non-US: } AED_{2030} = ED_{2030} + 1786.2\,TWh \times \frac{ED_{2030}}{\sum_{i=1}^{41} ED_{2030}}$$

Using these new *AED* values in place of *ED* values and following our calculations (sections 4.4-4.6), our model now shows zero change in energy demand. Carbon dioxide emissions also increase compared to our *ED* values, however, there is a difference between our original non-location restrictions scenario and our policy-implemented scenario:

$$14151\, Mt - 14059\, Mt = 92\, Mt$$

While this difference is marginal, it still is an improvement over our original scenario. Yet our policy also has another intended purpose: it restricts the locations of HPC, allowing us to concentrate renewable energy improvement efforts into a smaller area. These locations, in being more energy efficient, typically are more reliant on renewable energy, meaning they already have the resources to expand their renewable energy sources. By adding a second policy to double the expansion rate of renewable energy in these areas, we can include the effects of our recommendation into our model.

$$GT_{2030} = GT_{2024} \times (1.05 \times 2)^{6} \ \ldots$$

Proceeding with our model (Steps 4.4-4.6), we discover that our recommendation has a large climate impact: only 12,481 megatons of CO_2 are produced by the power grid yearly.

$$\Delta CO_2 = 14151\, Mt - 12481\, Mt = 1670\, Mt$$

Recall our original value for the quantity of carbon dioxide emissions caused by data centers:

Original: 2948 Mt

$\frac{1670\, Mt}{2948\, Mt} = 43\%$ neutralization of data centers' energy consumption.

$$\Delta CO_2 = 1278 Mt = 0.1634\, ppm$$

$= 0.001634$°C reduction in global temperature per year by 2030.

5.2 Other Recommendations

The appropriate use of high-powered computing comes down to sustainability–a balance between optimal computing performance and the well-being of others. First, HPC has to run only when necessary; CO_2 emissions are unfortunately inevitable because many data centers are using fossil fuels to fuel their computations, so it is important for each center to figure out at what time or even at what weather conditions when they do not need much computing power. Second, more policies should require data centers to convert to renewable energy. These centers are competing with each other for energy that is nonrenewable, meaning these resources will eventually run out; however, at this current rate in which global demands for high-powered computing are rising, fossil fuels will be depleted by 2060 [24]. This leads to our third recommendation: to restrain the mining of nonrenewable energy sources. Mining not only emits CO_2 into the atmosphere but also involves labor that can unfortunately include children [15]. We must eliminate child labor and recognize the effects mining has on low-income families, especially those who live near and are threatened by mines.

6 Model Sensitivities

It is important to note that our models rely on the consistency of current growth in CO_2, demand for energy, demand for specific energy sources, etc. Notably, the CO_2 and Lithium Model are subject to variable change. Model sensitivities consider the change and viability of our models under changes in variables. They assess the adaptability and generalizability of our model.

6.1 CO_2 Model

The carbon dioxide model relies on electricity consumption and demand and is data-intensive. Some limitations of our model include a lack of data globally; however, we compensated for our shortcomings in this model and compared our model to other expert predictions. We discovered that the margin of error between our model and expert models is relatively insignificant; thus, our model is accurate. Our model is also flexible, as it can take into account many different factors. If some data changes, the general form of our model remains the same, allowing us to adapt.

6.2 Lithium Model

The lithium model relies on the amount of unrecycled lithium-ion batteries by 2030. A clear limitation is that we excluded recycled batteries, which can still emit a lot of carbon dioxide due to mining contributions; lithium is also not the best generalization for e-waste as a whole. Nevertheless, lithium is the major ingredient in powering data centers, so analyzing its snowball effect on the environment is essential to our model.

7 Strengths and Weaknesses

7.1 Strengths

- Our models take into account several variables, especially within our CO_2 model, to be modified and generalized into different situations easily.
- The models we made are consistent with each other, briefly discussed in section 4.7.
- We utilize simple proportionality to project growth in Energy Demand and CO2 to improve consistency and help guide our mathematical processes.
- Most variables are kept consistent, enabling us to extend our model easily.
- We used exponential regression models to capture the behavior of a few of our models, utilizing data from the past several years to back up the reliability of our model.

7.2 Weaknesses

- Though having many variables increases our function's modularity, we lose concision and so, our functions themselves (the piecewise material that produces the figures throughout our report) become less readable.
- The data for some of our models are dated to 2023, while many of our calculations start with 2024. The missing data in this year may cause our model to have a slight error.
- When considering e-waste as our environmental concern, we did not do a general census of e-waste. Instead, we specifically chose to focus on the impact that lithium and its ion batteries have on carbon emissions, while also calculating the amount of lithium e-waste produced.
- Our usage of standard deviations to find a range within our prediction of CO_2 emissions by 2030 may be inaccurate if both we and Reuters are off by a significant magnitude. However, that is unlikely.

8 A Letter to the United Nations Advisory Board

Dear United Nations Advisory Board,

As carbon dioxide (CO_2) emissions across the world increase and global temperatures continue to rise, the future of our planet is in danger. The emergence of new AI technology is only exacerbating this problem: AI is heavily energy-intensive, requiring high-powered computing—a collection of supercomputers performing complex calculations—to operate. These computers rely on data centers, which have been increasingly stressful to nations' power grids.

Governing AI for Humanity, the September report published by the U.N. outlines steps on how to approach emerging AI technologies for global advancement and safety, but overlooks addressing its emission concerns. On Page 29 of this report, Figure 2.n shows widespread expert concern on the impact of AI on the environment. Without further studying of its potential harms, AI growth could quickly disrupt power grids and expand carbon emissions. Therefore, we conducted further research of the environmental impacts of high-powered computing machines and examined its effects in the scheduled development goals for 2030.

Our findings support our concerns. By modeling the electricity consumption and carbon dioxide equivalent emissions for 2030, we found a yearly .004℃ increase in global temperatures from data centers, which will produce a whopping 2,948 megatons of CO_2 in 2030. While it may not seem like a significant temperature change, this model tracks a short period of time and only accounts for the beginning of the AI boom. After 2030, AI is expected to continue its exponential ascent, taking with it an increased electricity demand from data centers. Furthermore, carbon dioxide-related temperature increases will remain present in our atmosphere for thousands of years, and these small increases quickly compound one another. Any dent we can make in our climate emissions matters.

Another environmental effect of HPC is e-waste in the form of lithium, which would require 700,000 metric tons to meet 2030 demand. This requires extensive mining, creates more global harm through carbon emissions, and generates toxic waste. This has already raised ethical concerns in the U.S., where a lithium mine bordering Indigenous land is sparking controversy.

To address the growing problem that HPC poses to our environment, our team has devised a set of recommendations for the U.N. to implement. Our primary recommendation consists of two parts: limiting HPC activity and data centers to countries with a carbon intensity less than or equal to that of the United States (see Appendix C) and accelerating renewable energy growth in these countries to double the current rate of growth (5% yearly). Our model predicts this will reduce global carbon dioxide emissions by 1,278 megatons, which will slice the emissions from data centers roughly in half (lowering global emissions by 0.002℃). Other recommendations include limiting HPC use to only when necessary, encouraging renewable energy usage by data centers, and limiting the mining of nonrenewable resources such as lithium.

Two of the U.N.'s 17 goals are climate action and affordable/clean energy. By implementing our recommendations, the U.N. can progress toward realizing these goals.

Sincerely,
Team #16162

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Appendix A

2024 Data (TWh)	B	G	H	S	W	N	HS	C	G	O	U	ED
Åland Islands					0.2							0.3
Sweden			65.9	1.3	34.2	46.6					7.3	163
Iceland		4.4	11.5							1.7		15.9
Norway			130		14.1		1.4		1.4			159
France	6.2		50.6	21.5	47.9	319			28.0			501
Costa Rica		1.5	8.3		1.4					0.7		12.3
Brazil			442	42.6	95.1	14.5					57.1	651
Switzerland	6.3		22.1	4.3		23.5	6.9				5.1	90.0
Finland	5.6		13.9	0.7	18.9	27.8		5.2	1.8		0.7	84.4
New Zealand		7.6	26.0		3.2			1.6	2.5			41.6
Uruguay	1.1		3.4	0.4	4.8					0.9		12.1
Denmark	4.7			3.1	19.5			3.3	1.9	0.3		51.7
Colombia	0.8		63.1	1.0				7.0	7.5	1.2		80.9
Portugal	2.9		9.9	3.6	12.9		1.2		9.9		0.2	55.7
Spain	5.3		24.2	40.4	61.1	54.4		3.9	54.4			260
Austria	2.3		34.5	2.4	8.3		2.6		6.4			75.7
Belgium	3.0			7.2	14.1	31.3			15.3		6.0	95.2
Lithuania	0.7		0.4	0.6	2.4		0.2		0.6		0.1	15.0
Latvia	0.2		3.7		0.3				1.4		0.2	9.1

Georgia			10.9						3.5			18.7
Great Britain	12.7		3.0	11.9	57.5	35.8		2.6	82.3		2.4	243
Peru	0.4		28.2	1.0	2.3				21.3	0.8		53.9
Slovakia	0.8		4.6	0.5		18.3	0.1	1.0	2.1	0.4	1.4	39.3
Slovenia	0.1		4.8	0.3		5.3	0.3	2.9	0.4			21.6
Hungary	0.9		0.2	4.4	0.6	15.0		2.7	6.5		0.5	49.3
Croatia	0.7		6.9	0.1	2.6		0.4	1.2	3.4	0.1	0.2	23.0
Luxembourg	0.2			0.3	0.5				0.1			4.7
Netherlands	6.5	1.3		22.2	29.2			7.8	47.6		2.2	134
Estonia	0.6			0.7	0.8			2.0	0.5			11.9
Panama			6.1	0.8	0.8			2.1	2.7	1.6		14.4
Guatemala	1.3	0.3	5.4	0.2	0.3			1.8		0.6	2.1	13.9
El Salvador	0.5	1.5	1.4	0.7	0.2					3.1		7.9
Romania	0.4		18.3	1.5	7.5	11.2		8.2	9.6			61.2
Italy	6.4	5.4	35.9	24.2	23.3		1.9	12.1	101	1.4	16.3	281
Nicaragua	0.7	0.8	0.4		0.7					2.1		5.7
Bolivia	0.3		2.3	0.4	0.5						7.8	11.3
Russia			192			217					709	1120
Honduras	0.6	0.1	2.6	0.9	0.7			0.6		4.7	0.9	12.4
Argentina			40.7	3.2	14.6	9.7	1.6				77.2	155
Greece			3.4	8.6	9.4		0.7	4.6	15.6			50.3
Germany	44.6		14.4	55.2	142	6.7	2.9	118	50.1	3.0	2.8	498
Nigeria			7.1						22.3			29.4
U.A.E.				10.4		28.6			126			165
Sri Lanka	0.1		5.7	0.1	0.8			3.9		3.1		13.8
Ireland	0.7		0.7		11.4			2.7	13.8	0.6		31.8
United States			248	151	424	776		685	1640		57.0	4040
Bulgaria	0.2		3.1	3.0	1.5	16.1		12.2	3.3			43.6
Montenegro			2.0		0.3			1.5				9.0
French Polynesia			0.2	0.0						0.3		0.5
Moldova	0.1		0.3						5.4			7.5
Hong Kong						12.0		10.3	20.6			43.0
Turkey	8.1	10.1	63.7	3.9	33.7			118	66.4			311
South Korea			3.0	9.7		180		181	160		32.0	572
Faroe Islands	0.0		0.1		0.1					0.2		0.5
Japan	17.9		65.4	92.6	6.9	72.0	3.3	257	288	28.4	33.8	868
Oman				2.0					35.9	0.8	0.2	38.9
Qatar				2.2					50.4			52.7
Bosnia and H.			5.5		0.2		0.3	8.5				16.2
Singapore				0.9					54.3		1.1	56.5
Australia			15.3	41.4	30.7		1.3	124	18.0			230
Serbia	0.3		12.0		0.9		0.6	21.5	0.6		0.2	41.1

North Macedonia			1.2		0.1			2.6	1.3	0.3		8.8
Czechia	2.1		2.0	3.0	0.7	30.1	0.7	32.1	2.6		0.2	83.2
Israel				6.8				21.2	64.8			93.4
Taiwan			15.3	41.4	30.7		1.3	124	18.0			230
Malaysia	1.3		32.3	3.3				81.5	70.0		1.2	190
Aruba					0.1					0.8		1.0
Dominican R.	0.2		1.2	1.1	1.1			7.2	6.1	3.0	4.1	23.9
Bangladesh			0.7	0.8				20.4	47.9	14.4	8.4	98.4
Philippines	0.9	6.5	9.8	2.5	1.2		0.3	70.5	18.3	1.4	4.7	117
Indonesia		18.7	23.3					216	61.3	8.4		328
India			140	91.2	31.2	47.7		1270	29.7		9.1	1620
Kosovo					0.1			5.1				8.3
South Africa			2.0	6.4	11.6	8.1		166		5.1		205
Cyprus	0.1			0.8	0.2					4.2		5.2
Poland				13.2	22.1			96.7	12.9	2.5		168

Appendix B

2024 CO_2 (Mt)	B_C	GT_C	H_C	S_C	W_C	N_C	HS_C	C_C	G_C	O_C	U_C	T_C
Åland Islands					0.00							0.00
Sweden			0.71	0.05	0.43	0.24					1.87	3.30
Iceland		0.17	0.28									0.44
Norway			3.11		0.16		0.05		0.70			4.33
France	1.41		0.54	0.65	0.60	1.64			14.3	1.50		21.5
Costa Rica		0.06	0.20		0.02					0.43		0.72
Brazil			10.6	1.92	1.05	0.17					40.0	53.7
Switzerland	1.45		0.53	0.13		0.28	0.51				0.83	3.23
Finland	1.28		0.15	0.03	0.24	0.14		4.05	1.08		0.51	7.49
New Zealand		0.29	0.62		0.04			1.27	1.22			4.03
Uruguay	0.26		0.08	0.02	0.05					0.62		1.03
Denmark	1.08			0.11	0.25			2.60	0.81	0.29		5.15
Colombia	0.19		1.51	0.05				5.74	3.69	0.81		12.0
Portugal	0.67		0.11	0.09	0.16		0.15		4.91		0.13	6.06
Spain	1.21		0.26	1.07	0.77	0.28		5.05	28.3			37.9
Austria	0.52		0.37	0.07	0.10		3.55		3.21			4.41
Belgium	0.69			0.26	0.18	0.16			7.85		4.18	13.3
Lithuania	0.16		0.00	0.02	0.03		0.00		0.31		0.09	0.62
Latvia	0.05		0.04		0.00				0.67		0.11	0.87
Georgia			0.26						1.70			1.96
Great Britain	2.92		0.03	0.47	0.73	0.18		2.15	40.3		1.69	48.5
Peru	0.09		0.68	0.04	0.03				10.4	0.54		11.8
Slovakia	0.19		0.05	0.02		0.09	0.00	0.79	1.30	0.36	1.00	3.79
Slovenia	0.03		0.05	0.01		0.03	0.09	3.15	0.21			3.49

Hungary	0.21		0.00	0.13	0.01	0.08		3.49	3.67		0.37	7.97
Croatia	0.16		0.07	0.00	0.03		0.12	1.34	1.81	0.05	0.06	3.53
Luxembourg	0.06			0.01	0.01				0.04			0.12
Netherlands	1.49	0.05		0.81	0.37			6.66	25		0.74	35.1
Estonia	0.14			0.03	0.01			2.19	0.26			2.64
Panama			0.15	0.04	0.01			1.74	1.34	1.05		4.33
Guatemala	0.30	0.01	0.13	0.01	0.00			1.44		0.39	1.17	3.45
El Salvador	0.12	0.06	0.03	0.03	0.00					2.04		2.27
Romania	0.09		0.20	0.04	0.09	0.06		10.5	6.59			17.6
Italy	1.48	0.20	0.38	0.64	0.29		0.54	12.9	54.1	1.58	11.4	83.0
Nicaragua	0.17	0.03	0.01		0.01					1.37		1.58
Bolivia	0.06		0.06	0.02	0.01						3.79	3.93
Russia			4.62			2.60					402	410
Honduras	0.14	0.00	0.06	0.04	0.01			0.53		3.08	0.32	4.18
Argentina			0.98	0.14	0.16	0.12	0.59				54	55.9
Greece			0.04	0.23	0.12		0.41	5.84	8.04			14.3
Germany	10.3		0.15	1.94	1.80	0.03	0.00	127	26.6	2.62	1.93	172
Nigeria			0.17						10.9			11.1
UAE				0.47		0.34			61.8			62.9
Sri Lanka	0.02		0.14	0.00	0.01			3.23		2.03		5.44
Ireland	0.16		0.01		0.14			3.37	8.21	0.57		12.5
United States			5.94	3.96	4.66	9.32		719	865		0.04	1630
Bulgaria	0.05		0.03	0.08	0.02	0.08		14.5	1.77			16.5
Montenegro			0.02		0.00			1.25				1.27
French Polynesia			0.00	0.00						0.22		0.23
Moldova	0.01		0.01						2.65			2.67
Hong Kong						0.14		8.46	10.1			18.7
Turkey	1.87	0.38	1.53	0.10	0.37			96.9	32.5			135
South Korea			0.07	0.44		2.16		149	78.2		20.6	252
Faroe Islands	0.00		0.00		0.00					0.20		0.21
Japan	4.12		1.57	4.17	0.08	0.09	1.50	211	141	18.5	23.6	402
Oman				0.09					17.6	0.52	0.11	18.3
Qatar				0.10					24.7			24.8
Bosnia and H.			0.06		0.00		0.22	6.95				7.02
Singapore				0.04					26.6		0.78	27.4
Australia			0.37	1.86	0.34		0.00	102	8.82			113
Serbia	0.06		0.13		0.01		0.34	17.6	0.29		0.17	18.3
North Macedonia			0.01		0.00			2.16	0.64	0.23		3.04
Czechia	0.48		0.02	0.10	0.01	0.15	0.31	35.7	1.25		0.14	37.9
Israel				0.30				17.4	31.8			49.8
Taiwan			0.37	1.86	0.34		0.00	102	8.82			113
Malaysia	0.29		0.77	0.15				66.9	34.3		0.86	103
Aruba					0.00					0.54		0.55

D.R.	0.05		0.03	0.05	0.01			5.87	2.96	1.94	2.88	13.8
Bangladesh			0.02	0.04				16.7	23.4	9.38	5.89	55.5
Philippines	0.20	0.25	0.23	0.11	0.01		0.22	57.8	8.96	0.89	3.28	71.7
Indonesia		0.71	0.56					177	30	5.32		214
India			3.36	4.10	0.34	0.57		1040	14.5		0.24	1070
Kosovo					0.00			4.17				4.17
South Africa			0.05	0.29	0.13	0.10		136		3.29		140
Cyprus	0.02			0.02	0.00					3.69		3.72
Poland				0.46	0.28			110	6.85	2.25		121

Appendix C

Intensity	2023	b	a	ab^30	2030/2023
Åland Islands	22	0.8185018489	2019.542898	4.964128614	0.2256422097
Sweden	25	0.9723176474	50.01466821	21.54479858	0.8617919431
Iceland	28	0.9974056822	29.34032676	27.14064022	0.9693085794
Norway	34	0.9700980583	67.52014921	27.15829194	0.7987732924
Finland	53	0.9905957049	77.46828885	44.63209366	0.8421149748
Portugal	71	1.030874774	27.90327526	46.66462275	0.6572482078
Switzerland	82	0.918365784	707.6045203	47.25780626	0.5763147105
Brazil	84	0.9005172281	1095.753286	54.98717881	0.6546092715
France	92	0.881349876	1973.316863	58.34681867	0.6342045508
Costa Rica	97	0.9974315871	105.3679143	69.47563901	0.7162437011
Spain	97	1.179878187	2.764823947	76.3442473	0.7870540959
Denmark	133	0.9158199506	1140.499579	81.54514947	0.6131214246
Faroe Islands	148	1.031648916	71.65442508	86.12767025	0.5819437179
New Zealand	152	0.8402073752	8657.511501	97.5443028	0.6417388342
Austria	154	0.9012331567	1728.468552	110.9543321	0.720482676
Estonia	158	0.9315017339	932.46864	120.5004656	0.7626611744
Latvia	178	0.9540685769	513.6177153	121.4873682	0.6825133045
Lithuania	183	0.9238406009	1330.988181	123.619089	0.6755141478
Belgium	195	0.9124584705	1897.308311	125.3221279	0.6426775791
Guatemala	211	1.093354098	27.77177476	129.6052514	0.6142428977
Great Britain	213	0.9487420806	724.3947177	149.4239411	0.7015208501
Greece	219	1.027321682	109.9303158	163.5515707	0.746810825
Colombia	235	0.9452563551	1001.98364	182.4739186	0.7764847599
Luxembourg	247	0.9650965027	572.1974332	183.5107074	0.7429583296
Slovakia	258	0.9572837266	744.3120221	185.075447	0.7173466939
Netherlands	270	0.9774995467	460.8368022	190.7675219	0.7065463772
Slovenia	273	0.9344842897	1401.203692	197.0916203	0.7219473272
Hungary	284	0.9606930695	635.2793037	200.8978635	0.7073868433
Romania	291	0.8790756086	5757.074174	207.0167251	0.7113976809
Croatia	302	1.026064952	152.8248057	232.8327642	0.7709694179
Peru	303	0.9164284203	1776.912845	246.780648	0.8144575841
Montenegro	307	1.052625592	75.53599797	258.6793952	0.8426038932

Germany	312	0.9365673648	1478.545929	290.2093275	0.9301581011
Moldova	323	0.9920039948	422.3929074	295.2675098	0.9141408973
Honduras	332	1.048238983	95.72004683	326.5976677	0.9837279148
Panama	349	1.002051206	314.8805058	330.7040034	0.947575941
Italy	365	0.9993055616	374.0935723	331.9856015	0.9095495932
Bolivia	368	0.9930277495	402.87613	334.8445415	0.9099036454
French Polynesia	369	1.047293871	134.8535269	337.956147	0.9158703171
El Salvador	369	0.8914886163	5130.747742	351.8614665	0.9535541098
United States	371	0.9583471895	1039.980415	354.0338319	0.9542690887
Bosnia and H.	378	1.002656047	354.0495316	355.0120968	0.9391854413
Russia	380	1.165644172	11.18834053	366.3779936	0.9641526148
Australia	395	0.9934339837	467.1904118	375.511453	0.9506619064
Bulgaria	405	1.002054718	371.2281768	380.4862842	0.9394723068
South Korea	409	0.9778509958	693.2091643	382.0823111	0.9341865797
Nigeria	412	0.9784907821	730.5279619	383.3746106	0.9305208995
Sri Lanka	414	0.9428676902	1510.912188	383.4107568	0.9261129392
Turkey	420	0.9781205538	656.2794385	390.801181	0.9304790023
Nicaragua	426	0.9420091102	1772.403403	393.3798424	0.9234268601
Ireland	435	1	435	394.8062738	0.9076006295
Uruguay	437	0.9872154837	574.9063668	395.1687981	0.9042764258
Georgia	443	0.9787168295	728.5263155	404.0440743	0.9120633732
Japan	448	0.7901234568	100993.645	421.43604	0.9407054465
Hong Kong	460	0.9853282623	656.6039272	435	0.9456521739
Czechia	471	1	471	449.8179372	0.9550274675
Serbia	471	1.017278618	317.6163397	453.9282251	0.9637541934
North Macedonia	485	0.955464295	1392.54513	455.818644	0.9398322558
Oman	488	0.998546138	506.2290778	471	0.9651639344
Singapore	493	0.9573370343	1388.920518	484.608667	0.9829790405
Malaysia	498	0.9814282257	796.5826931	499.4212669	1.00285395
Taiwan	512	0.9834228357	752.6332929	503.6204464	0.9836336844
Qatar	514	0.9822606173	769.5464065	531.0070901	1.033087724
Argentina	533	1.000052286	539.8324251	539.4102147	1.012026669
Israel	538	0.9921009043	638.8927926	540.6798335	1.004981103
Aruba	544	0.9885247184	706.0590566	561.4799064	1.032132181
Cyprus	562	1.003892364	499.7119035	591.0307933	1.051656216
Philippines	577	1.016888895	388.9807385	627.6046325	1.087703003
Kosovo	604	1.017320821	396.7234261	629.8367755	1.042776118
D.R.	620	1.000921255	610.5043922	642.8849156	1.036911154
India	652	1	652	648.0669204	0.9939676693
Indonesia	658	1.000671536	635.145836	652	0.990881459
Bangladesh	676	0.9814730949	1103.763558	664.0883238	0.9823791772
South Africa	702	0.9932581645	822.2156268	671.1970439	0.9561211451
Poland	711	0.9666026828	1637.458201	675.2044556	0.9496546492
UAE	749	0.9764510826	1380.131796	1111.08062	1.483418718