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MEASURING THE IMPACT OF DATA CENTERS IN THE UNITED STATES ECONOMY: MONETARY DAMAGE FROM AIR POLLUTION AND GREENHOUSE GAS EMISSIONS.

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ABSTRACT

This paper quantifies the environmental externalities associated with electricity consumption by data centers in the United States, focusing on damages from local air pollution and greenhouse gas (GHG) emissions. Using facility-level data for approximately 2,800 operational data centers in 2025, combined with electricity grid characteristics and emissions data, the analysis estimates pollution impacts through the AP4 integrated assessment model and applies the social cost of carbon for GHG valuation. Results indicate that data centers consume roughly 250 TWh of electricity—about 5–6% of U.S. generation—and generate approximately $25 billion in gross external damages (GED), with a range of $10–$33 billion. These damages are highly geographically concentrated, with Texas and Virginia accounting for 30%of the national total. While GED comprises about 5% of industry GDP, this ratio varies widely across states, exceeding GDP in some regions. Planned data center expansion could increase electricity demand and associated damages by up to 85% in the near term. Despite these environmental costs, preliminary comparisons suggest that the damages attributable to AI-related energy use are small relative to potential productivity gains.

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I. Introduction

The rapid growth of data centers in the United States (U.S.) is raising concerns because of the potentially wide-ranging impacts of this growth on the energy system and on environmental conditions in local communities (Blunt and Hiller, 2026; Hudson, 2026; Rust and Parker, 2026). At a systems level, data centers are electricity-intensive, and the surge in demand for power is straining regional electricity grids, complicating long-term planning and potentially increasing electricity prices. Quick expansion of a sector with large loads means that in some regions, utilities must accelerate investments in generation, transmission, and distribution infrastructure (Brown, 2026). In other cases, older generation assets that had been retired are being brought back online (Plumer, 2024). The disruptive change associated with data centers may have significant implications for ratepayers and it may create regulatory challenges (Wall Street Journal, 2026). At the local level, development of large data centers generates tensions over land use, water consumption for cooling, noise and air quality (Hudson, 2026). This research provides an up-to-date assessment of electricity use by data centers and it quantifies the social costs from pollution emitted during electricity production to meet this load. Thus, the paper contributes one critical dimension to the analysis of the net impact of data centers in the U.S.

This research focuses on measuring the social costs from criteria air pollutants and greenhouse gases (GHGs) caused by electricity production used to power data center operations. Together, these pollutants cause damages that amount to an appreciable share of economic output (Mohan et al., 2023). These calculations rely on several data sources. The location and power usage of existing and planned data centers as of 2025 is provided by S&P Global Insights (S&P Global, 2025). Critical to determining the pollution impacts of data centers and electricity used by data centers, is the nature of power plants that produce the electricity that supports operations. For example, social costs from emissions differ markedly depending on whether power plants burn coal, natural gas or rely on renewable or nuclear technology. The locations, technologies, and fuel used to generate electricity that powers these facilities is provided in publicly available data issued by the United States

Department of Energy (USDOE) and the United States Environmental Protection Agency (USEPA), (USDOE, 2026; CAMPD, 2026; eGRID, 2026).

With data characterizing the electricity grids and associated emissions, the next step in the empirical estimation of social cost is to connect emissions to impacts. For local air pollution this study relies on the AP4 model (Tschofen et a., 2019; Dennin et al., 2025). This integrated assessment model connects emissions of several economically significant local air pollutants to public health consequences, and social costs. Emissions of GHGs are valued using the social cost of carbon (SCC). Monetary damages from air pollution and GHGs are combined to calculate Gross External Damages (GED), a monetary measure of impacts from environmental pollutants used in the prior literature (Muller, Mendelsohn, and Nordhaus, 2011). This analysis then compares the GED to measures of the economic benefit that data centers provide. These include Gross Domestic Product (GDP) and personal income from the data processing, hosting, and related services industry.

There has been considerable research on energy consumption by data centers[1]. Most related to this analysis is an unpublished working paper by Han et al., (2024). This research connects data center energy use to emissions and health consequences in a similar fashion to the present paper. There are several key differences. First, Han et al., (2024) use energy consumption data from 2023 which, though only two years old, is outdated given rapid industry growth. In contrast, this analysis uses energy consumption information from data centers in 2025. Second, Han et al., (2024) use state-level energy consumption data whereas the present paper uses Quarter 3 (Q3) 2025 data for the fleet of roughly 2,800 operational data centers at the facility level. Third, Han et al., (2024) track electricity load from operational data centers in 2023. The present analysis also encompasses expected emissions and social costs from planned facilities. Fourth, Han et al., (2024) emphasize their 2030 forecast impacts. The focus of this paper is to quantify impacts in 2025 and to compare the GED to GDP to gauge the magnitude of impact.

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[1] EPRI, 2024; Koomey, 2008; Mytton and Ashtine, (2022)

The central results of this analysis are summarized as follows. First, damages from electricity consumption at data centers in 2025 amount to $25 billion ($10 to $33 billion)[2]. The GED vary considerably across space. In one sense this should be obvious, a priori, as data center development exhibits clustering which reflects regional demand, electricity prices, and regulatory contexts. However, the extent of this variation and the underlying factors causing it are noteworthy. The GED from data centers in Virginia and Texas amount to 30% of the national total. Commercial electricity prices in these states were well below the national average in 2025. Further, data centers in just 10 states produce 70% of the total GED. Second, to make sense of the magnitude of these cost estimates, the GED are compared to GDP and personal income from the information technology data processing, hosting, and related services industry. For all data centers, the GED comprise just 5% of GDP. In North Dakota and Wyoming, the GED from electricity generation to power data centers are more than 5 times and 2 times larger than GDP from the data processing, hosting, and related services industry, respectively. Third, the expected damages associated with planned data centers suggest rapid near-term increases in power consumption and social costs. Estimated GED from planned facilities totals $21 billion which is roughly equivalent to GED from operational facilities in Q3 2025. Particularly large increases in load and social costs are projected to occur in Virginia, Ohio, and Texas. Finally, in a series of provisional calculations, the magnitude of GED from AI-related activities at data centers appears to be small relative to estimates of the associated productivity benefits. For example, if one assumes that AI exhibits a 0.5% boost to GDP, the associated GED comprise just 2.4% of the productivity gains.

The remainder of this report proceeds as follows. Section II covers data and methods. Section III reports results, and Section IV concludes.

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[2] All monetary values are reported in $2025.

II. Methods and Data

This section begins with the methods and data used to calculate electricity consumption by data centers before covering the model used to estimate the impact of local air pollution. The section concludes with the approach to estimating damages from GHGs.

S&P Global Insights provides both the location and detailed physical attributes of every data center in the U.S. (S&P Global, 2025). Among these, there are approximately 2,800 operational facilities. For each data center, net utilized power is reported in kilowatts (kW). We convert this to megawatt hours (MWh) of electricity consumed as shown in equation 1. This calculation multiplies net utilized power, power usage efficiency (*PUE*), the number of hours in a year, and a load factor, which governs the fraction of total facility capacity in use that draws power from the grid. *PUE* is the standard metric for measuring data center energy efficiency. This metric is unique to each facility, and it is reported by S&P (S&P Global, 2025) It is calculated as the ratio of total facility power to IT equipment power. Leveraging guidance from S&P Global, the load factor ranges from 50 to 60% and is set to 55% in the default scenario. The load factor is varied in a sensitivity analysis.

$$Mwh_{f,t} = \left(\frac{kW_{f,t}}{1{,}000}\right) \times PUE_{f,t} \times 8{,}760 \times LF_{f,t} \qquad (1)$$

The next step in the empirical analysis connects facility-level electricity load and emissions. The requires information on locating facility in an electricity grid region. The paper adopts eGRID subregions which were developed by USEPA to estimate the mix of power plants supplying electricity to each region in a given year (eGRID, 2026). The EIA form 923 (USDOE, 2026) reports generation data and the USEPA Clean Air Markets Program Data (CAMPD, 2026) reports emissions. Both data sets are resolved at the power plant level for the year 2025. CAMPD includes plant level information on emissions of GHGs (carbon dioxide - CO_2) and local air pollution including sulfur dioxide (SO_2) and nitrogen oxides (NO_x). Emissions of primary fine particulate matter ($PM_{2.5}$), volatile organic compounds, and ammonia (NH_3) are provided by eGRID for 2021. Newer data for these species are not available.

The analysis calculates uniform emission rates within each sub-region. Data center load is multiplied times these subregion-specific emission rates to estimate emission levels for each data center (f) as shown in (2). The denominator in (2) includes all generation in a given region, inclusive of emitting and non-emitting generators.

$$E_{f,s,t} = MWh_{f,t} \times \left[\left(\frac{\sum_{p=1}^{P} E_{p,s,t,g}}{\sum_{p=1}^{P} MWh_{p,s,t,g}} \right) \right] \qquad (2)$$

where: $E_{f,s,t}$ = emissions of pollution species (s), from data center (f), during year (t).

This approach implicitly assumes that data centers comprise average load which is met predominantly by baseload generation assets.

This study uses the AP4 integrated assessment model to connect emissions of local and regional air pollution from electric power generation to their consequences on society (Dennin et al., 2025). The AP4 model[3] facilitates detailed facility level estimates of pollution cost, through air quality modeling, epidemiology, and economic valuation modules. AP4 is the latest version of the APEEP family of models (Muller and Mendelsohn, 2007; 2009; Muller, Mendelsohn, and Nordhaus, 2011). Earlier versions of the AP4 model have been subject to rigorous comparison with other similar models[4]. AP4's predictions have been analyzed relative to the network of monitors used by the USEPA to enforce air quality standards (Dennin et al., 2025).

AP4 begins with the National Emissions Inventory (NEI), which is an inventory of local air pollution emissions for all reported emissions in the contiguous United States (USEPA, 2026). Using this inventory, AP4 estimates baseline concentrations of $PM_{2.5}$ accounting for all emissions in the US economy. Importantly, AP4 models the connection between emissions of precursor species and ambient $PM_{2.5}$. These precursor species include SO_2, NO_x, NH_3, volatile organic compounds, and primary $PM_{2.5}$. AP4 models these relationships through a reduced-complexity chemistry module that accounts for interactions among

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[3] Publicly available here: https://nickmuller.tepper.cmu.edu/APModel.aspx

[4] Gilmore et al., (2018).

inorganic species. Each of these precursor species contributes to the concentrations of total $PM_{2.5}$ which AP4 predicts at the county levels.

Using these estimated concentrations, the model then uses detailed population estimates to calculate exposures for every county in the contiguous US. Populations are disaggregated by age groups because prior epidemiological research has shown that susceptibility to pollution exposure is a function of baseline health status (Krewski et al., 2009). The model contains spatially detailed information on baseline health status including mortality risks by county and age group. These data are provided by the Centers for Disease Control and Prevention (CDC, 2025).

Then, AP4 uses peer-reviewed concentration response functions to link exposure to $PM_{2.5}$ to elevated premature mortality risk (Krewski et al., 2009; Lepeule et al., 2012). AP4 focuses on premature mortalities for two reasons. First, prior research has shown that premature mortality risk comprises the vast bulk of damages from local air pollution (Muller, Mendelsohn, Nordhaus, 2011; USEPA, 2011). Second, if the model included mortality and morbidity health states in the damage estimates, one might be concerned about double counting if, say, short run health effects like emergency room visits from asthma are followed eventually by a premature death.

The model calculates the deaths attributable to $PM_{2.5}$ exposure ($M_{a,j,t}$). This calculation is shown in equation (3).

$$M_{a,j,t} = Pop_{a,j,t}\gamma_{a,j,t}\left(1 - \frac{1}{exp(\beta \Delta PM_{j,t})}\right) \tag{3}$$

where: $Pop_{a,j,t}$ = population of age-group (a), in county (j), year (t).
$\gamma_{a,j,t}$ = baseline mortality risk of age-group (a), in county (j), year (t).
β = statistically estimated parameter from Krewski et al., (2009).
$\Delta PM_{j,t}$ = change in ambient $PM_{2.5}$ in county (j), year (t).

Once the mortality risk from air pollution is estimated using equation (3), AP4 attributes a monetary value to these risks. In both academic literature and in policy analyses, the standard way to monetize mortality risk uses the value of a statistical life (VSL). The VSL is the marginal rate of substitution between income and mortality risk. It is a measure of the willingness to pay to reduce mortality risk. There are two ways in which the VSL is estimated empirically. In revealed preference studies, the VSL is estimated from the relationship between wages and on the job mortality risk. In stated preference studies, the VSL is estimated based on individual responses to highly structured surveys. This analysis uses what had been the USEPA's preferred VSL of $10 million (USEPA, 2025), which has been adjusted to $2025. In this study, as is standard practice, the VSL is applied uniformly to persons of all ages and income levels. USEPA's preferred VSL is a combination of both revealed and stated preference studies.

AP4 is applied in two ways in this paper. First, marginal damage, or $/ton damages, for each of the local air pollutants are calculated. These facility level damages are averaged by state to match the eGRID subregions. The $/ton damages are multiplied times the estimated tonnage of emissions produced from electricity generation to power data centers. Second, AP4 is run with and without data center load, and the associated emissions. This strategy is used to produce figures 3, 4, A2, and A3.

In order to model the social cost from greenhouse gas emissions, this study uses the SCC. The SCC represents the present discounted value of damages from carbon dioxide equivalents on a per ton basis. While there is deep structural uncertainty associated with the SCC, numerous peer reviewed estimates have been produced by environmental economists and policy analysts. Two different SCC values are used in this study. The default value is approximately $190/ton $CO_{2,}$ and it was reported by the Biden Administration's Interagency Working Group on the Social Cost of Carbon (USEPA, 2023). The second value is an earlier estimate also from the Biden Administration resulting from a meta-analysis of multiple models. The second value is approximately $50/ton CO_2 (White House, 2021). These SCC estimates are multiplied times the CO_2 emitted by the power plants producing electricity to power data centers.

The data provided by S&P Global (2025) include information on both operational and planned data centers. The central results presented here focus on operational data centers in the quarter 3 of 2025. A second set of calculations focus on the social costs from planned facilities. This is intended to provide a sense of growth in both power consumption and social costs from power consumption in the near term as these new facilities come online.

Throughout this report we refer to the damages, or social costs, associated with local air pollution and greenhouse gases as the gross external damages, or GED. The GED was introduced by Muller, Mendelsohn, and Nordhaus (2011). This term reflects the fact that damages from air pollution and greenhouse gases comprise an externality. In the context of datacenter power consumption, the external costs from power generation are borne by consumers exposed to $PM_{2.5}$. Damages from greenhouse gases manifest many years following emission, and hence, reflect an externality borne by future generations. Further, the social costs from pollution emissions are *gross* (not net) since they do not account for payments made to reduce pollution removal or abatement, nor do the costs account for payments made to purchase tradable allowances in cap-and-trade programs.

In addition to the data discussed above, the analysis makes use of other publicly available datasets. These specifically include data from the state and regional national income and product accounts (NIPAs) reported by the US Bureau of Economic Analysis (USBEA, 2026a) In particular, the data used are gross domestic product, or GDP, by industry, with a particular focus on information technology: data processing, hosting, and related services. These data are matched by state to the location of data centers. The GED are compared to the GDP by state, aggregating over facilities within each state. An analogous comparison is made to personal income for information technology: data processing hosting and related services (USBEA, 2026b). It is important to note the limitations associated with making these comparisons. First, GDP is an imperfect measure of the value of services provided by these facilities. By definition, GDP does not capture spillover effects or positive externalities associated with data hosting facilities. In addition, personal income statistics do not measure multiplier effects associated with households and consumers in each state having incrementally more income, and the benefits associated with additional expenditures on state and regional economies. Nonetheless these comparisons gauge the magnitude of the damages relative to conventionally used measures of the benefits of these facilities for state and regional economies.

III. Results

The bottom row in Table 1 reports the total power consumption and damages across all datacenters in the contiguous U.S. in 2025 (S&P Global, 2025). The datacenters consumed approximately 250 terawatt hours (TWh) of electricity. This was between 5 and 6% of total electricity produced in the US[5]. The associated GED is estimated to be $24.6 billion. A sensitivity analysis reported in table A2 suggests a range of the GED from $10 billion to $33 billion. Specifically, when using a higher run rate at the data centers (75% rather than the default of 55%) the GED increase to $33.6 billion. Employing the lower SCC of $50/ton CO_2, the GED decrease to $9.9 billion. And employing the higher PM-mortality dose-response function increases the GED to $30.7 billion.

Four findings emerge from table 1. First, data center activity is highly concentrated. Facilities in just 10 states contribute 70% of total GED. Within these 10 states, facilities in Texas and Virginia cause 30% of the GED. Second, the GED from GHGs comprise 80% of the total, though this share is sensitive to modeling assumptions. Third, the GED/MWh are large relative to commercial electricity prices. In 6 of the 10 states in table 1, the GED/MWh *exceeds* the state average commercial electricity price. Fourth, electricity prices in all 10 states in table 1 are less than the national average commercial price in 2025 which was $0.13 per kWh[6]. In Texas and Virginia, prices are 30% lower than the national average.

Air Quality Impacts. Figure 2 displays the total power consumption by state. Texas and Virginia stand out with consumption levels over 25 TWh. Several other states in the Midwest and on the West coast exhibit large electricity loads from data centers. Figure 3 displays the change in ambient $PM_{2.5}$ from data center power consumption. Exposures to these changes comprise the GED from air pollution. Figure 3 indicates areas of elevated $PM_{2.5}$ occur in Texas, Virginia and the Carolinas, Pennsylvania and Ohio, Wyoming, Nebraska, Iowa, and

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[5] This estimate is roughly in line with forecasts made by EPRI (2024).

[6] https://www.eia.gov/electricity/monthly/epm_table_grapher.php?t=table_5_03

North Dakota. Intuitively, the regions that incur elevated $PM_{2.5}$ have (or are downwind from areas with) large data center load as reported in table 1. The regionally widespread changes in $PM_{2.5}$ manifest because power plants that meet data center load may not be proximal to data centers, and second, because air pollutants disperse often long distances once they are emitted. Further, the electricity grid is more pollution-intensive east of the Rocky Mountain states.

Figure 4 shows where the GED from air pollution exposures occur. Recall, as shown in equation (3), the air pollution GED are calculated in each county using the estimated incremental concentrations of $PM_{2.5}$ (shown in figure 3) together with county level population and mortality rate data. Figure 4 makes clear the importance of population. That is, the counties exhibiting the highest damage are in large cities. For example, Houston, Dallas, and San Antonio in Texas, each incur an estimated GED from local air pollution above $10 million. Large cities in the Midwest also exhibit elevated $PM_{2.5}$ damages, including Chicago, Pittsburgh, Detroit, Columbus, and Cleveland, Ohio. In addition, even very small changes in ambient $PM_{2.5}$ that manifest in populous metropolitan areas result in significant damages. This is evident in Los Angeles, Phoenix, Las Vegas, and Boston.

Total GED. Figure 5 displays the total GED by state, inclusive of GHGs and local air pollution emissions. In this figure, the GED are attributed to the state in which data centers operate, not where the GED occur. Table 1 shows the top 10 states ranked by the GED caused by power consumption from data centers in each state. Figure 5 and table 1 clearly indicate that data center activity in Texas and Virginia cause the largest GED. Even among the 10 states shown in table 1, Virginia and Texas are outliers. For example, the GED in Texas and Virginia are about 2 times larger than the GED from data centers in Ohio, the state causing the third highest GED. Commercial electricity prices in Virginia and Texas are under $0.10/KWh, which is well below the national average of $0.13/KWh. Because of the importance of electricity costs to the overall cost structure faced by data centers, these low prices are likely an important determinant of facility location.

GED, GDP, and Personal Income. Table 2 relates the GED to state-level GDP contributed by information technology (IT) facilities that provide data processing, hosting, and related services. The states in this table are ranked in descending fashion according to the share the GED comprises of GDP from this industry by state. Importantly, the most recent GDP data available is for 2024. Nationally, GED from all data centers amounts to $25 billion, while GDP for this industry was $544 billion in 2024. This relatively small share masks significant heterogeneity.

Data centers in North Dakota generate $665 million in GED and just $121 million in GDP from IT data hosting services. GED was over 5 times larger than the value of economic production from IT data hosting services in this state. North Dakota is clearly an outlier. The next largest share of GED relative to GDP is in Wyoming. In this state GED from electricity load for data centers amounts to $244 million which is about 2 times larger than GDP contributed by these facilities. Data centers in Iowa and Oklahoma cause GED that is between 50% and 80% of state GDP. The remaining 6 states in table 2 contain data centers that produce GED under 40% of GDP. Virginia, as noted above, contains data centers that consume the most electricity load and that contribute the largest share of GED. The GED from data centers in Virginia comprises nearly 18% of total GED. However, the state GDP from data centers in Virginia amounts to just under 3% of national GDP from this industry. In contrast, data centers in California contribute 37% of national GDP and just 2% of the GED.

It is important to consider how to Interpret these comparisons of GED to GDP. Specifically, the GDP tracked here is that reported for data processing, hosting, and related services in 2024. By definition, GDP attributed to this industry does not measure positive externalities associated with data hosting services such as productivity effects that spill over to other areas in the economy. Nor does GDP attribute local stimulus (job creation or expenditures by employees) to GDP for this industry. Thus, the comparison between GED and GDP is intended as an illustrative scaling exercise. Further, as mentioned above, GDP reported here is for 2024. Considerable growth in this industry between 2024 and 2025 suggested GDP in 2025 may have been considerably higher than in 2024.

It is also worth considering the geographic scope of the GED and GDP measures. The GED is associated with electricity consumption by data centers located in each state. For air pollution, we know that the consequences of exposures tend to extend well beyond state boundaries. As such, the damages encompass regional or national exposures, and these are attributed back to the location of electricity generation. For greenhouse gases, of course, the GED is global. Thus, the fraction of GED from greenhouse gases accruing in the state where the data centers are located is likely quite small. In contrast, GDP is reported for each state inclusive of economic flows that manifest within each state.

In pursuit of another way to characterize the magnitude of the GED produced from electricity generation to power data centers, Table 3 reports the GED as a fraction of personal income from data processing, hosting, and related services. Table 3 ranks the states in descending order by the fraction that GED comprises of personal income. Like Table 2, the states at the top of Table 3 include North Dakota, Wyoming, and Iowa. The use of personal income to gauge the magnitude of GED is motivated by the fact that personal income from data processing, hosting, and related services is a measure of local economic stimulus from these economic activities. Much like Table 2, Table 3 shows that North Dakota is an outlier in terms of the magnitude of GED relative to personal income. Specifically, GED is 15 times larger than personal income from data hosting facilities. Using this measure, 5 of the remaining 9 states in table 3 exhibit GED in excess of personal income. Together, Tables 2 and 3 show, albeit imperfectly, that the GED associated with power generation to meet data center load amounts to an appreciable share of the measurable economic benefit of these facilities.

Planned Facilities. The next set of results examines damages from planned facilities (as of Q3 2025). Table 4 shows the 10 states with the largest GED from planned data centers. One should view these estimates with caution since power consumption is, by definition, estimated and forward-looking. Total planned capacity is estimated to consume 210 TWh with an associated GED of $21 billion. These estimates, coupled with operational facilities, suggest increases in electricity load and the GED of up to 85% in the near term. Virginia exhibits the largest expected GED from planned data centers of just under $7 billion. This is

60% more than the GED from operational data centers in Virginia and it is more than one-quarter of total damages from all operational data centers in 2025. In Ohio, the GED from planned data centers is estimated to be just over $2 billion. This reflects roughly a 40% increase over the GED from existing data centers operating in 2025. Table 4 suggests that GED from data center activity in Illinois, Pennsylvania, and Arizona may double. Substantial increases are also estimated to occur in Texas, Missouri, Georgia, Iowa, and North Dakota. These comparisons, while provisional, are indicative of the rate of growth in data center capacity, electricity use, and in the social costs from this high growth industry. Figures A2 and A3 in the appendix demonstrate the expected change in ambient $PM_{2.5}$ and the air pollution GED from planned facilities. The areas exhibiting the highest ambient $PM_{2.5}$ occur along the East coast from the Carolinas up through Pennsylvania. Much like the results for operational data centers, the air pollution GED from planned facilities manifest in large cities, with large, exposed populations.

Data Center Types. Table A1 in the appendix decomposes the electricity use and GED by the type of data centers in the S&P Global Insights data (S&P Global, 2025). There is a total of 2,816 operational facilities in the data. Of these, 1,509 are retail and 525 are wholesale facilities. Together, these data centers contribute about $7 billion (29%) of the GED and 34% of electricity consumption. There are 432 hyperscale facilities. These (large) facilities contribute 41% of the GED and consume 40% of the electricity load. Facilities devoted to cryptocurrency mining are about as large as hyperscale facilities, but the power consumption per square foot is 80% larger. As a result, even though there are only 121 crypto mining centers, they produce one quarter of the GED while consuming 20% of the total power for all facilities.

AI: The core value of AI lies in up leveling productivity, through model building, task deployment, and data acquisition. At this early stage of global AI deployment, precisely estimating the impact of AI on economic performance is challenging and largely beyond the scope of the present research. Further, a precise understanding of the share of GED reported in this paper that is attributable to AI training and inference activities remains out of reach. However, in order to obtain a preliminary estimate of the GED from AI activities and to gauge the magnitude of this estimate, the following provisional calculations are executed. First, IEA (2025) reports that roughly 15% of all energy use at data centers is due to AI activities. Using the results in Table 1, this suggests that 38 TWh and $3.7 billion in GED are due to AI activities. Recent estimates of the impact of AI on GDP are generally under 10% by 2030 (Goldman Sachs, 2023). Figure 6 combines these data points to demonstrate the comparison between the GED and GDP effects from AI. In sum, the GED effects appear very small relative to potential increased output. For example, if AI boosts GDP by 1%, the GED amount to 1% of the value of enhanced output. If AI boosts GDP by 0.5%, the GED constitute just 2.4% of increased GDP. Finally, if AI adds 0.1% to GDP, a very small increase in output, the GED would in this case comprise about 12% of the additional output from AI.

IV. Conclusions

This paper estimates the damages from local air pollution and GHG emissions from electricity powering data centers in the U.S. in 2025. The GED, which total $24 billion, comprise just 5% of the GDP contributed by data storage and data hosting facilities as measured using the national income and product accounts. However, the GED are highly concentrated; 30% of the GED stem from facilities in Virginia and Texas. Lower than average commercial electricity prices in these states may play a central role in facility location decisions. Planned facilities may increase electricity load and associated GED by up to 85% in the near term. This will likely have substantial impacts on regional electricity grids and public health. Finally, unless the effect of AI activities on GDP are exceedingly small, the GED from AI-based energy use within data centers appears to be very small relative to the possible benefits of this technology.

Tables and Figures

Table 1: Power Consumption and Damages from Operational Data Centers in 2025.

Data Center State	Elec. Load[A] (Gwh)	Total GED[B]	GED GHG	GED LAP	GED ($/Mwh)	Electricity Price[C] ($/Mwh)
VA	46,400	4,290	3,420	869	92	95
TX	36,200	3,230	2,760	468	89	86
OH	13,500	1,740	1,330	419	129	116
IA	9,459	1,440	1,050	391	152	110
GA	13,700	1,420	1,240	182	104	115
IL	10,700	1,410	1,050	363	132	131
OR	18,200	1,210	1,060	150	66	106
AZ	13,600	1,090	987	101	80	124
TN	4,855	717	546	172	148	129
NE	5,098	712	568	145	140	88
All States	251,000	24,600	20,000	4,590	101	134

A = electricity load from S&P Global.

B = GED in ($millions), author's calculations.

C = state average commercial electricity price.

Table 2: Power Consumption and Damages from Operational Data Centers and State GDP.

State	Elec. Load^{A} (Gwh)	GED ($ million)	GDP ($ million)	GED/ GDP
ND	6,511	665	121	5.51
WY	2,167	244	114	2.15
IA	9,459	1,440	1,904	0.76
OK	3,199	456	805	0.57
NE	5,098	712	1,876	0.38
AL	3,297	493	1,329	0.37
KY	3,045	466	1,277	0.37
NM	2,684	208	641	0.32
OH	13,500	1,740	5,619	0.31
VA	46,400	4,290	13,952	0.31
All States	251,000	24,600	544,148	0.05

A = electricity load from S&P Global.

GED = authors calculations.

GDP = GDP for Data processing, hosting, and related services. These are industries in the Data Processing, Hosting, and Related Services subsector group establishments that provide the infrastructure for hosting and/or data processing services. (USBEA, 2026)

Table 3: Power Consumption and Damages from Operational Data Centers and Personal Income.

State	Elec. Load^A (Gwh)	GED ($ million)	Personal Income ($ million)	GED/ Personal Income
ND	6,511	665	44	15.18
WY	2,167	244	45	5.45
IA	9,459	1,440	581	2.48
NE	5,098	712	350	2.03
OK	3,199	456	230	1.99
NM	2,684	208	179	1.16
AL	3,297	493	524	0.94
OH	13,500	1,740	1,854	0.94
KY	3,045	466	519	0.90
VA	46,400	4,290	4,841	0.89
All States	251,000	24,600	116,390	0.21

A = electricity load from S&P Global.

GED = authors calculations.

Personal income = Private nonfarm earnings, for data processing, hosting, and related services. These are industries in the Data Processing, Hosting, and Related Services subsector group establishments that provide the infrastructure for hosting and/or data processing services. (USBEA, 2026)

Table 4: Power Consumption and Damages from Planned Data Centers.

State	Elec. Load Planned (Gwh)	GED Planned ($ million)	GED Planned/ GED 2025
VA	75,000	6,940	1.62
OH	19,200	2,490	1.43
TX	21,700	1,920	0.59
MO	8,817	1,390	8.97
IL	9,637	1,270	0.90
GA	10,600	1,110	0.78
AZ	12,900	1,030	0.95
PA	6,420	614	0.95
IA	3,939	601	0.42
ND	5,244	533	0.80
All States	210,000	20,800	0.85

A = electricity load from S&P Global for data centers marked as planned (not operational as of Q3 2025).

GED = authors calculations.

Figures

Figure 1: Location of Data Centers in the Contiguous United States (https://www.datacentermap.com/usa/).

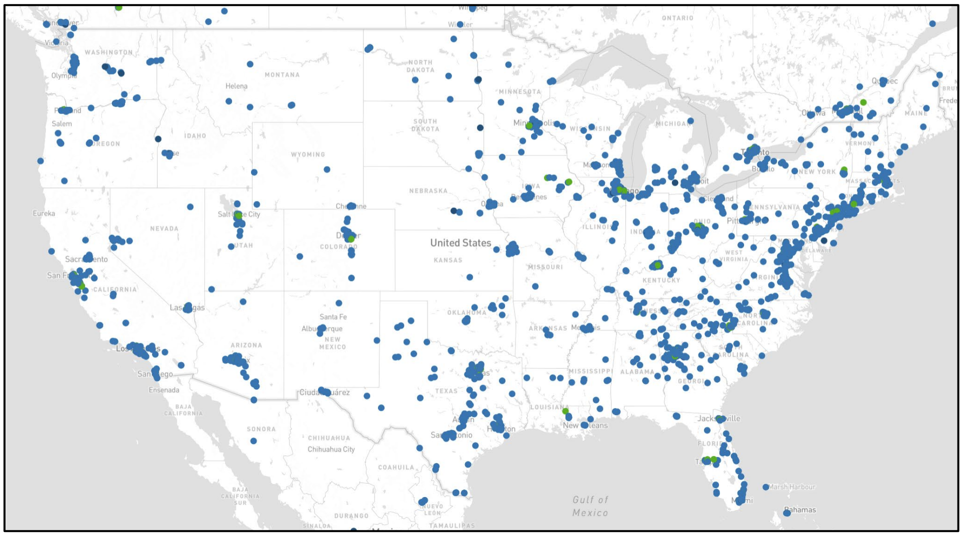
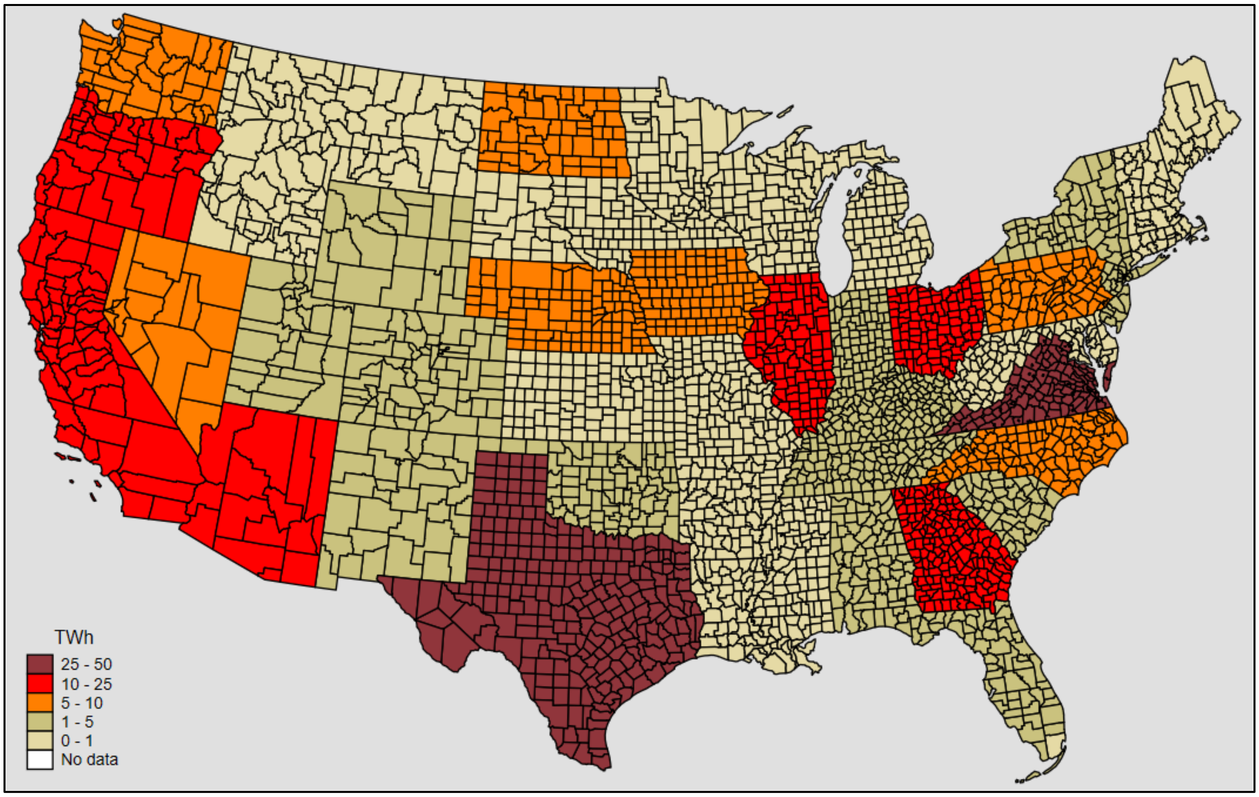
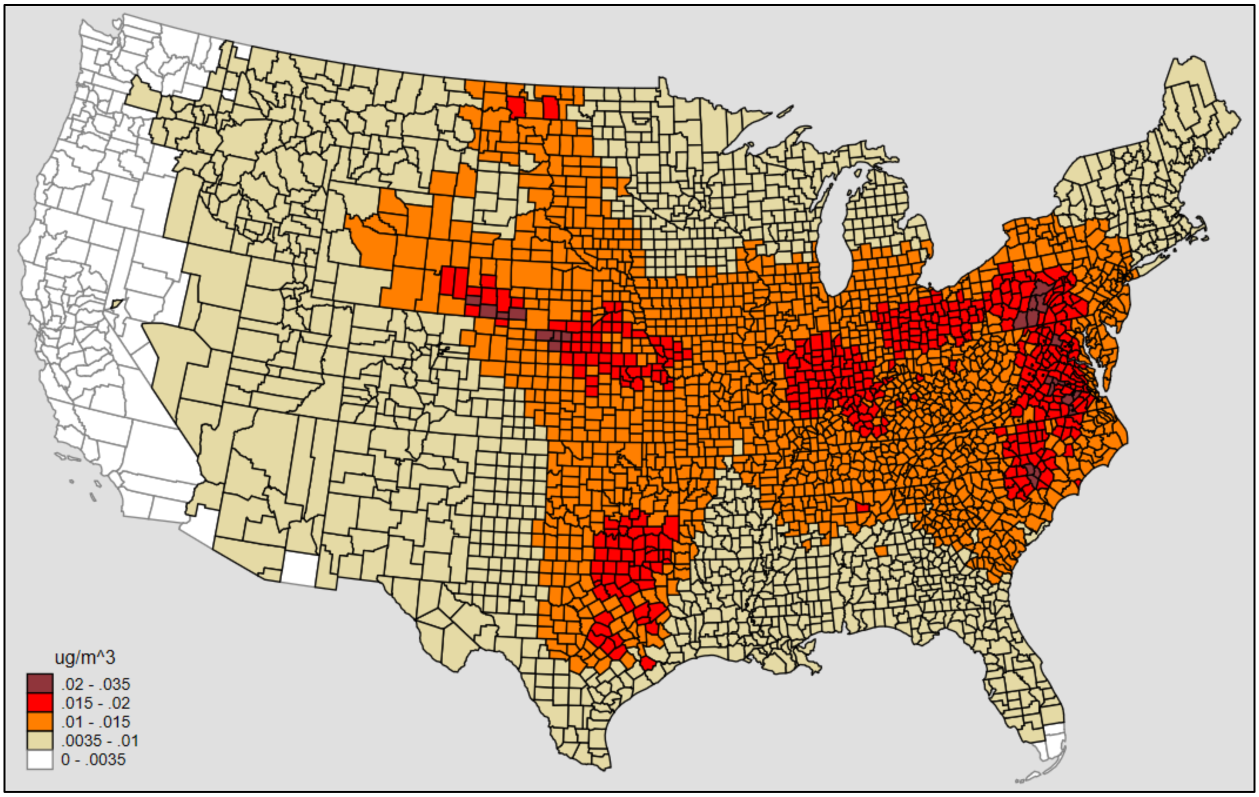


Figure 2: Electricity Consumption from Data Centers by State.



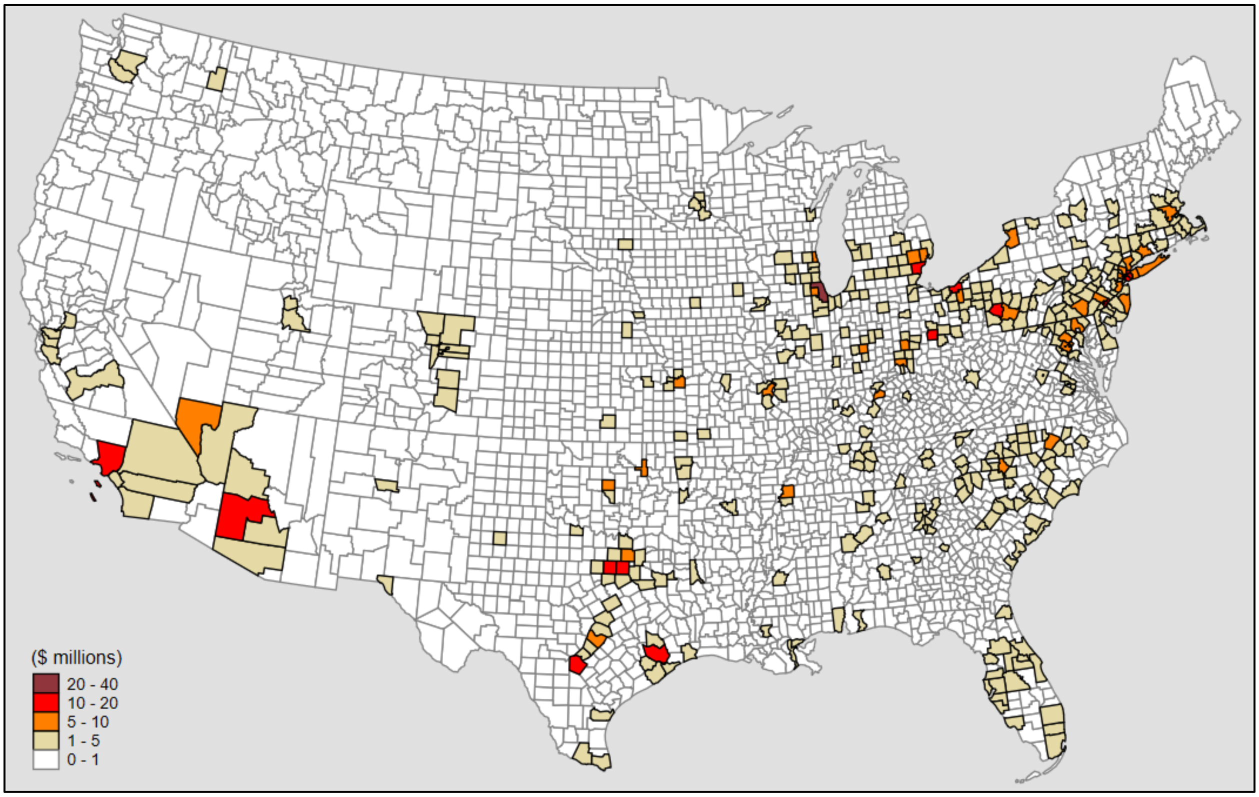
Source: S&P Global (2025) and author’s calculations.

Figure 3: Change in $PM_{2.5}$ Concentrations from Data Center Power Consumption.



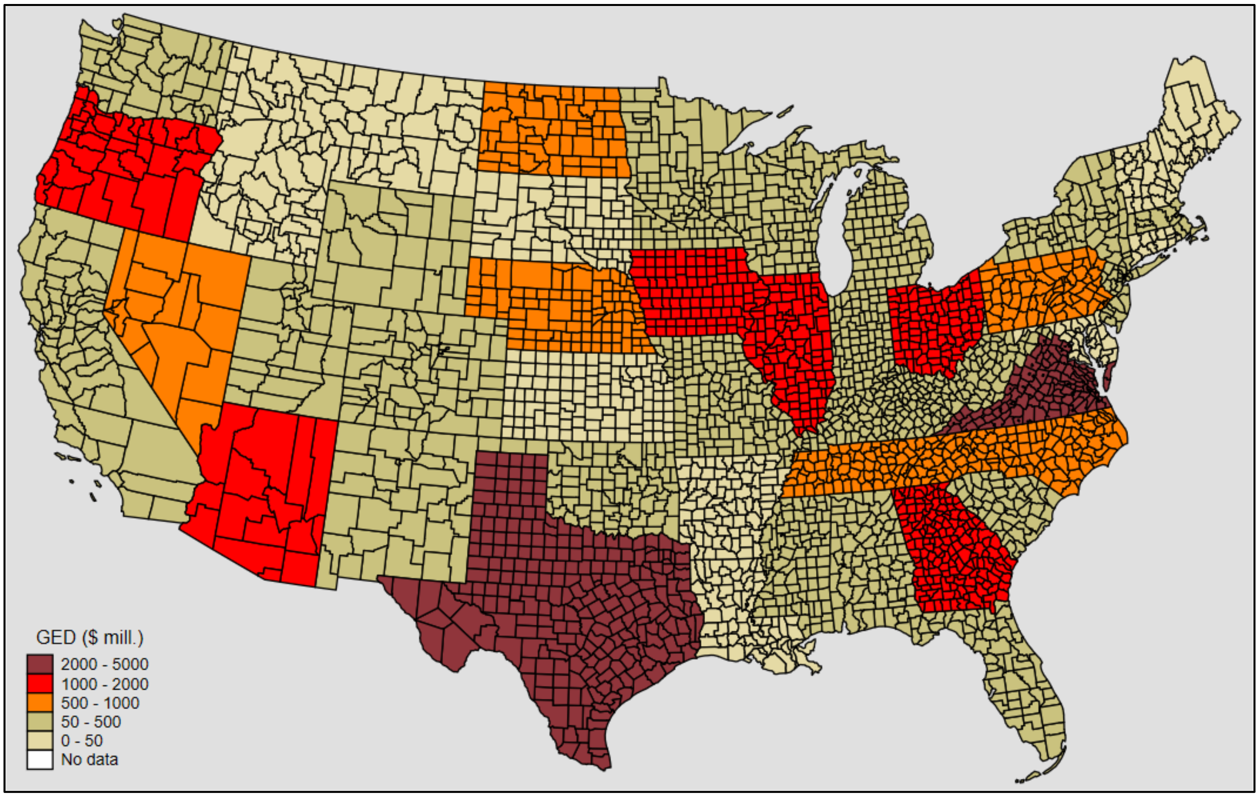
Source: Author's calculations.

Figure 4: Air Pollution GED by County of Incidence from Data Center Power Consumption.



Source: Author's calculations.

Figure 5: GED from Data Centers by State Location of Data Centers.



Source: Author’s calculations. The GED in figure 5 includes both GHGs and criteria air pollution. Damages are reported according to the state where operational data centers are located.

Figure 6: Comparing AI GED and Contribution to GDP.

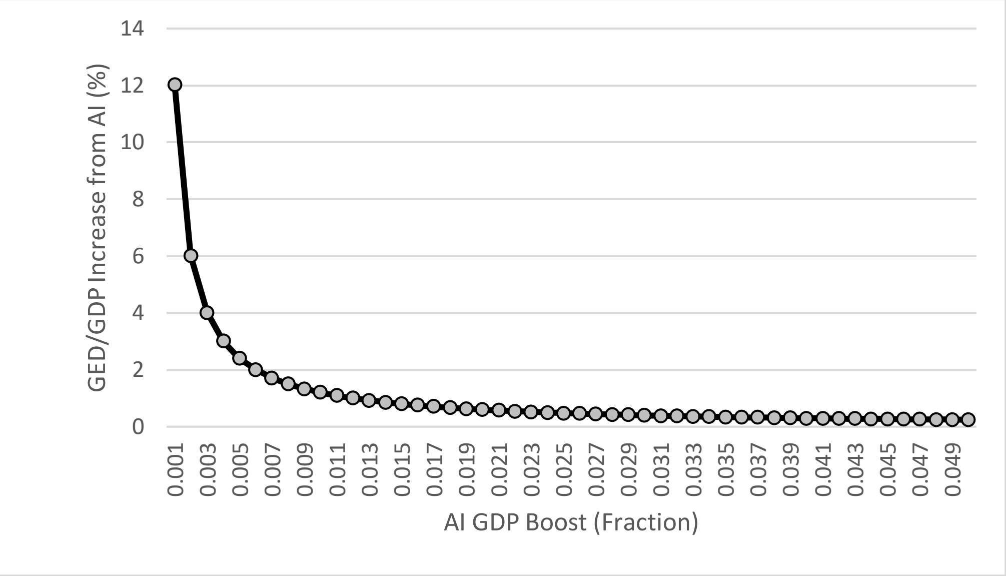


Figure 6 assumes that 15% of all data center activity powers AI training and inference (IEA, 2025). Author's calculations.

References.

1) Blunt, K., and J. Hiller. 2026. “America’s Biggest Power Grid Operator Has an AI Problem-Too Many Data Centers.” *Wall Street Journal,* Jan. 12, 2026. https://www.wsj.com/business/energy-oil/power-grid-ai-data-centers-1235f296
2) Brown, C. 2026. “Data Centers and Your Power Bill.” *New York Times*. Feb. 19, 2026. https://www.nytimes.com/2026/02/19/climate/data-centers-power-bills.html
3) Centers for Disease Control and Prevention (CDC), 2025. https://wonder.cdc.gov/
4) Datacentermap.com. 2025. https://www.datacentermap.com/datacenters/
5) Dennin, L. et al., 2025. "Modeling wildland fire smoke damages in the U.S. and unpacking impact disparities by social vulnerability." *Nature Communications: Earth and Environment*. 6(190): 1 - 19.
6) eGRID, 2026. https://www.epa.gov/egrid
7) EPRI, 2024. “Powering Intelligence: Analyzing Artificial Intelligence and Data Center Energy Consumption.” Electric Power Research Institute.
8) Gilmore, E. et al., 2018. "An Inter-Comparison of Air Quality Social Cost Estimates from Reduced-Complexity Models" *Environmental Research Letters*: 14(2019) 074016 https://doi.org/10.1088/1748-9326/ab1ab5.
9) Goldman Sachs, 2023. “Generative AI Could Raise Global GDP by 7%.”
10) Han Y., Z. Wu, P. Li, A. Wierman, S. Ren. 2024 “The Unpaid Toll: Quantifying the Public Health Impact of AI.” https://arxiv.org/pdf/2412.06288
11) Hudson, C. 2026. “Locals Are Using AI to Fight Data Centers Being Built in Their Backyards.” *Wall Street Journal*. April 8, 2026. https://www.wsj.com/pro/sustainable-business/locals-are-using-ai-to-fight-data-centers-being-built-in-their-backyards-d0642630
12) IEA, 2025. https://www.iea-4e.org/wp-content/uploads/2025/05/Data-Centre-Energy-Use-Critical-Review-of-Models-and-Results.pdf
13) Krewski D, Jerrett M, Burnett RT, Ma R, Hughes E, Shi Y, Turner MC, Pope CA 3rd, Thurston G, Calle EE, Thun MJ, Beckerman B, DeLuca P, Finkelstein N, Ito K, Moore DK, Newbold KB, Ramsay T, Ross Z, Shin H, Tempalski B. 2009. “Extended follow-up and spatial analysis of the American Cancer Society study linking particulate air pollution and mortality.” *Res Rep Health Eff Inst*. May;(140):5-114; discussion 115-36. PMID: 19627030.
14) Koomey, J.G. 2008. “Worldwide electricity used in data centers.” *Environmental Research Letters*. 3: 034008.
15) Lepeule, Johanna, Francine Laden, Douglas Dockery, and Joel Schwartz. 2012. “Chronic Exposure to Fine Particles and Mortality: An Extended Follow-up of the

Harvard Six Cities Study from 1974 to 2009." *Environmental Health Perspectives*, 120(7): 965–970. https://www.jstor.org/stable/41548777.

16) Mohan, Aniruddh, N.Z. Muller, Akshay Thyagarajan, Randall V. Martin, Melanie S. Hammer, Aaron van Donkelaar. 2024. "Measuring global monetary damages from particulate matter and carbon dioxide emissions to track sustainable growth." Nature Communications: Earth and Environment. 5, 264. https://doi.org/10.1038/s43247-024-01426-3
17) Muller, N.Z., R.O. Mendelsohn. 2007. "Measuring the Damages of Air Pollution." *Journal of Environmental Economics and Management*. 54(1): 1 – 14.
18) Muller, N.Z., R.O. Mendelsohn. 2009. "Efficient Pollution Regulation: Getting the Prices Right." *American Economic Review*. 99(5): 1714 – 1739.
19) Muller, N.Z., R.O. Mendelsohn, W.D. Nordhaus. 2011. "Environmental Accounting: Methods with and Application to the U.S. Economy." *American Economic Review*. 101(5): 1649 – 1675.
20) Mytton, D. and M. Ashtine. 2022. "Sources of data center energy estimates: A comprehensive review." *Joule*. 6: 2032 – 2056.
21) Plumer, B.2024. "Three Mile Island Plans to Reopen as Demand for Nuclear Power Grows." *New York Times*. Sept. 20, 2024. https://www.nytimes.com/2024/09/20/climate/three-mile-island-reopening.html
22) Rust, M. and W. Parker. 2026. "These Cities and States Are Taking Aim at Data Centers." *Wall Street Journal*. April 7, 2026. https://www.wsj.com/tech/ai/these-cities-and-states-are-taking-aim-at-data-centers-3b98adf1?mod=article_inline
23) S&P Global (2025) Data Center KnowledgeBase, December 2025. S&P Global Energy Horizons.
24) Tschofen, P., et al., 2019. "Fine Particulate Matter Damages and Value Added in the United States Economy," *Proceedings of the National Academy of Science*. https://doi.org/10.1073/pnas.1905030116.
25) United States Bureau of Economic Analysis (USBEA). 2026a. Gross Domestic Product. https://www.bea.gov/data/gdp/gdp-state
26) United States Bureau of Economic Analysis (USBEA). 2026b. Personal Income by County, Metro, and Other Areas.https://www.bea.gov/data/income-saving/personal-income-county-metro-and-other-areas
27) United States Department of Energy (USDOE). 2026. Form 923. https://www.eia.gov/electricity/data/eia923/
28) USEPA. 2011. The Benefits and Costs of the Clean Air Act: 1990--2020. Final Report. Office of Air and Radiation, Office of Policy, Washington, D.C.
29) USEPA, 2023. https://www.epa.gov/system/files/documents/2023-12/epa_scghg_2023_report_final.pdf

30) USEPA. 2025. https://www.epa.gov/environmental-economics/mortality-risk-valuation#whatisvsl
31) USEPA, 2026. https://www.epa.gov/air-emissions-inventories/national-emissions-inventory-nei
32) USEPA, 2026. Clean Air Markets Program Data. https://campd.epa.gov/data/custom-data-download
33) Wall Street Journal, 2026. "AI and the Data Center Backlash." https://www.wsj.com/opinion/ai-companies-data-centers-electricity-trump-administration-df665913
34) White House. 2021. "Technical Support Document: Social Cost of Carbon, Methane, and Nitrous Oxide. Interim Estimates Under Executive Order 13990." https://www.energy.gov/sites/default/files/2023-04/57.%20Social%20Cost%20of%20Carbon%202021.pdf

Appendix

Table A1: Operational Data Center Power Consumption and GED by Facility Type.

Facility Type	Count	Elec. Load[A] (Twh)	Facility Area[B] (ft^2)	Power Density (Mwh/ft.^{2})	GED ($ mill.)	GED($)/ Mwh
Cryptocurrency	121	50,600	192,321	2.61	5,150	102
Hyperscale	432	103,000	186,549	1.36	10,700	104
Retail	1508	25,300	20,273	0.79	2,340	93
Wholesale	525	59,100	113,645	0.97	5,240	89
Other	229	13,700	53,449	0.92	1,190	87
All Facilities	2815	250,000	73,298	1.00	24,620	98

A = electricity load from S&P Global.

B = Average across all facilities of each type.

GED = authors calculations.

Table A2: Sensitivity Analysis.

Scenario	Elec. Load[A] (Gwh)	Total GED[B]	GED GHG	GED LAP	GED ($/MWh)	GED (%) IT GDP[C]
Default	251,000	24,600	20,000	4,590	101	4.7
High Run Rate	343,000	33,600	27,300	6,260	101	6.4
Low SCC	251,000	9,870	5,280	4,590	40	1.9
High Dose Response	251,000	30,700	20,000	10,700	126	5.8

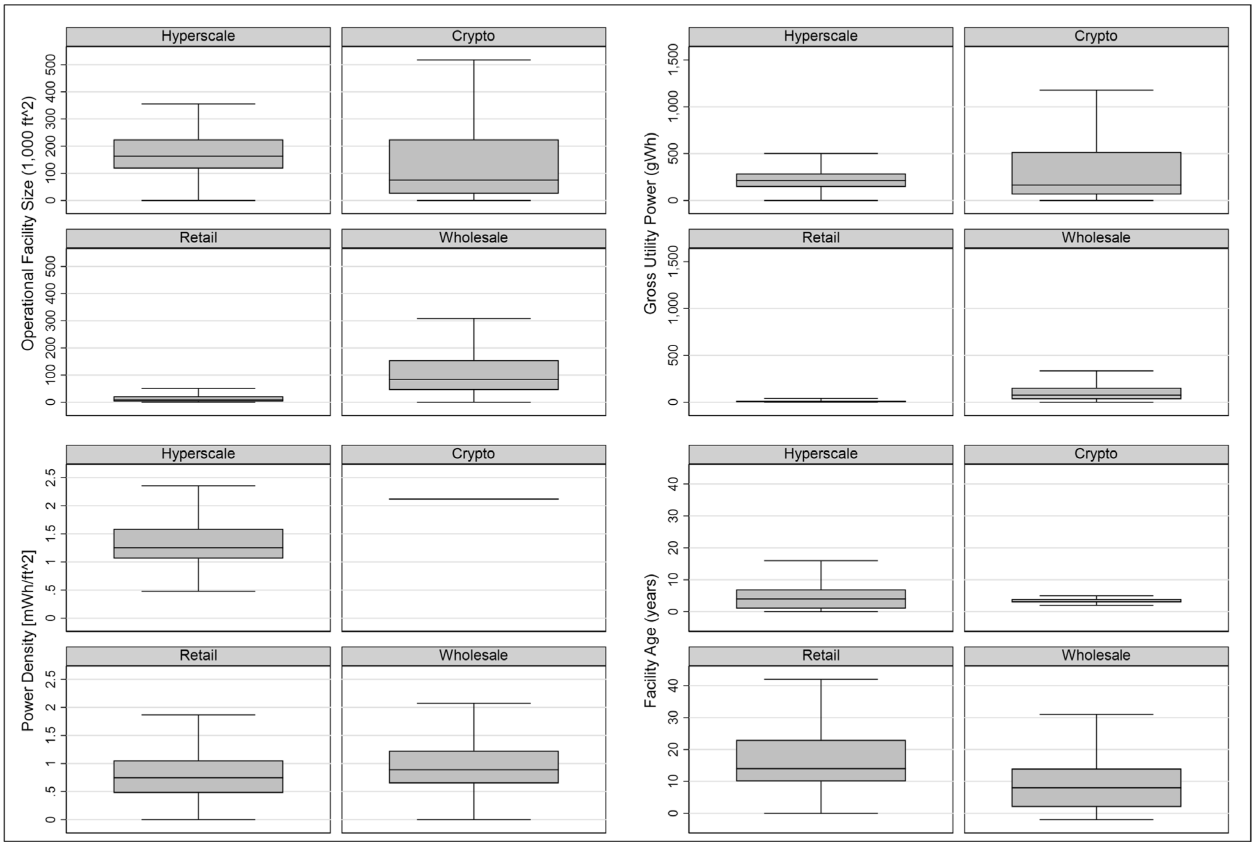
A = electricity load from S&P Global.

B = All GED values in table 5 are in ($millions), expect when expressed relative to MWh.

C = GDP for Data processing, hosting, and related services. These are industries in the Data Processing, Hosting, and Related Services subsector group establishments that provide the infrastructure for hosting and/or data processing services. (USBEA, 2026)

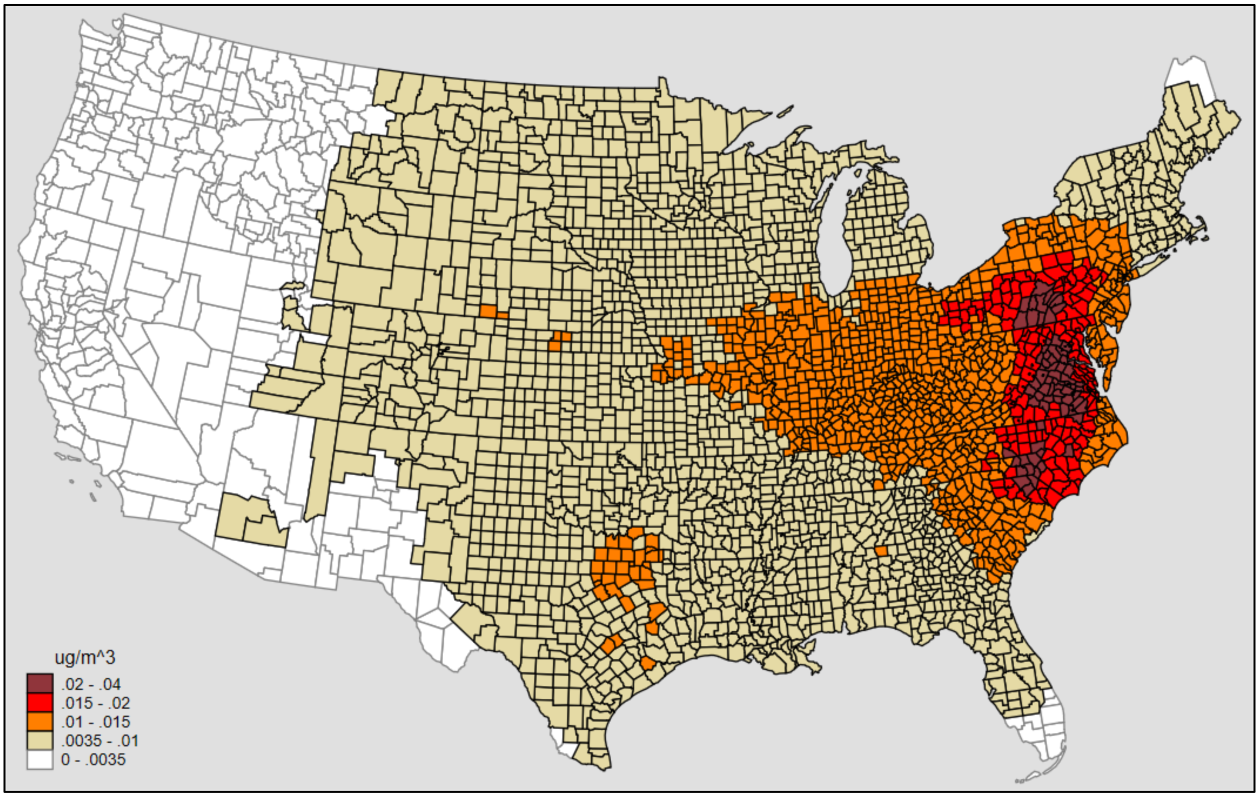
Figures.

Figure A1: Summary Statistics for Data Centers by Type.



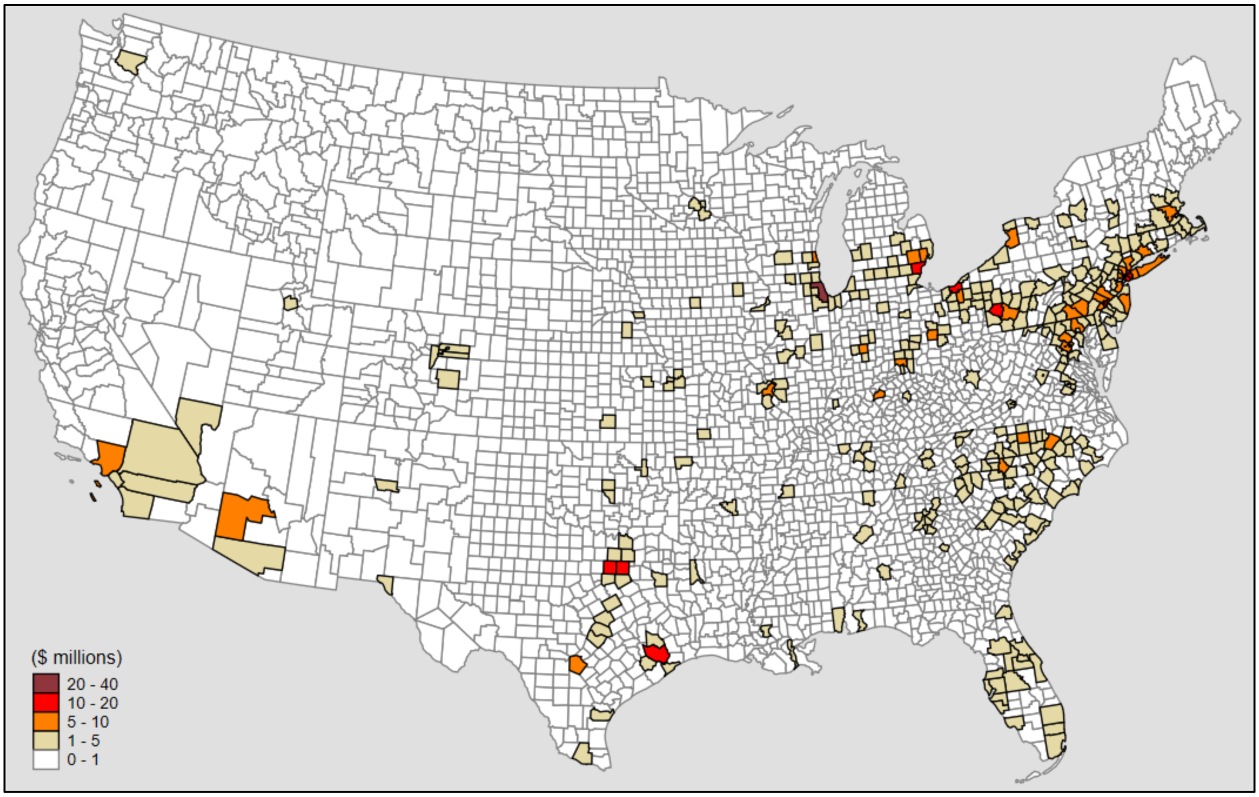
Source: S&P Global (2025) and Author's Calculations.

Figure A2: Change in $PM_{2.5}$ Concentrations from Power Consumption at Planned Data Centers.



Source: Author’s calculations.

Figure A3: GED from Power Consumption at Planned Data Centers.



Source: Author’s calculations.