Problem Chosen

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Summary Sheet

This report addresses the environmental impacts of high-performance computing (HPC), particularly its significant energy consumption and carbon emissions driven by artificial intelligence (AI) and data center operations. The study develops models to evaluate these impacts under different energy mixes by 2030, incorporating additional environmental factors. Key assumptions include the accuracy of data projections, global consistency in energy costs, and stability in energy production unaffected by climate variability or extreme events.

Our team created three interconnected models to analyze the problem. The Energy Suitability Model evaluates energy sources across a wide variety of geographies, factoring in dispatchability, availability, variability, predictability, and safety risks. Subsequently, a score is computed and further transformed to act as an electricity cost multiplier for final calculations. The Electricity Model estimates energy consumption proportions by source for data centers, using 2022 and 2030 trends, and predicts exponential growth in HPC energy demands. The Carbon Emissions Model computes emissions by energy type and quantifies their societal impacts using two social cost standards: $51/ton and $190/ton. Combined, these models provide insights into the environmental and economic costs from HPC energy consumption.

Key findings indicate that global HPC carbon emissions are projected to rise from 244 Mt in 2022 to 1175 Mt by 2030. Energy costs are expected to increase from $62.13 billion to $324.90 billion (or $445.90 billion under EPA standards). Geothermal energy is identified as an ideal fit for data centers due to its dispatchability, reliability, and consistency across temporal scales. However, it remains difficult to adequately implement geothermal energy into all settings, as the power source is restricted to select geological settings requiring high geothermal gradients and available subterranean fluids. However, with new technological breakthroughs such as hot dry rock technology, super-deep drilling, and enhanced geothermal systems, we remain optimistic about its potential.

The report's strengths lie in its clear parameters, comprehensive consideration of energy sources, and integration of regional variability. However, weaknesses include simplified assumptions about future AI trends and limited consideration of complex societal and economic factors. In conclusion, adopting sustainable energy sources such as geothermal energy could significantly reduce global carbon emissions and energy costs. The findings underscore the critical need to integrate environmental and energy sustainability into AI policymaking to ensure a balance between technological advancement and ecological preservation.

Contents

1 Introduction

1.1 Background

As an emerging technology, **high-powered computing** can change the social and cultural landscape for decades to come. Much repetitive and menial labour can be replaced or assisted mainly by **artificial intelligence**, saving time and cutting capital costs of projects for private and public sectors. There are, however, no free lunches when it comes to benefits offered by AI. According to the laws of thermodynamics, energy has to be used as an input for any meaningful work to be done. While AI largely displaces the metabolic energy usage of humans in the form of food, it nevertheless consumes other forms of energy, primarily electricity from utility-scale power generation.

In particular, energy consumption from data centers alone accounts for roughly 1 to 1.5% of global electricity use [3]. AI and cryptocurrency mining comprise a large proportion of data center electrical consumption. Due to its sizable energy intake, high-powered computing contributes to carbon emissions and, subsequently, climate change and its myriad of negative impacts. It is, therefore, paramount to calculate the monetary costs stemming from electricity consumption and carbon emissions to weigh against the value added by AI. This paper explores the costs of high-powered computing using different energy mixes and standardized using a 2022 value of 460 TWh [3] and a 2030 predicted value of 2000 TWh. The energy mixes are computed using existing geographies, with a suitability-adjusted coefficient multiplied by the electrical costs to account for local differences. Ultimately, the model's strength comes from its configurable parameters, unlike many black box models that are more opaque with the output.

1.2 Problem Restatement

The end goal of this report is to determine the carbon emissions of high-powered computing using different energy mixes projected into 2030, with the following steps:

1. Develop a model to determine the environmental impact of total carbon emissions resulting from energy consumption of High-Powered Computing (HPC), using different energy mixes from a varied proportion of energy sources.

2. Use the model to reconstruct for future changes with the growth of HPC and the increasing demand for energy in other sectors, specifically in 2030. Investigate the effects of increased and complete renewable energy usage on carbon emissions, as well as potential challenges.

3. Refine the model to account for another environmental aspect of HPC.

4. Write a letter to UN Advisory Board addressing the environmental impacts of HPC using our findings to support recommendations.

2 Variables and Assumptions

2.1 Variables

Subscripts (x)

Symbol	Definition	Symbol	Definition
F	Fossil fuels (oil, gas, coal)	w	Wind
g	Natural Gas	s	Solar
c	Coal	gt	Geothermal
p	Oil	nc	Nuclear
R	Sources excluding fossil fuels	bm	Biomass
h	Hydroelectric	$total$	All sources

Table 1: Subscripts for x (energy source)

The above table lists out all major sources of energy. For convenience, fossil fuels are grouped into gas, solid, and liquid forms of hydrocarbons as natural gas, coal, and oil. All other sources are grouped together (regardless of whether renewable) including nuclear, as R. Tidal's contribution in the energy mix is minuscule and grouped with hydro for convenience. Geothermal excludes energy from heating and cooling and only accounts for electricity. Biomass is an all-encompassing category with a very diverse set of combustible material.

The locations below are selected based on relevance, interest and curiosity. Energy mixes were found globally for 2022 and 2030 as a part of the requirement, and USA for its dominance in the AI sector. For 2030, Canada, China, and India were used for their unique geographies and development, as well as their varied energy mixes. 2030 projections of the energy sector was difficult to find for Iceland and Germany, but were kept for interest due to anomalous energy policies, especially Iceland. Idealland featured data systems powered only using geothermal, with "ideal" conditions such as no solar or wind variability (perhaps possible on a axial tilt similar to Uranus) for suitability calculations.

Location Index

Number	Location	Number	Location
1	2022 Global	8	2020 Iceland
2	2022 USA	9	2030 India
3	2030 Global	10	2022 Germany
4	2030 USA	11	Moon
5	2030 Canada	12	Mars
6	2030 China	13	Io
7	2030 Idealland	14	Titan

Table 2: Subscripts for y (locations)

Other solar system objects were also used out of curiosity to test the generalizeability of the suitability matrix. Further information about the selection process is described in section 4.1.

Variables and Derived Calculations

Symbol	Denotation
EP_x	Annual electrical production (TWh)
p_x	Proportion of electrical use by source
E_x	Electricity usage of data centers by source (TWh)
E_{year}	Electricity usage of data centers by year (TWh)
$\mathrm{CO2}_x$	Annual carbon emissions by data centers by source (g)
$\mathrm{CO2}_{totalMt}$	Total annual carbon emissions by data centers in Megatons
CC_A	Annual social costs of carbon emissions using estimate A (billions USD)
CC_B	Annual social costs of carbon emissions using estimate B (billions USD)
EC_x	Annual electricity costs of data centers by source (USD)
EC_{Bil}	Total annual electricity costs of data centers (billions USD)
TC_A	Combined annual costs of data centers using estimate B (billions USD)
TC_B	Combined annual costs of data centers using estimate B (billions USD)
$z_{x,y}$	Suitability score of resource x by location y
$Z_{x,y}$	Adjusted suitability coefficient
$ZCost_x$	Adjusted annual electricity costs based on geography by source (billions USD)
Z_{norm}	Normalized total adjusted annual electricity costs of data centers (billions USD)
k	Normalization factor
FC_A	Final annual adjusted cost of data centers using estimate A (billions USD)
FC_B	Final annual adjusted cost of data centers using estimate B (billions USD)

Table 3: Variables used

2.2 Assumptions

1. **Data used is accurate and projections will continue as expected into 2030.**
   Justification: Data is generally extracted from reputable sources (IEA projections, government statistics, peer-reviewed research, etc.), and point values are used instead of distributions. Some input requires subjective judgment and can only be used as reference values. These considerations are always explained in this report and are highly adjustable in the model for expert fine-tuning. Projections into 2030 follow sources such as the International Energy Agency and are the best available estimates. However, as humans, we are epistemically limited from absolute future knowledge. Extreme outlier events or unexpected feedback due to the butterfly effect can cause forecasts to stray from expectations. It is, therefore, paramount to note this limitation in our (and any) predictive models.

2. **The cost is consistent globally for each energy source.**
   Justification: Adjusting the energy source costs for each country or locality will add another dimension to our model and further complicate calculations. The important consideration is the

energy mix and proportion of each energy source used rather than specific costs per megawatt hour for local variability. Also, using distributions for energy costs will introduce stochastic and probabilistic calculations, which are beyond our abilities and time restraints.

3. **Availability of each energy source does not change from 2022 to 2030.**
   Justification: It is possible that the effects of petroleum depletion will be felt somewhat by 2030, or catastrophic events such as a Hormuz blockade will occur. It is also possible for Yellowstone to erupt or nuclear warfare to break out and cause a volcanic/nuclear winter, essentially disabling solar radiation on the surface of Earth. Scenarios like this are left out of our model due to their unforeseeability and the drastic effects that are difficult to predict. These events can be mentioned as thought exercises but are impractical to implement for our purposes.

4. **Energy production remains unaffected by climate variations.**
   Justification: El Niño–Southern Oscillation and other climate fluctuations such as the Atlantic multidecadal oscillation, Pacific decadal oscillation, and Indian Ocean Dipole may cause energy variability in output for solar, wind, and hydroelectric energy sources. Additionally, anthropogenic climate impacts may further trigger events such as AMOC collapse and Sahara/Taklamakan greening. These reversals to previous climate regimes feature tipping points that are difficult to pinpoint, affecting biomass, solar, wind, and hydro resource availability. Introducing these factors will make the model overly complicated for our purposes.

5. **Price for each energy source remains constant from 2022 to 2030.**
   Justification: Policy shifts, warfare, technological developments and natural disasters, the main factors causing energy price fluctuations in our model, are excluded from this report due to their complex and random nature. They cannot be adequately accounted for in our (or most) model(s) and are only briefly mentioned here.

6. **Any other energy sources not considered amount to negligible values.**
   Justification: Some energy categories, such as marine energy (tidal and currents), are not considered due to negligible generation in most geographies. Excluding them from the model does not affect calculations in any significant amount.

7. **Artificial Intelligence development does not encounter discontinuous breakthroughs and progress, and grows exponentially.**
   Justification: Events such as AI singularity, hostile AI takeover, accidental alien contact, coming of the Messiah, etc., are not considered for AI development, which is assumed to be exponential with no discontinuities. While possible, they are beyond the scope of this report.

8. **Cryptocurrency mining grows exponentially.**
   Justification: We assumed that the growth of the cryptocurrency mining industry would be exponential, similar to AI, to avoid overcomplicating our model. This assumption is crucial for maintaining the simplicity and accuracy of our model.

3 Data and Methodology

For the grams of carbon emission per kilowatt-hour estimates, the following sources were used for coal and biomass [10], natural gas [14], solar and nuclear [7], wind [15], hydro [11], and geothermal [6]. For carbon emissions with a range of values, the median is used as the distribution tends to be skewed. $CO2_{tx}$ is computed in grams per terawatt-hours for multiplication convenience. Levelized cost of electricity (LCOE) values are sourced from EIA [2], and LFSCOE values are sourced from [9]. The conservative values of Texas were used in favor of Germany due to its relative climatic representativeness for global wind and solar storage needs. Levelized full system costs of electricity (LFSCOE) consider costs such as storage in addition to energy production. The average utilization rates are only used for reference since LCOE values already account for capacity factors in the calculation. The energy cost ranges (USD per MWh) are compiled from multiple sources, and a final estimate value is used based on the median of which and subjective estimates.

	g CO2/KWh	Average value	g/TWh (CO2_tx)	Average utilization rates
Coal	**1040**	**1040**	1040000000000	55%
Gas	**560**	**560**	560000000000	87%
Oil	**915**	**915**	915000000000	-
Hydro	**6**	**6**	6000000000	54%
Wind	**5-8**	**7**	7000000000	41%
Solar	**10-50**	**30**	30000000000	29%
Geothermal	**35**	**35**	35000000000	90%
Nuclear	**4-100 (12)**	**12**	12000000000	90%
Biomass	**49**	**49**	49000000000	83%
	Total LCOE	Total LFSCOE	Energy cost range	Final estimates (LFSCOE_x)
Coal	117.27		70-145	90
Gas	39.94		35-45	40
Oil	-			105
Hydro	64.27		35-130	65
Wind	40.23	291	225-600	300
Solar	36.49	413	200-1500	400
Geothermal	39.82		35-100	45
Nuclear	88.24	122	80-140	120
Biomass	90.17	117	90-130	115
	($/MWh)	($/MWh)	($/MWh)	($/MWh)

Figure 1: Data parameters used

Some things to note here: Solar and wind are usually quite cheap to produce, but due to irregularities in time, their cost is heavily increased with storage considerations. Geothermal power is theoretically inexpensive to produce, but the value is inflated (or deflated) by existing power plants only built on sites with high geothermal gradients and suitable geological conditions, which is a form of survivorship bias. Hydro should technically be cheaper, but the scale of the engineering projects inflates costs significantly.

The values E_{2022} and E_{2030} (annual electricity usage from data centers) are estimated to be 460 TWh and 2000 TWh, based on a model of exponential growth using data from [3]. Data centers from AI used about 340 TWh while cryptocurrency mining accounted for the rest of 120 TWh. These key values will be used in most later calculations, which makes them critical assumptions.

4 Model Design

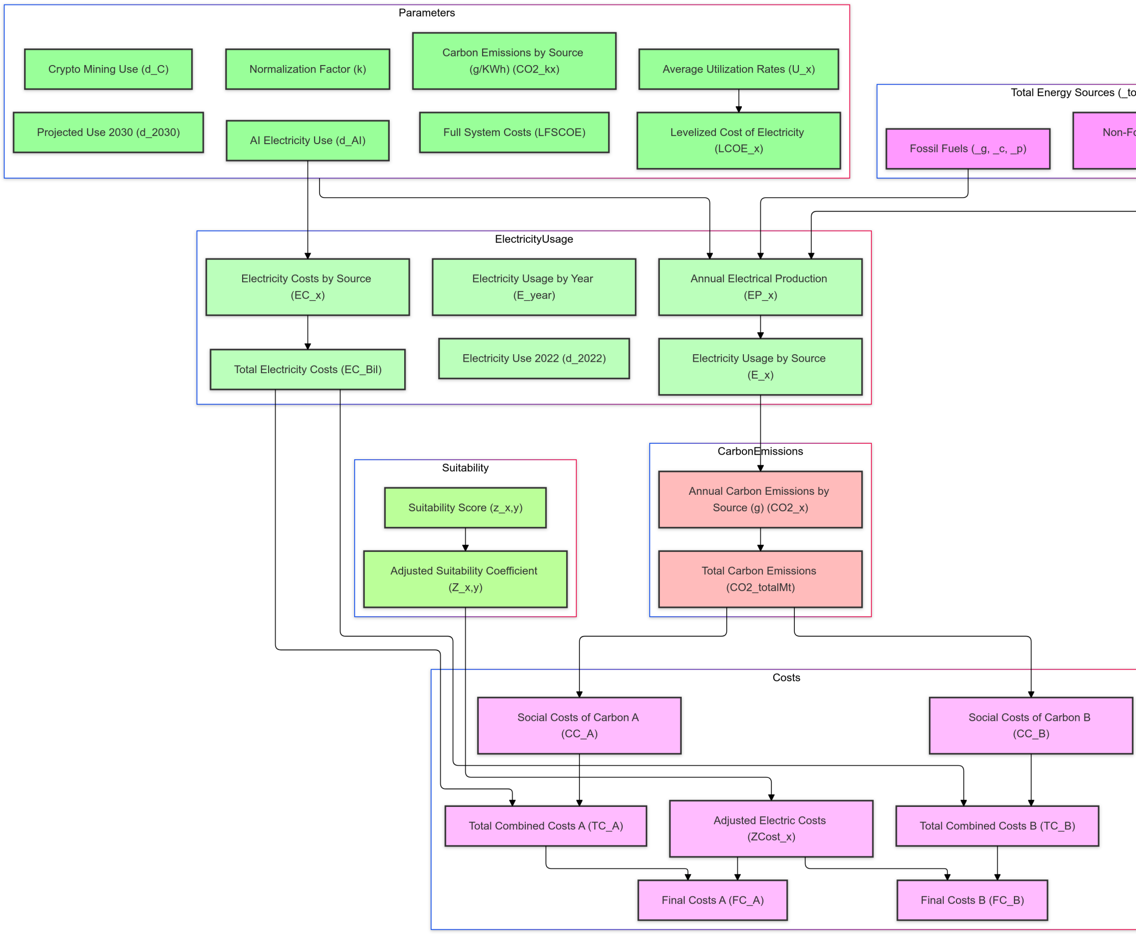


Figure 2: Flowchart for calculations used in the model

4.1 Country selection

We selected the US, Canada, China, Iceland, Germany and India to model electricity usage and the subsequent cost of data centers. We chose the US and China specifically for their government-subsidized high-powered computing (HPC) investments. We aim to create an all-encompassing model accommodating most geographical, infrastructural, and economic scenarios. In the process, we created Idealland as a control with ideal energy generation. Assuming perfect conditions where the sun shines, the wind blows with no variability or downtime, and geothermal is available in all locations with equally high resources, Idealland relies purely on geothermal to supply its data center energy needs. This is in consideration of the fact that geothermal energy is the most ideal for data centers using our suitability matrix. Iceland was another wildcard; the scale of its energy generation, aside from geothermal and hydroelectric, was minimal. Adding in Iceland provides a real-life example of nearly 100% renewable energy use. The rationale behind choosing India is that they are one of the fastest growing digital economies. We used the 2030 projection of India's energy mix to compare and contrast with Western development [13]. Canada was one of our options because of its green energy policies. Canadian society is especially pushing for a greener energy sector, with its geographic location also offering many types of renewable energy generation. Hydroelectricity is dominant, generating around 60% of Canada's power, but the country also features a different energy mix from Iceland [8]. Lastly, we included global averages and the global projection for 2030.

4.2 Energy Mixes and Suitability Model

Before creating our model, we needed to create multiple suitability matrices corresponding to each country. A suitability factor is important because it adds a dimension to the model, accounting for geographical variability in resource availability and variability.

4.2.1 Dispatchability

Dispatchability measures how easy it is to scale (ramp up or down) the resource production within a short time frame. For example, hydroelectric power plants can dispatch quickly by allowing more water flow in response to demand, but photovoltaics can only generate power proportional to the solar irradiance levels. The dispatchability rating ranges from 0 to 3, with zero being non-dispatchable and three having short dispatching times. Dispatchability is constant for each location.

4.2.2 Geographic Availability

Geographic availability measures the country's accessibility to a resource and is therefore variable by location. For example, solar energy is more suited to areas with low cloud cover and high solar irradiance, while geothermal energy is limited by the temperature gradients and presence of pressurized underground steam. The availability rating could also indicate resource abundance, such as the amount of oil in a region. The Geographic availability rating ranges from 0 to 3, with a three being the most accessible. For non-terrestrial environments, we used much larger values to highlight availability contrasts.

4.2.3 Variability

Variability measures how much temporal variation a resource usually entails at a location. For example, nuclear power plants can generate power in all weather conditions (although not very dispatchable), but solar power can only generate energy during the daytime. Variability is also geographically dependent and higher values indicate little diurnal, seasonal, or market variation.

4.2.4 Predictability

Predictability measures to what degree the energy output can be anticipated in advance. This factor is a constant across geography since location has limited influence. For example, wind is much less predictable than solar since wind speeds are more chaotic than day-night cycles and cloud cover. Predictability ranges from 0 to 4, four being the most predictable.

4.2.5 Safety Risk

Safety risk measures the security risks of generating energy for the workers, environment, and the surrounding community. The safety risk is a constant factor across all geographies, having a high negative coefficient of -8, due to its paramount priority in energy considerations. Safety risk ranges from 1 to 3, with three being the most prone to catastrophic events. Hydroelectricity and nuclear energy are the most dangerous due to ecosystem damage and the potential for dam failures and meltdowns, respectively.

4.2.6 Generating Suitability Rating Scores

All of these factors (after being multiplied by a constant selected to model the weights of each category) contribute to the overall suitability of that particular resource in that location; all factors are added except availability, which is multiplied with the rest due to the practical difficulty of generating energy in places which do not support them. Due to negative values of wind and solar, 8 is arbitrarily added to the suitability score except in Idealland to reflect government subsidies and public interest.

$$z_{x,y} = \frac{(3d + 6v + 2p - 8s) * 0.4a}{50}$$

Symbol	Definition
$z_{x,y}$	Suitability score
x	Energy source
y	Location
d	Dispatchability
v	Variability
p	Predictability
s	Safety risks
a	Availability

1	Energy Source	Dispatchability	Geographic Availability	Variability	Predictability	Safety Risk	Suitability	out of 50
Global	Importance coefficient	3	0.4	6	2	-8		
	Location dependent?		Y	Y				
	Coal	3	3	3	4	2	22.8	0.456
	Gas	3	2	3	3	2	13.6	0.272
	Hydro	3	0	2	2	3	0	0
	Wind	0	1	1	0	1	7.2	0.144
	Solar	0	2	0	1	1	3.2	0.064
	Geothermal	3	0	4	4	1	0	0
	Nuclear	0	2	4	4	3	6.4	0.128
	Biomass	2	2	2	3	2	6.4	0.128
	Oil	3	2	1	2	2	2.4	0.048

Figure 3: Suitability matrix for 2022 globally

1			2			3			4			5		
Global	Geographic Availability	Variability	2022 USA	Geographic Availability	Variability	2030 Global	Geographic Availability	Variability	2030 USA	Geographic Availability	Variability	2030 Canada	Geographic Availability	Variability
Coal	3	3		3	3		3	3		3	3		2	3
Gas	2	3		3	3		2	3		3	3		3	3
Hydro	0	2		1	2		0	2		1	2		1	2
Wind	1	1		2	1		1	1		2	1		2	2
Solar	2	0		3	0		2	0		3	0		2	0
Geothermal	0	4		2	4		0	4		2	4		2	4
Nuclear	2	4		2	4		2	4		2	4		3	4
Biomass	2	2		3	2		2	2		3	2		3	2
Oil	2	1		3	1		2	1		3	1		3	1

6			7			8			9			10		
2030 China	Geographic Availability	Variability	2030 Idealland	Geographic Availability	Variability	2020 Iceland	Geographic Availability	Variability	2030 India	Geographic Availability	Variability	2022 Germany	Geographic Availability	Variability
Coal	3	3		3	4		0	4		3	3		2	3
Gas	2	2		3	4		0	4		2	2		1	2
Hydro	1	2		3	4		4	3		1	2		1	2
Wind	1	1		3	4		2	3		1	1		3	1
Solar	2	0		3	4		1	0		2	0		3	0
Geothermal	2	3		3	4		3	4		0	3		2	3
Nuclear	3	4		3	4		0	4		2	4		0	4
Biomass	3	2		3	4		1	1		3	2		3	2
Oil	1	1		3	4		0	0		1	1		1	1

11			12			13			14		
Moon	Geographic Availability	Variability	Mars	Geographic Availability	Variability	Io	Geographic Availability	Variability	Titan	Geographic Availability	Variability
Coal	0	0		0	0		0	0		0	0
Gas	0	0		0	0		0	0		25	4
Hydro	0	0		0	0		0	0		1	2
Wind	0	0		3	2		0	0		0	0
Solar	5	2		1	1		0	0		0	0
Geothermal	0	0		0	0		15	4		6	4
Nuclear	8	4		2	4		12	4		3	4
Biomass	0	0		0	0		0	0		0	0
Oil	0	0		0	0		0	0		25	4

Figure 4: Geographic variations of suitability

Suitability Coefficient		2022 Global	2022 USA	2030 Global	2030 USA	2030 Canada	2030 China	2030 Idealland
	Coal	**0.456**	0.456	**0.456**	0.456	0.304	**0.456**	0.600
	Gas	0.272	0.408	0.272	0.408	0.408	0.176	0.552
	Oil	0.048	0.072	0.048	0.072	0.072	0.024	0.504
	Hydro	0.000	0.008	0.000	0.008	0.008	0.008	0.312
	Wind	0.144	0.128	0.144	0.128	0.224	0.144	0.384
	Solar	0.064	0.016	0.064	0.016	0.064	0.064	0.432
	Geothermal	0.000	**0.528**	0.000	**0.528**	**0.528**	0.432	**0.792**
	Nuclear	0.128	0.128	0.128	0.128	0.192	0.192	0.192
	Biomass	0.128	0.192	0.128	0.192	0.192	0.192	0.480
		2020 Iceland	2030 India	2022 Germany	Moon	Mars	Io	Titan
	Coal	0.000	**0.456**	0.304	0	0	0	0
	Gas	0.000	0.176	0.088	0	0	0	**4.6**
	Oil	0.000	0.024	0.024	0	0	0	4.2
	Hydro	0.224	0.008	0.008	0	0	0	0.008
	Wind	0.320	0.144	0.112	0	0.096	0	0
	Solar	0.112	0.064	0.016	0.24	0	0	0
	Geothermal	**0.792**	0.000	**0.432**	0	0	**3.96**	1.584
	Nuclear	0.000	0.128	0.000	**0.512**	**0.128**	0.768	0.192
	Biomass	0.016	0.192	0.192	0	0	0	0

Figure 5: Matrix of all suitability coefficients, 8 added to values in magenta

More on the adjusted suitability coefficient can be found in Section 4.7.

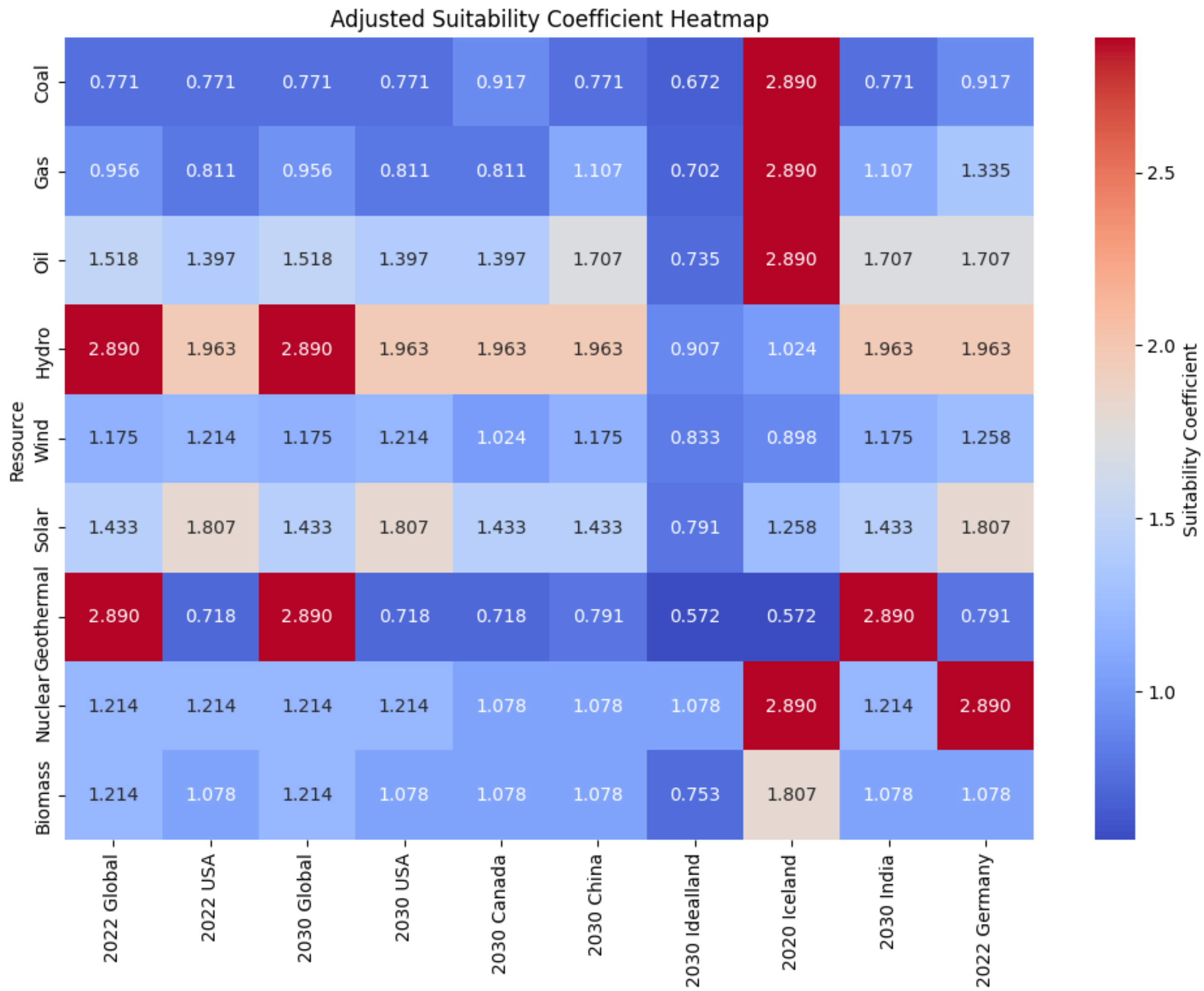
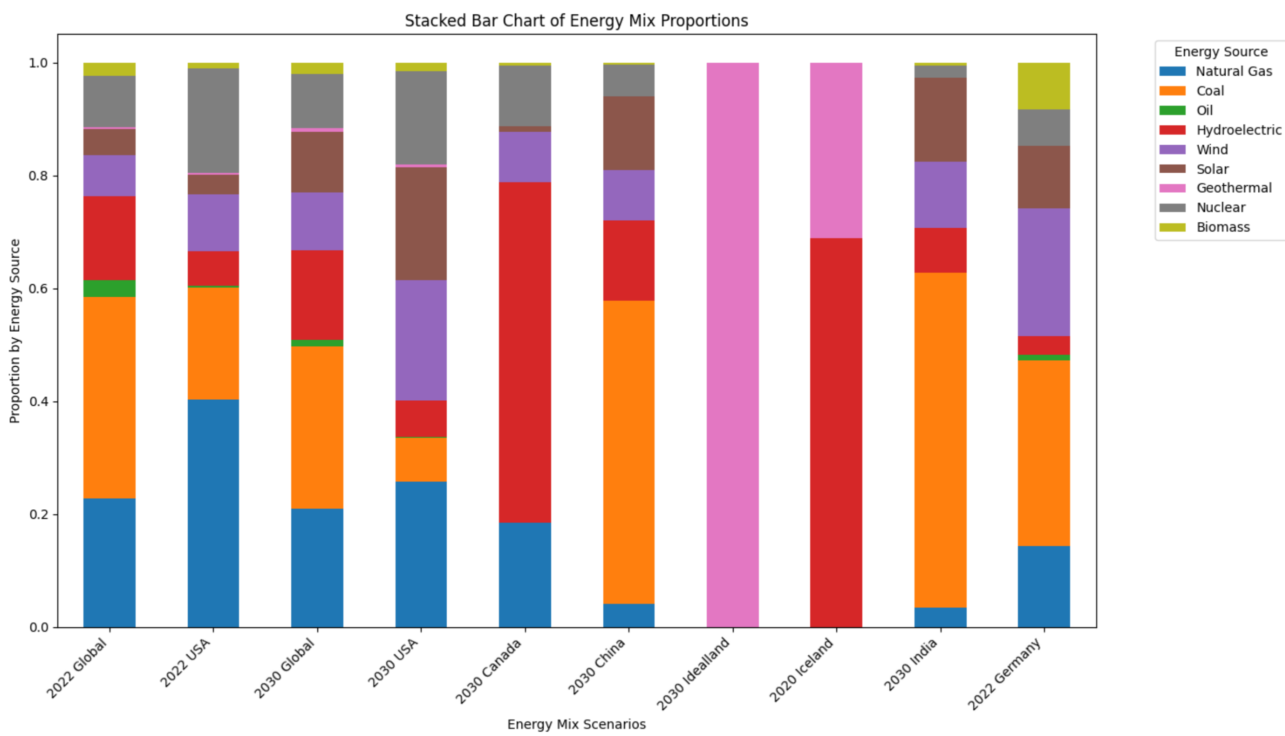


Figure 6: Heatmap of Adjusted Suitability Coefficient (This is a cost modifier, red values are worse resources locally and blue values are suitable resources.)

4.3 Electricity Model

4.3.1 Electricity Consumption Module

Firstly, we found the energy mix–the ratio of all of the different types of energy generation. We chose only primary sources of energy: biomass, solar, wind, hydro, nuclear, oil, gas, and coal. This is important to make distinct, since every country has a different energy mix and generating the same amount of energy could have different costs depending on the type. We split the above into two categories, renewable energy and fossil fuels to have a frame of reference for the proportion between the two. In our model we have the amount of energy generated in a year (2020, 2022, 2023), as well as the predicted average global generation and the predicted USA generation in 2030. Using these values, a table of proportions is generated, which we multiply by a coefficient of 460 TWh (terawatt hours) for the total energy required by all global data centers annually from this decade, and a coefficient of 2000 TWh as the predicted consumption value by data centers in 2030. This gives us a numerical representation of the energy consumed by these different data centers. It also further outlines the energy problem with increasing growth of HPC usage.



4.3.2 Electricity Generation Cost Module

Before calculating the average electrical cost of a data center, we first found the average cost of each type of generation (wind, solar, oil, etc). We referred to the LCOE (levelized cost of electricity) and suitability , as explained in the research by Robert Idel in his paper: "...the expected lifetime generation. . . and the expected costs. . . are calculated. After dividing total costs by total generation, the final number (usually in USD/MWh) is derived" [3]. The purpose of using the LCOE is to factor in all of the costs of each energy method. For example in a hydroelectric plant, we need to factor in the building costs, costs of rerouting the water path, repair costs, permit costs and etc. Overall the LCOE is a more realistic metric than metrics such as CapEx and Power Capacity Metrics. We also referred to the LFSCOE (Levelized Full System Costs of Electricity)–which factors in the variability of sources like wind and solar energy– to estimate the final cost in USD/TWh after comparing both.

4.3.3 Data Center Electricity Module

After obtaining the types of energy used to power a data center for each region, we multiply each value by the corresponding cost of energy generation (we found this in 4.3) to obtain the average cost. Totalling the energy types, we find the average electrical cost of a data center by the billions in USD. With this data, the variability between the cost of a data center and the location of the data center can be represented. This variability is a correct depiction of challenges and benefits each country has, with understandable and detailed factors.

4.4 Carbon Emissions Model

4.4.1 Evaluation Factors

In order to determine the carbon emissions of data centers we first evaluated the emission of carbon dioxide equivalents per megawatt hour (KgCO2 eq./Kwh) and the results from the electricity use model to evaluate the amount of carbon emissions based on energy generation type. Using a metric created by the Biden administration that estimates the social cost of carbon at $51 per ton of CO2, and a metric created by the Environmental Protection Agency that puts the social cost of carbon closer to $190 per ton. The metrics discussed by Elijah Asdourian and David Wessel allow us to more accurately measure the impact of carbon emissions on society.

	Suitability Adjusted Score of Data Centre Costs										
	SCENARIOS	**2022 Global**	**2022 USA**	2030 Global	2030 USA	2030 Canada	2030 China	2030 Idealland	2020 Iceland	2030 India	2022 Germany
	Energy Mixes	1	2	3	4	5	6	7	8	9	10
	Z_g	4.014104282	6.007812203	15.98306131	16.65561081	11.94321005	3.658758488	0	0	2.965961006	3.538757692
	Z_c	11.38914578	6.33328898	40.05425092	10.93998564	0	74.51652452	0	0	82.49587609	12.45250711
	Z_p	2.158113793	0.2543903096	3.792221194	0.4507810218	0	0.03691462922	0	0	0.1445760932	0.8569538958
	Z_h	12.87428946	3.566250237	59.08452531	16.5761768	154.0865873	36.23816012	0	21.0783278	20.27524328	1.883643158
	Z_w	11.7965116	16.98432003	72.10383892	154.6134348	55.23930366	62.59379963	0	0	82.1901677	39.50688636
	Z_s	12.0949596	11.40513365	124.7403951	289.0983089	9.659816282	150.5335465	0	0	170.1644765	36.5710805
	Z_gt	0.1903815986	0.05675039678	1.563809494	0.298009243	0	0	51.52423267	3.694007225	0	0.005971164761
	Z_nc	6.132784138	12.33320595	27.70011231	48.4785868	27.96780384	14.33030415	0	0	6.112111635	10.09597228
	Z_bm	1.504602915	0.6390235306	5.92449146	3.699043384	1.392336555	1.072109186	0	0	1.599586328	4.792639284
	Z_total	62.15489316	57.58017528	350.9467061	540.8099374	260.2890576	342.9801173	51.52423267	24.77233503	365.9479986	109.7044115
	Z_norm	$49.68	$46.02	$280.50	$432.25	$208.04	$274.13	$41.18	$19.80	$292.49	$87.68
FINAL ADJUSTED COST	Z_TOTALA	$62.13	$56.34	$324.90	$456.51	$219.17	$334.08	$44.24	$20.15	$358.12	$98.04
(Billions USD)	Z_TOTALB	$96.06	$84.48	$445.90	$522.62	$249.50	$497.46	$52.58	$21.11	$536.98	$126.26

Figure 7: Suitability Adjusted Costs of Data Centers

4.4.2 Model Construction

To construct our carbon emission model we used previous literature on the carbon emissions of all the energy generation types we studied, and metrics that estimate the social cost of carbon emissions.

The social cost of carbon metric is used to estimate the social impacts of emissions from new building projects or power plants. The metric has evolved greatly over the years: "The Obama administration initially estimated the social cost of carbon at $43 a ton globally, while the Trump administration only considered the effects of carbon emissions within the United States, estimating the number to be between $3 and $5 per ton. As it stands, the official estimate from the Biden administration is $51, but in November 2022, the EPA proposed a nearly fourfold increase to $190" [5]. Using the social cost of carbon emissions, we can generate an economic representation of the emissions generated by our data centers.

4.4.3 Carbon Emissions Module

To calculate the carbon emissions of each energy source we multiplied our results from the consumption of each type of generated energy, by its corresponding Carbon dioxide equivalent (gCO2 eq./TWh), which is a metric that compares the energy absorption ability of different molecules in the atmosphere and converts them to a standardized unit of carbon dioxide, for each energy type in each country during the years 2022 and 2030. Note that although fossil fuels have a significantly higher carbon footprint, renewable energies also emit a significant amount of carbon. For example biomass emits around 49,000,000,000 g /TWh, and even solar power plants emit carbon dioxide. This brings to attention the need to not only use renewable energy sources–but to also contribute other actions to lower humanities carbon footprint.

4.4.4 Social Cost of Carbon Module

We took our values from the carbon emission for each energy source and multiplied them by the social cost of carbon (SCC) values created by the Biden administration and the Environmental Protection Agency to obtain our final results for the estimated social cost of each energy source in the context of powering data centers. This social cost of carbon value allows us to evaluate the impact of carbon emissions on society and when combined with our results from the cost of electricity production and suitability metrics we are able to construct a model for the overall socioeconomic impact of each energy source depending on the country and time period.

4.5 Combined Model

To evaluate the overall suitability of different power sources in countries in the year 2022 and 2030 we constructed a model integrating our suitability matrices, our electricity cost model and our social cost of carbon model to get an estimate of the transformed cost of each energy source. To arrive at this we added the social cost of carbon results from our first model to the suitability adjusted data center energy cost. The suitability adjusted costs were created by multiplying the cost of energy production per TWh by the suitability scores described by the suitability analysis matrices, which take into account five factors into determining the overall suitability of an energy source for a specific region. These final results allow us to analyze the overall impact of each type of energy source while adjusting for how suitable the power source is.

4.6 Formulas

$Z_x = Cost_x \times Z_{x,y}$

$Z_{norm} = \frac{Z_{total}}{k}$

$Z_{totalA} = Z_{norm} + Cost_{BilA}$

$Z_{totalB} = Z_{norm} + Cost_{BilB}$

$Cost_{BilA} = C_{totalMegaton} \times FC_A$

$Cost_{BilB} = C_{totalMegaton} \times FC_B$

$C_x = E_x \times CO2_{kx}$

Carbon Emissions of Data Centres		g							
SCENARIOS	**2022 Global**	**2022 USA**	2030 Global	2030 USA	2030 Canada	2030 China	2030 Idealland	2020 Iceland	2030 India	2022 Germany
Energy Mixes	1	2	3	4	5	6	7	8	9	10
C_F	241794255637346	200127754156231	855876983127676	454084723441615	206067415730337	1.16282E+15	0	0	1.27415E+15	198456483676819
C_g	58775195468907	103658424329159	234026693528079	287374890254609	206067415730337	46258111031002	0	0	37498991528842	37115447747583
C_c	170627280158580	94882609612403	600075547720977	163898156277436	0	1.11637E+15	0	0	1.23592E+15	156965456866679
C_p	12391780009859	1586720214669	21774741878620	2811676909570	0	188484910907	0	0	738200887455	4375579062557
C_R	2362949280351	2297414783542	14629816167212	21526777875329	12157303370787	12580492326707	60000000000000	6918284518828	12628479225494	4589513040306
C_h	411209671213	167732293381	1887182070008	779631255487	7247191011236	1704397981255	0	1899665271967	953610326745	88593835492
C_w	234251879462	326416219439	1431818181818	2971466198420	1258426966292	1242970439798	0	0	1632109721662	732912639066
C_s	633079225488	473304615385	6529211785444	11997366110623	505617977528	7879287259244	0	0	8906817265026	1517672806858
C_gt	51236877739	61443053071	420863762277	322651448639	0	0	60000000000000	5018619246862	0	5872697428
C_nc	505131508610	1015834046512	2281541173508	3992976294996	2595505617978	1329900092698	0	0	503428801936	349341601313
C_bm	528040117839	252684555754	2079199194158	1462686567164	550561797753	423936553713	0	0	632513110125	1895119460150
C_total	244157204917698	202425168939773	870506799294888	475611501316945	218224719101124	1.1754E+15	60000000000000	6918284518828	1.28678E+15	203045996717126
C_totalMegaton	**244.1572049**	**202.4251689**	**870.5067993**	**475.6115013**	**218.2247191**	**1175.401586**	**60**	**6.918284519**	**1286.78338**	**203.0459967**
Cost_carbonA	$12,452,017,451	$10,323,683,616	$44,395,846,764	$24,256,186,567	$11,129,460,674	$59,945,480,894	$3,060,000,000	$352,832,510	$65,625,952,400	$10,355,345,833
Cost_carbonB	$46,389,868,934	$38,460,782,099	$165,396,291,866	$90,366,185,250	$41,462,696,629	$223,326,301,370	$11,400,000,000	$1,314,474,059	$244,488,842,275	$38,578,739,376
Cost_BilA	$12.45	$10.32	$44.40	$24.26	$11.13	$59.95	$3.06	$0.35	$65.63	$10.36
Cost_BilB	$46.38	$38.46	$165.40	$90.37	$41.46	$223.33	$11.40	$1.31	$244.49	$38.58

Figure 8: Carbon Emission Matrix

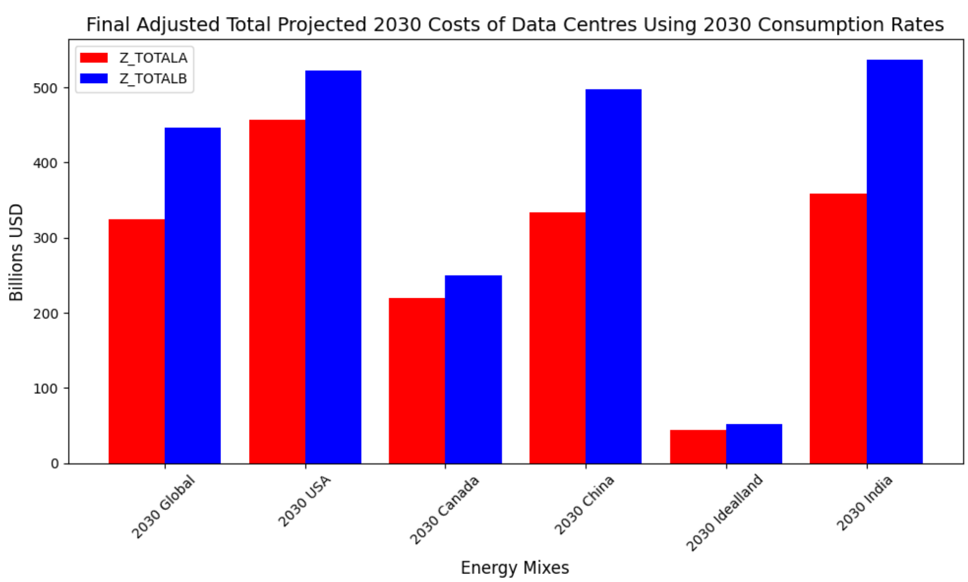


Figure 9: Final Adjusted Costs (2030)

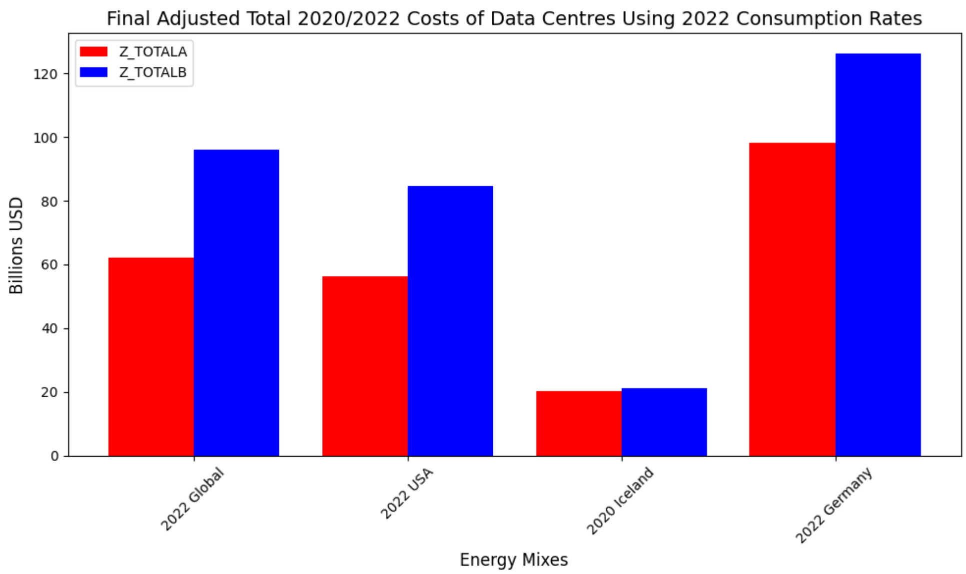


Figure 10: Final Adjusted Costs (2022)

4.7 Energy Mixes and Localization

Now that we have our suitability matrices, electricity model, and carbon emissions model, we can combine them to find the average cost. In order to account for localization factors of energy generation, we use the suitability matrix and apply it to the costs of our electricity model. This creates a higher degree of flexibility in our model, due to the realistic variables related to location. Each value (for example the cost of generating energy with wind power in Canada), is multiplied by its corresponding suitability rating, after adjustment. We adjust the rating so that more suitable values are lower. Here is the adjustment equation we used:

$$adjusted\ suitability = (1.5 + (0.2 - rating0.25))2$$

The suitability adjusted electricity cost is then added to two carbon emissions costs: one with the carbon cost estimate by the Biden administration and one by the Environmental Protection Agency. Converting to billions of USD, we arrive at our modelled cost of every data center, by location. Observe that by 2030, the costs have been multiplied by a factor of around 5.

5 Strengths, Weaknesses, and Limitations

5.1 Strengths

Our model has clear parameters and variables, allowing easy fine tuning to fit each specific energy mix. We also tested the robustness of our model against a wide variety of energy mixes, ensuring that our model can stand against any energy mix. We also included a wide variety of energy sources, ensuring that our model stays accurate and relevant to real world complexities.

We used data from industry experts and comprehensive research, while also considering finer details such as life expectancy of power sources and dispatchability, allowing us to form a realistic model of this situation.

5.2 Weaknesses

We included a simplified prediction of future AI trends. The complexity of real-world AI trends makes it very difficult to model, needing to consider policies, economics, public opinions, and many more factors.

The energy cost is not consistent across the world. We obtained a range as the energy cost for each source, so we simplified the range to a single reasonable value using our subjective judgment, since it would be unrealistic to create a model that takes a range as an input.

On a similar note, our initial suitability matrix also was sourced from our subjective judgment. Having arbitrary suitability scores means that a key variable in our model is prone to bias. However, such is often the case with complex models, with bias also causing the discrepancy in the Biden carbon cost estimate and the EPA carbon cost estimate. This can somewhat be overlooked as our model only provides an estimate and uses reasonable values for our suitability matrix.

Our model doesn't have a sensitivity analysis. We used a fairly linear, deterministic model, so we concluded that a sensitivity analysis would not be necessary for our model.

5.3 Limitations

We only considered the costs of AI, not the benefits. AI is providing significant amounts of benefit to society, from being a tool to seek advice to being able to save time. Cryptocurrency also stimulates the economy and can be beneficial if regulated correctly.

We did not take into consideration the effects of policy changes on AI trend. It will be difficult to future political changes and adjust the model accordingly.

We used a deterministic forecast, which provides both benefits and downsides. It is easy to rerun with different parameter values, but our model doesn't take statistical uncertainties into account.

We did not consider the distribution of data centers worldwide. This is important because global data centers skew towards the US energy mix. There is a significant majority of data centers in the US, resulting in an uneven energy mix in the global data center consumption.

6 Conclusion

In conclusion, we determined that generally the most suitable energy source for most countries is geothermal energy due to its high dispatchability. In addition, while geothermal energy is dependent on volcanically active regions it is still readily available in many countries. Furthermore, geothermal energy is a very stable energy source since "the average life expectancy of a geothermal power plant is very long, usually between 20 to 30 years" [12]. Apart from lasting a long time, it also provides a long term uninterrupted and predictable power output since the earth's temperature does not vary noticeably, being able to meet the 24/7 demand of data centers. The only downside is that the exploitation of geothermal energy is, on rare occasions, dangerous. Geothermal is often extracted in remote areas, limiting the medical aid available in case of an incident. Due to geothermal's high suitability in most regions, we can predict that a phasing out of fossil fuels for geothermal would not only reduce our carbon emissions from 244 Mt to 70 Mt of global CO2 predicted for 2030, resulting in a reduction of over 3 times. Furthermore, it would represent a cost reduction of 178 billion us dollars in the year 2030.

7 United Nations Advisory Board Letter

Dear United Nations Advisory Board,

In September of this year, you released a report titled "Governing AI for Humanity." In this report, you advocated for the ethical development of AI, laid out governance mechanisms for AI, and discussed the benefits and risks associated with AI. You analyzed AI with lenses concerning socio-economic equity, information integrity, weaponization, etc. We noticed that all of these lenses concerned societal, economic, and ethical sustainability.

However, we believe this report was missing crucial aspects of sustainability, including environmental and energy sustainability. We believe that the energy consumption risks associated with AI—and High-Powered Computing (HPC) in general—require further clarification. Our group of environmentally dedicated individuals has taken it upon ourselves to conduct extensive research into the subject of HPC and energy generation. We have come up with a forecast of future HPC energy consumptions with varying energy mixes, which we hope will prove to be useful insight for your future reports.

Firstly, we would like to introduce the data center, the critical infrastructure keeping all of the internet and—in effect—technological civilization–alive. Data centers store data, perform giant computations (including AI), connect the global economy, and secure our information. However, these functions come at a great cost; it is estimated that all of the combined data centers in the world right now have consumed 460 terawatt-hours of electricity an hour in 2022! That is enough to power 43 million U.S. homes for a year. It is also projected that by 2030, this number will increase to 2000 terawatt-hours. [4]

As such, you can begin to visualize the importance of energy when it comes to AI and HPC. The number one thing that our economic world cares about when it comes to energy is the cost, and the environment is after the cost. Thus, we created a model that would calculate the cost of generating electricity for a few chosen countries, as well as future projections. In our model, we have two main categories, the cost of electricity and the cost of carbon emissions, to satisfy the above criteria.

For the cost of electricity, we considered the different ways a country generates electricity, and combined with many other factors, we calculated an average cost based on the value of 460TWh mentioned earlier. In our carbon emissions cost, we looked at the average emissions created by each type of energy generation and calculated the costs corresponding to those emissions. For your reference, the 2022 estimated global emissions from generating electricity for data centers was 244.1572049 megatons, the same as the annual emissions of around 53 million gas cars.

Totalling these costs, we estimated that the global cost of generating electricity for all global data centers was $62.13 billion USD based on the carbon cost estimated by the Biden administration and $96.06 billion USD based on the carbon cost estimated by the EPA, projected to rise to $324.90 billion USD and $445.90 billion USD respectively.

After presenting our data, we want to use it to stress the importance of considering the technical side of HPC, not just the political and ethical side of things. As important as they are, protecting our earth's environment and maintaining an energetically sustainable way to use HPC reigns supreme.

Remember this? “To limit global warming to 1.5°C, greenhouse gas emissions must peak before 2025 at the latest and decline 43% by 2030.” [1] We cannot be creating policies for governance, if we cannot even keep our planet alive! In summary, we are strongly advocating for you, and in fact, the whole world, to put the environmental and energy costs of AI and HPC first, and we are eagerly awaiting your updated report.

Thank you,

Bruce Ji, Jasper Edens, Steven Su, Jonathan He

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