Problem Chosen	2024 HiMCM/MidMCM Summary Sheet	Team Control Number
B		16209

SUMMARY

Have you considered the consequences of using an AI bot to do your homework? Sure, you are likely not helping yourself in your learning journey, and AI bots can hallucinate incorrect answers. However, the AI model was trained on vast amounts of data, requiring high power/performance computing (HPC) and energy in the process. Problem B consisted of several subtasks, (1) modeling the environmental impact from carbon emissions of HPC, (2) considering the impact of using renewable energy sources, and (3) coming up with actionable recommendations to reduce negative environmental impacts of HPC.

We first modeled the carbon emissions of HPC using data from the TOP500 list of most powerful supercomputers. We computed the total energy consumption of the supercomputers with their energy efficiency and their maximum computing speeds; this value was scaled based on the utilization rate. Then from the carbon intensity of regions from their energy production, we computed the total carbon emissions.

Next, to determine the environmental impact of these emissions, we developed models to quantify HPC's impact on air quality using AQI and ocean acidification using shellfish deaths. Using the value we derived for the carbon imprint of HPC.

After that, we extrapolated values for our parameters to the year 2030. Thus, we found a big increase in the environmental impacts in 2030, assuming no change was made to improve the energy efficiencies of the supercomputers or to change to clean energy sources.

Then we determined the impact of switching to a clean energy source, which we found to drastically decrease the carbon footprint produced by an order of magnitude. Consequently, the environmental impact of HPC likewise decreased.

Overall, our model provides successfully predictions for the carbon emissions from HPC and their effects on the environment. Also, our model is easily adaptable based on data from supercomputers.

Contents

1 Introduction

1.1 Background

With the current hype of artificial intelligence technologies like ChatGPT and Copilot, high-powered computing (HPC) has become more and more important, resulting in an increased reliance on data centers that consume copious amounts of energy. Global data centers used 460 trillion watt hours and this amount is projected to more than double by 2026, reaching some amount somewhere between 650TWh and 1,050TWh. [10]. Thus, concerns have been raised about the carbon footprint and sustainability of HPC, and efforts have been made to reduce HPC's environmental impact. In this paper we develop a mathematical model of the environmental impact of energy consumption from HPC depending on the source of the energy. We conclude with a set of actionable recommendations to reduce the environmental impact of HPC.

1.2 Problem Restatement

1. Develop and apply a model that determines the environmental impact of total carbon emissions coming from HPC energy usage, based on energy mixes.
2. Model the impact of increasing the usage of renewable energy on carbon emissions and the environment.
3. Determine actionable methods to reduce the environmental impact of HPC and model the impact of a method.

2 Part 1: Modeling Carbon Emissions

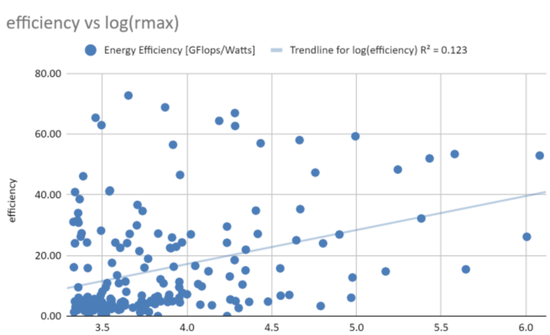
2.1 Problem Analysis

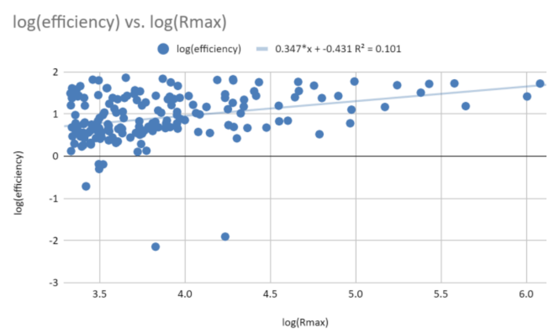
Calculating the carbon emissions resulting from HPC energy usage involves first computing the annual energy use from supercomputers in a certain region and then computing the amount of carbon emitted from the energy mixes at each location.

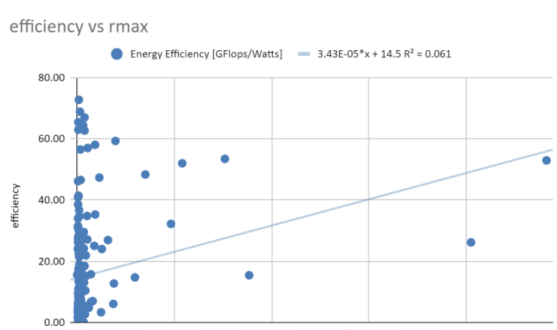
2.2 Assumptions

#	Assumption	Justification
1	Only supercomputers on the TOP500 list are relevant.	The 500th supercomputer is already only around $\frac{1}{10000}$ the sum of top 500, so the energy consumption of the smaller supercomputers is too small to affect our results.
2	Energy mixes of a country are constant and uniform.	As we are considering HPC worldwide, the variations of the mixes inside each country are not important. [20]
3	The energy efficiencies of the supercomputers whose energy efficiencies weren't given on the TOP500 list had an efficiency equal to the average of the given efficiencies.	Energy efficiencies of supercomputers are not dependent on any of their other properties and are independent of aspects like location; graphing various quantities with respect to energy efficiency of the supercomputers whose data we had produced little association with correlation coefficients of around 0.1, even after transforming the data. Thus, we resolved to take the average of the existing data for the data points we didn't have and assume that that was the energy efficiency.
4	The average utilization rate of a supercomputer is equal to that of the Frontier supercomputer.	Frontier is one of the fastest supercomputers in the world, so much data about it was available, including its average utilization rate. It is reasonable to assume the other supercomputers have a similar utilization rate to it.

Below is the image of the plots used for the justification of assumption 3:







2.3 Model Overview

Based on data from the TOP500 list, we computed the total annual energy use of the supercomputers by using the maximum computing rate and energy efficiency for each assuming full capacity. We also found the actual energy consumption assuming average utilization rates through data from Frontier's rates [18] that was applied to all supercomputers at the end of the model. Finally, by a dataset with the carbon intensity from each country [9], we determined the carbon footprint supercomputers had on each country and summed it up for the footprint worldwide. This considers energy mixes of each region that had a distinct carbon intensity.

Below is a table of variables used throughout our model:

Variable	Symbol	Description
energy efficiency	E_{eff}	a measures how energy-efficient the supercomputer is, equals supercomputer's performance divided by its rate of electrical flow, measured in Flops/Watt
maximum rate	R_{max}	maximum computing speed of supercomputer, measured in Flops/s
power	P	power consumption of supercomputer, measured in watts
carbon intensity	CI	measures how much carbon dioxide is emitted per unit of activity
carbon footprint	Carbon	a calculation of the total amount of greenhouse gases emitted by an activity

2.4 Calculations

For the supercomputers for which their energy efficiency weren't given, the efficiency was assumed to be the average energy efficiency of the other supercomputers:

$$\text{Unknown } E_{\text{eff}} = \text{avg}(\text{Known } E_{\text{eff}}). \tag{1}$$

Then, to calculate the energy usage per year of each supercomputer at full capacity, we use the equations

$$\text{Power} = \frac{R_{\text{max}}}{E_{\text{eff}}} \tag{2}$$

and

$$\text{Energy} = \text{Power} \cdot \frac{8760 \text{ hours}}{1 \text{ year}}. \tag{3}$$

Next, we multiply the energy usage of each computer by its region's carbon intensity from the dataset with the equation

$$\text{Carbon} = \text{CI} \cdot \text{Energy}. \tag{4}$$

Lastly, to find the carbon footprint of all the supercomputers, we add up the carbon footprint of each individual supercomputer with the equation

$$\text{Carbon}_{\text{tot}} = \sum_{s \in \text{TOP500}} \text{Carbon}_s. \tag{5}$$

To adjust for computer systems not running at full power, we multiply the carbon output by the ratio between the actual power usage and the full capacity power usage of Frontier:

$$\text{Carbon}_{\text{tot adjusted}} = \text{Carbon}_{\text{tot}} \cdot 12200\ \text{kW}/22786\ \text{kW}. \tag{6}$$

We find that the carbon emissions from HPCs running at full power are 1836959 metric tons and that the adjusted amount for average utilization rates is 983538 metric tons, or nearly one million metric tons of CO2 emissions.

3 Part 2A: Applying the Model for Environmental Impacts - Air Quality

3.1 Problem Analysis

Carbon dioxide (CO2) emissions resulting from HPCs are a pressing issue that indirectly affects air quality through their impact on atmospheric chemistry and related processes. These emissions primarily originate from the fossil fuel energy sources powering HPC systems. Elevated CO2 levels contribute to climate changes that intensify secondary air quality issues, such as increased ground-level ozone and particulate matter (PM2.5) formation. Understanding the relationship between increased CO2 levels and average air quality is crucial for analyzing how CO2 emissions influence these cascading effects on air quality.

3.2 Assumptions

To accurately model the link between CO2 emissions from HPCs and air quality, the following assumptions are made:

#	Assumption	Justification
1	Constant Atmospheric Baseline	The model considers a fixed baseline atmospheric composition, aside from the changes induced by HPC-related emissions.
2	Uniform Distribution of Emissions	CO2 released from HPC operations is evenly distributed across the atmosphere, minimizing regional variations.
3	Primary and Secondary Pollutants	While CO2 is the primary focus of this model, it also extrapolates air pollutants that directly affect air quality, such as NOx and volatile organic compounds (VOCs).

3.3 Model Overview

The proposed model quantifies the impact of CO2 emissions on air quality by simulating pollutant concentration changes over time.

1. Inputs:
    - Total CO2 emissions from HPC operations (in metric tons per year).
    - Baseline atmospheric concentrations of CO2, NOx, SO2, and VOCs.
    - Energy source composition (percentage of nonrenewable vs renewable energy).

2. Processes:
    - $CO2$ emissions contribute to global radiative forcing, impacting temperature and photochemical reaction rates.
    - Increased temperatures drive higher ozone production and enhance particulate formation rates through secondary chemical processes.
    - Direct emissions of NOx and SO2 from power plants further deteriorate air quality.
3. Outputs:
    - Changes in pollutant concentrations
    - Air Quality Index (AQI) scores indicating human health impacts

This framework links the CO2 emissions caused by HPCs to tangible air quality outcomes, enabling an evaluation of both local and global implications.

3.4 Model Development

In the following sections we list the factors considered in developing this model.

3.4.1 Carbon Dioxide Emissions from HPCs

This section gives an alternative but less accurate approach to finding the carbon emissions from HPC. The total carbon dioxide emissions, ΔC from HPC operations is calculated as:

$$\Delta C = P_{HPC} \cdot EF_{CO_2} \tag{7}$$

where:

- P_{HPC} is the Power Consumption of HPCs (kJ/year), predicted in the model above
- EF_{CO_2} is the CO2 emission factor (metric tons of CO2/kW), derived from the energy mix percentages

The Energy Mix Percentages can be calculated based off the following values[1]:

Fuel	Energy Density (kJ/t fuel)[17]	CO2 Output (t CO2 / t fuel)[3]	Consumption Percent [1]
Oil	41.9	2.56	31.70
Coal	29.5	1.91	26.47
Natural Gas	53.6	2.59	23.30

[1] This table only includes nonrenewable energies; however, the percentages include renewable energies, meaning they do not add up to 100% in the table, to properly account for them

Therefore:

$$\begin{aligned} EF_{CO_2} = 2.56\frac{\text{tons of CO2}}{\text{tons of oil}} \cdot \frac{1}{41.9}\frac{\text{tons of oil}}{\text{kJ}} \cdot 0.317 \\ + 1.91\frac{\text{tons of CO2}}{\text{tons of coal}} \cdot \frac{1}{29.5}\frac{\text{tons of coal}}{\text{kJ}} \cdot 0.2647 \\ + 2.59\frac{\text{tons of CO2}}{\text{tons of gas}} \cdot \frac{1}{53.6}\frac{\text{tons of fuel}}{\text{kJ}} \cdot 0.2330 \\ = 0.0478\ \frac{\text{tons of CO2}}{\text{kJ}} \end{aligned} \tag{8}$$

3.4.2 Link CO2 to Radiative Forcing RF

Radiative forcing is a measure of how the Earth–atmosphere system's energy balance is affected. CO2 indirectly affects air quality by increasing radiative forcing ΔF), which affects temperature and atmospheric chemistry. The relationship between additional CO2 emissions and radiative forcing is given by[13]:

$$\Delta F = \alpha \ln \frac{[C_0] + [\Delta C]}{[C_0]} \tag{9}$$

where:

- $[C_0]$ is the concentration of Carbon Dioxide in the atmosphere (420 ppmv) [16]
- $[\Delta C] = \frac{\Delta C}{V_{atm}}$ where V_{atm} is the volume of the atmosphere (4.34×10^9 kg) [21]
- α is the radiative efficiency of CO2 (5.35W/m^2) [13]

3.4.3 Impact of Radiative Forcing on Temperature

The change in global mean surface temperature (ΔT due to ΔF) is approximated using: [12]

$$\Delta T = \tilde{\lambda}\, \Delta F \tag{10}$$

where:

- $\tilde{\lambda} \approx 0.8$ K/(W/m^2) is the climate sensitivity parameter

3.4.4 Temperature Effects on Pollutant Formation

Increased temperature accelerates photochemical reactions, enhancing ozone production. Empirical studies [4] suggest that ozone production is proportional to increase in temperature:

$$\Delta[O_3] = \beta\, \Delta T \tag{11}$$

where the proportionality constant $\beta = 2.2$ ppb/K (This constant was derived from observational studies)

Table 1: Breakpoints for the AQI

These Breakpoints...		...equal this AQI	...and this category
O_3 (ppm)	$PM_{2.5}$ (μg/m^3)	AQI	
0.000 - 0.054	0.0 - 9.0	0 - 50	Good
0.055 - 0.070	9.1 - 35.4	51 - 100	Moderate
0.071 - 0.085	35.5 - 55.4	101 - 150	Unhealthy for Sensitive Groups
0.086 - 0.105	55.5 - 125.4	151 - 200	Unhealthy
0.106 - 0.200	125.5 - 225.4	201 - 300	Very unhealthy
0.201+	225.5+	301+	Hazardous

Similarly, temperature effects on fine particulate matter ($PM_{2.5}$) can be estimated using empirical studies that correlate changes in temperature with changes in concentrations. Studies often find a near-linear relationship: [7]

$$\Delta[PM_{2.5}] = \gamma\, \Delta T \tag{12}$$

where the ratio γ is the Temperature sensitivity of $PM_{2.5}(\mu g/m^3/K)$, which depends on Atmospheric Composition, baseline levels, and meteorological effects, but typically ranges from $0.2-1.5\ \mu g/m^3/K$.

Overall, the change in concentration of a certain pollutant, where β is its proportionality constant, can be directly related to energy consumption as:

$$\Delta[\text{Pollutant}] = \beta\tilde{\lambda}\alpha \ln \frac{[C_0] + \frac{P_{HPC}EF_{CO_2}}{V_{atm}}}{[C_0]} \tag{13}$$

3.4.5 Linking Pollutants to Air Quality Index (AQI)

To calculate the AQI, pollutant concentrations are converted using regulatory formulas[2]:

$$AQI = \frac{(I_{high} - I_{low})(C - C_{low})}{C_{high} - C_{low}} + I_{low} \tag{14}$$

where, following Table 1:

- I_{high} and I_{low} are the AQI values corresponding to the upper and lower boundaries of the AQI category
- C_{high} and C_{low} are the concentration values corresponding to the upper and lower boundaries of the AQI category
- C is the actual concentration of the pollutant in ppb

3.4.6 Final Model Equation

Combining Equations 13 and 14, the model estimates AQI as a function of HPC power consumption, where the final AQI is the maximum AQI for each pollutant:

$$AQI = f(P_{HPC}, \gamma, \beta, \text{Baseline Conditions}) \tag{15}$$

This equation reflects the cascading effects of HPC operations on CO2, radiative forcing, temperature, and air quality, capturing both direct and indirect impacts.

4 Part 2B: Applying the Model for Environmental Impacts - Acidification

4.1 Problem Analysis

In addition to land-based air quality is the less visible sister problem of ocean acidification. Similarly driven by carbon dioxide emissions, ocean acidification affects marine ecosystems, notably coral reefs and shellfish, which depend on aragonite for their skeletons and shells. Aragonite availability is inversely proportional to acidity, which is driven up as carbon dioxide dissolves in ocean-water as carbonic acid. When considering the environmental impacts of HPC, it would be remiss to ignore the oceans that contain 80% of Earth's biodiversity.

4.2 Assumptions

To model the relationship between CO2 emissions from HPCs and ocean acidification, the following assumptions are made:

#	Assumption	Justification
1	Constant Atmospheric Baseline	The model considers a fixed baseline atmospheric composition, aside from the changes induced by HPC-related emissions.
2	Uniform Distribution of Emissions	CO2 released from HPC operations is evenly distributed across the atmosphere, minimizing regional variations.
3	Representative Acidification	It is assumed that the pH measured at Station ALOHA [8] is representative of global acidification; ie. similar percentage changes will occur elsewhere. This follows from the Uniform Distribution assumption.
4	Linear Survival Rate	For small deviations below the optimal pH, the survival rate will be approximated linearly. This is motivated by the roughly bell shaped curve found by some studies and that this predicted mortality intends only to estimate magnitude.
5	Sole Factor	Factors besides CO2 levels and acidification are assumed to either be negligible or constant.

4.3 Model Overview

This model estimates the increase in mortality of marine organisms due to ocean acidification caused by rises in atmospheric CO2.

1. Inputs:
   - Total CO2 emissions from HPC operations (in metric tons per year).
2. Processes:
   - Carbon dioxide emissions drive increased amounts of CO2 dissolved in seawater.
   - The dissolved CO2, as carbonic acid, increases acidity.

- Lowered pH results in higher than natural death rates of marine organisms that are mal-adapted to the new acidity and its effects (eg. reduced availability of aragonite).

3. Outputs:

- pH
- Estimated magnitude of increased marine death

4.4 Model Development

4.4.1 Disolved Inorganic Carbon

From Henry's Law, we expect that

$$C_{onc} = k_h P_{CO_2} = k_h P \times X_{CO_2} \tag{16}$$

where

- C_{onc} is the concentration of CO2 (µmol/kg)
- k_h is the applicable Henry's Law constant
- P_{CO_2} is the partial pressure of CO2
- X_{CO_2} is the mole fraction (ppm)

However, because CO2 reacts with water to form carbonate and bicarbonate species and due to the ocean's buffering system, there exists a baseline amount of dissolved inorganic carbon (DIC). Thus, to model DIC, a constant term must be added:

$$C_{onc} = k_h P \times X_{CO_2} + B \tag{17}$$

Using Site ALOHA measurements [8], we empirically find the equation to be

$$C_{onc} = (0.548\mu mol/kg) \times X_{CO_2} + 1771\mu mol/kg \tag{18}$$

4.4.2 Resultant pH

Because pH is a logarithmic function of H+ concentration, we expect it to be logarithmically related to the concentration of DIC. Empirically, we find

$$pH = -5.8668 \times \log C_{onc} + 27.425 \tag{19}$$

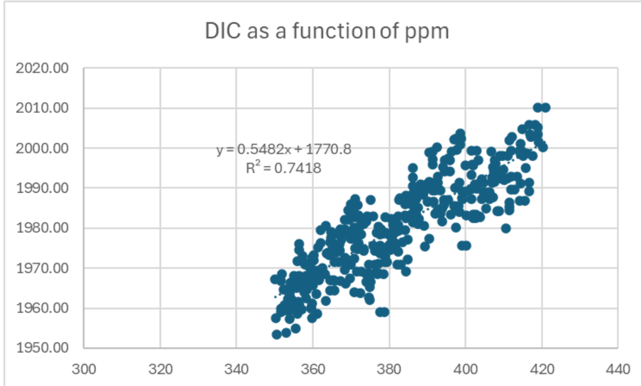


Figure 1: DIC concentration vs. CO_2 ppm

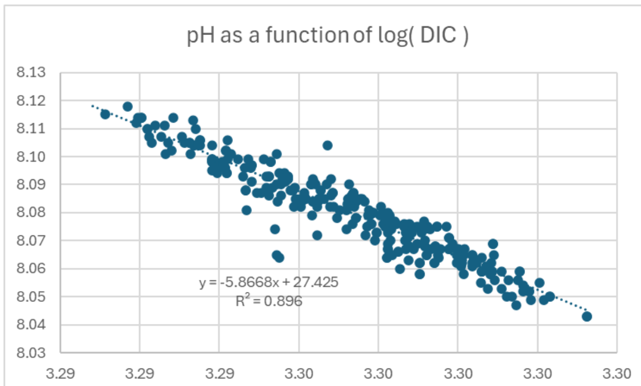


Figure 2: pH vs. $\log(C_{onc})$

4.4.3 Marine Mortality

Studies suggest that the function of shellfish survival rates against pH is roughly bell shaped. These curves are roughly linear around 1pH below optimal acidity [6]. Furthermore, a meta-analysis study suggests that the median LnRR of survival at 0.5pH below optimal is about -0.3, implying a median ratio of survival rates of about 75% [11]. Since there is not sufficient data to model it completely, we can make a rough estimate of the survival rate between 6.5pH and 7.5pH as

$$S \approx (pH - 6) \times 50\% \tag{20}$$

This lets us estimate the magnitude of impact on marine populations.

4.4.4 Final Mortality Relation

$$\Delta pH \approx (-5.8668) \log \left(1 + \frac{0.548\mu mol/kg}{0.548\mu mol/kg \times (420ppm) + 1771\mu mol/kg} \Delta X \right) \tag{21}$$

$$\Delta S \approx (0.50)(-5.8668) \log \left(1 + \frac{0.548\mu mol/kg}{0.548\mu mol/kg \times (420ppm) + 1771\mu mol/kg} \Delta X \right) \tag{22}$$

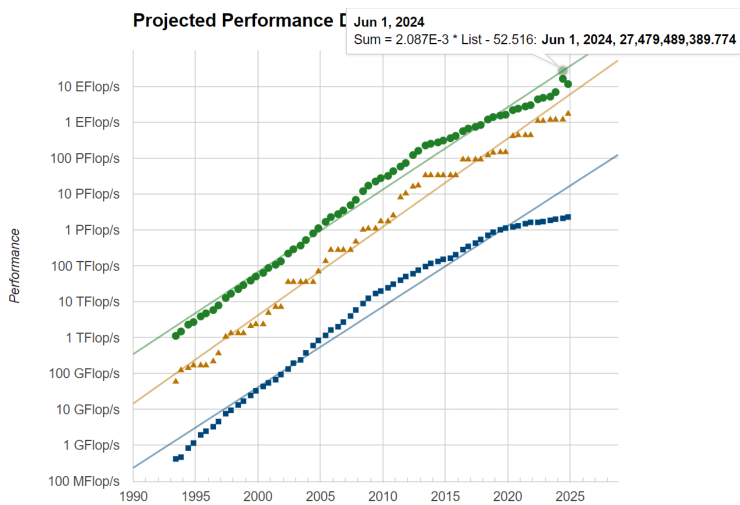
where ΔX is the increase in CO_2 due to HPC and ΔpH is the respective change in pH.

We can connect the emissions from HPC found in section 1 to ΔX through the relationship that one gigaton of CO2 adds roughly 0.12 ppm to atmospheric CO2[14]. Assuming the average shellfish lives for about 1 year before reproduction, and the shellfish biomass is on the order of 1 billion tons, current HPC levels correspond to the loss of tens of thousands of tons of shellfish per year.

5 Model Discussion

5.1 Extending Our Model to 2030

From the below linear regression line of the performance development taken from the TOP500, in 2030 the performance rate of the supercomputers will increase by approximately 125x, similarly increasing the impacts by the same magnitude. This phenomenon is due to the increasing reliance on HPC. [19],



5.2 Sensitivity Analysis

For part 1 of our model, the variance in the inverse of the energy efficiency for the reported values is 133.67. Thus, the standard deviation for the energy consumption when accounting for the variance due to the assumed energy efficiency values in TWh equals 4897.342 ± 188.385 assuming full capacity and 2622.118 ± 100.865 assuming average utilization rate. Note that although the range of the energy efficiencies of the supercomputers was very high, ranging from 0.19 to 72.73 Gflops/Watt, due to the assumption of independence for each unknown energy efficiency, the ultimate standard deviation was relatively low. Two supercomputers, one from Tohoku University and another from the German Meteorological Service, even had energy efficiencies of 0.01 Gflopps/Watt. These outliers were discarded from the standard deviation calculations because not much data is available about them. However, if they were included, then the standard deviations for both values would increase by a factor of 4.47 times.

5.3 Strengths

Strengths of our model include our ability to assess the impact of HPC on air quality and ocean acidification, two big concerns of environmental activists. Our model incorporates many hyperparameters into a single, robust framework, making it more generalizable; given a value for the total carbon emissions, we can numerically compute effects on the AQI index and number of shellfish deaths.

5.4 Limitations

Limitations of our model include our dependence on data of supercomputer properties to compute the total carbon emissions. Thus, we had to resort to assumptions like averaging all the energy efficiencies when we were missing data, potentially causing errors. Furthermore, innovations like breakthroughs in technology that abnormally increase the reliance on HPC were not considered in our extrapolation.

6 Part 3: Impact of Renewable Energy

6.1 Problem Analysis

We investigate the impact of switching to renewable energy sources on the carbon emissions and environmental impact of HPC.

6.2 Model Overview

We took the upper limit of 50g CO2 per kWh of electricity as the clean carbon intensity and applied that to each of the supercomputers:

$$\text{Carbon}_{\text{tot}} = \sum_{s \in \text{TOP500}} \text{Energy}_s \cdot CI_{clean} \tag{23}$$

We find that the total carbon footprint if all HPCs were switched to renewable energy is 131106 metric tons, a massive improvement over the current carbon footprint.

The carbon footprint is then applied to the model for environmental impacts. Substituting the new footprint into the ph/shellfish model results in an order of magnitude decrease in projected shellfish death; the new shellfish biomass loss is only in the thousands of tons.

7 Part 4: Recommendations

7.1 List

Here are some actionable recommendations we have to reduce the environmental impact of HPCs. By reducing the energy consumption of HPC, we can ensure that the impacts we analyzed, air quality and ocean acidification, will also be mitigated.

- **Switch to renewable energy sources** like nuclear energy or wind energy with relatively low carbon footprints: Our analysis showed significant improvement from switching to such sources.
- **Invest in the innovation of technology that focuses on reducing environmental impact of HPC**: For instance, California's Energy Commision sponsored the development of the Rack-CDU™ technology that applies high-performance liquid cooling directly to the hottest elements

in each server; this technology is predicted to annually save up to 2,400 gigawatt hours of electricity [5].

- **Establish benchmarks for carbon emissions**: This gives companies and regions concrete goals to work towards to build a more sustainable future.

- **Implement policies to increase transparency of companies' carbon footprints**: This can hold companies accountable to efforts to mitigate the environmental impacts and encourage sustainable efforts. For example, the Climate Corporate Data Accountability Act (SB 253) and the Greenhouse Gases: Climate-Related Financial Risk Act (SB 261) were signed into law last year in California. In particular, large businesses need to disclose their direct and indirect greenhouse gas emissions, along with preparing reports about their climate-related financial risks [15]. The public should also be made aware of these reports which can be posted on government websites.

- **Recycle generated heat**: Running HPC on supercomputers produces large amounts of unwanted heat; many resources, particularly water and extra energy, are used to cool the systems down, and excess heat contributes to thermal energy pollution. Thus, another way to reduce the environmental impacts involves reallocating the excess to heat nearby homes and buildings.

7.2 Letter to the UN

Dear Members of the Advisory Board,

We are writing in response to your September report on "Governing AI for Humanity." While it raises many valid points regarding Artificial Intelligence, we believe it is lacking in regards to the emergence of High Power Computing (HPC) and its potential negative environmental impacts. While HPC plays an instrumental role in underpinning many achievements in artificial intelligence, it currently accounts for nearly one million metric tons of global carbon emissions. As HPC infrastructure expands, these impacts will only grow.

Through a model that projects global HPC emissions using data from the top 500 supercomputers and their locations, we found HPC to produce around nearly one million metric tons of CO2 emissions. Additionally, we have projected a massive impact of HPC on air quality (AQI). Our model also predicted the impact of HPC on ocean acidification, finding tens of thousands of metric tons of biomass in dead shellfish. Our analysis shows that carbon emissions and these adverse environmental impacts are projected to increase as HPC becomes more and more important, especially with recent pushes for innovations in AI.

To help mitigate these impacts, we strongly urge the Board to adopt a more detailed set of goals regarding HPC for 2030. Specifically, we recommend the increased construction and implementation of renewable energy sources in areas with high concentrations of HPC, namely wind and nuclear power, which have the least carbon impact of renewable sources. This would decrease the carbon footprint by an order of magnitude.

We also urge the Board to implement various policies for a standardized, comprehensive global approach to this issue. These policies could include establishing international benchmarks for the emissions of data centers involved in HPC; this is one way to help countries stay on track to what they pledged to mitigate climate change at the 2015 Paris Agreement. The UN should also encourage countries to invest in innovations to reduce carbon emissions and increase energy efficiency of computing systems.

We hope the Board implements our suggestions and helps pave forward a future with responsible and environmentally-conscious HPC usage.

Sincerely,
Team 16209

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