From: Amy Burgess < >
Sent: Tuesday, March 25, 2025 3:18 PM
To: Velasquez, Enrique <EVelasquez@sanmarcostx.gov>
Subject: [EXTERNAL] PSA-25-01

Please do not change the zoning for this. I do not think our area can keep up with water needs for the growth we are experiencing. It is irresponsible to allow a data center in this area that will use an enormous amount of water daily. Please do right by your constituents and be responsible with our resources.

Thank you

From: Elise < >
Sent: Tuesday, March 25, 2025 11:07 AM
To: Velasquez, Enrique <EVelasquez@sanmarcostx.gov>
Subject: [EXTERNAL] PSA-25-01

Hello Mr. Velasquez,

I am writing with a grave concern regarding PSA-25-01, or the request by land owners at 900 Francis Harris Lane to change zoning. Their request to change their zoning is worrisome in that it is believed they are wanting to build a data center for AI which would use thousands of gallons of water a day.

Our water resources are already dwindling. This is a no brainer. We need water to survive. We need the river to sustain our community and economy. I'm sorry to say that it would be a stupid, yes stupid, mistake to allow a development such as this to come to fruition.

I watched many years ago as our city's officials disregarded popular public opinion, and allowed an eye soar of a monstrosity to be built downtown. What has it done for our community? Nothing. It's ugly. Please don't make an even graver mistake by allowing these land owners to change zoning requirements and thus guzzle thousands of gallons of water a day, taking from the people what they need most to live.

Thank you for your consideration and understanding. I know y'all will do the right thing by the people of San Marcos and surrounding communities.

Sincerely,

From: Lea Rice < >
Sent: Tuesday, March 25, 2025 2:37 PM
To: P&Z Commissioners <PZCommission@sanmarcostx.gov>
Subject: [EXTERNAL] Data CTR

Dear commissioners,

Considering our drought situation, how can you say yes to data centers in this area?

Please vote no!

Thank you,

Lea Rice

Sent from my iPhone

Good evening, my name is Abigail Lindsey and with me is Jennifer Lindsey. Our community members in Valley Acres have some questions and concerns regarding the proposed Data Center on Francis Harris Lane. PSA-25-01.

Clarify:

Tract 2 has 93 acres according to Hays CAD. Are the 60 acres of Tract 2 being sold or leased to Highlander SM One, LLC? Will the data center have access to the remaining 30 acres either above or below the ground?

With the floodplain extending into Tract 2 and the land contour elevations flowing downward from tract 1 into tract 2 will there be any resilient building or hazard mitigation plans?

Community Impact:

How long will construction impact the surrounding areas?

How many employees are anticipated? Are operational hours standard M-F 8-5 or specialized?

Air/Noise/Light:

- Any noise pollution, decibel range we need to be aware of?
- Will wildlife friendly or dark skies lighting be implemented on the outside of buildings?

Roads:

- Will the roads be widened or repaved on Francis Harris Lane?
- Will any drainage features be improved along the roads?

Environmental Impact:

Will an Environmental Impact Assessment be required?

If not required, will the company conduct one to address any concerns the public or neighbors might have?

Wildlife:

- Will the local wildlife that includes wild turkeys and bobcats be part of the Environmental Impact Assessment?

Water/Wetlands:

- Does the proposed data center use water as a cooling method and if so, how many gallons per day would be used?
- If water is used as a colling method, how does the data center plan to handle the discharge of water and how many gallons per day would be discharged?
- How do you plan to treat the discharged water in relation to water quality standards?
- Where will the water be discharged to? A retention pond or do you plan to discharge into York Creek?
  - How will a retention pond affect the runoff from tract 2 into York Creek?
  - Will either of the existing ponds or tanks on the property be used as retention ponds?
  - Will there be a plan to have rainwater catchment systems in place to adhere to any potential water stage restrictions?

Land:

- A there any plans to plant native trees, plants or grasses to mitigate clearing of the land?
- Will any consideration be made to save well-established trees?
- Will there be any open space or green space incorporated and if so, how many acres?
- Will the cemetery on the property remain intact or be removed?

From: Pam Parr <[redacted]>
Sent: Saturday, March 1, 2025 1:12 PM
To: Council Members Mail Group <CouncilMembers@sanmarcostx.gov>
Subject: [EXTERNAL] Concerns regarding the proposed Data Center in Hays County

Dear City Council members,

I am writing to you as a concerned constituent regarding the proposed Cloudburst Data Center in rural Hays County. The site, located at 2955 Francis Harris Lane, seems to be especially ill-suited for this type of commercial development. It is a beautiful piece of pasture and cultivated land on the banks of York Creek, a watershed property. It is home to many native species of wildlife and boasts a gorgeous grove of mature oak, elm and pecan trees. This property is also the location of the iconic Earth House, a true marvel of design and engineering.

What this datacenter location is NOT:

- Environmentally and ecologically conducive to a large concrete structure and paved parking lots.
- Easily accessible for the traffic associated with commercial construction.
- Covered by any reliable water service and ZERO sewer service
- Above the flood plain
- Zoned commercial
- A logical place to put a huge data center

My questions and concerns:

1. This area's water is provided by Crystal Clear, a water co-op with an aging system of old pipes that continually break. Has anyone contacted Crystal Clear to ask if they can even support the enormous water usage that a data center creates?

2. This area also does not have a sewer system; instead, all the houses have septic systems. What does Cloudburst plan to do about sewage?

3. The roads in this area cannot support the travel of semi and other large commercial and industrial trucks. All "through trucks" are not allowed to travel down Francis Harris and York Creek, to try and mitigate the constant repairs that were needed when they chose to utilize them as shortcuts. How do they plan to get construction equipment to the site?

4. Approximately half of the property, which is closest to the creek, is in a flood plain. How do they plan to address that, and what impact will that have on those who also enjoy the flash floods that heavy rains in the area always create? If they try to alter the natural flow and overflow of the creek, it could have devastating effects on those living both upstream and downstream.

5. Has any type of environmental impact study been done to address any or all of these concerns?

6. Have any plans or drawings of the proposed development been submitted to any governing bodies for approval?

7. Have any building permits been applied for?

8. It is my understanding that Cloudburst refuses to comment on the proposal and has hidden the purchase of the land under a shell company. Why are they being so uncommunicative and just downright sneaky? What are they trying to hide?

I hope I can count on your support to help keep the peaceful, quiet, and rural way of life so many of us enjoy in this part of Central Texas. Our concerns for noise and light pollution, heavy commercial traffic on narrow country roads, and lack of adequate infrastructure at the site make it a poor choice to develop, and Cloudburst needs to find a more appropriate site on which to locate this facility.

Thank you for your time and I look forward to your response.

Sincerely,

Pamela J. Parr

From: Gena Fleming <[redacted]
Sent: Tuesday, February 18, 2025 3:49 PM
To: Council Members Mail Group <CouncilMembers@sanmarcostx.gov>
Subject: [EXTERNAL] Proposed Rezoning and Annexation for AI Data Center

Dear Mayor Hughson and City Council Members,

I would like to share with you this article from the San Francisco Examiner:

AI-induced pollution could kill hundreds, cost billions, researchers say

https://www.sfexaminer.com/news/technology/ai-induced-pollution-could-kill-hundreds-cost-billions-researchers-say/article_6449a044-e811-11ef-88d2-473a3ec5a724.html

A copy of the research article referenced in the newspaper article is attached below.

I am signed up to speak during public comments this evening. However, if I am not present when called upon, please know it's because I teach an online class at night and I had to leave before my time came up.

Thanks for your consideration.

Gena Fleming

Article attached to email received from G. Fleming

The Unpaid Toll: Quantifying the Public Health Impact of AI

Yuelin Han, *UC Riverside*
Zhifeng Wu, *UC Riverside*
Pengfei Li, *UC Riverside*
Adam Wierman, *Caltech*
Shaolei Ren[1], *UC Riverside*

Abstract

The surging demand for AI has led to a rapid expansion of energy-intensive data centers, impacting the environment through escalating carbon emissions and water consumption. While significant attention has been paid to AI's growing environmental footprint, the public health burden, a hidden toll of AI, has been largely overlooked. Specifically, AI's lifecycle, from chip manufacturing to data center operation, significantly degrades air quality through emissions of criteria air pollutants such as fine particulate matter, substantially impacting public health. This paper introduces a methodology to model pollutant emissions across AI's lifecycle, quantifying the public health impacts. Our findings reveal that training an AI model of the Llama-3.1 scale can produce air pollutants equivalent to more than 10,000 round trips by car between Los Angeles and New York City. The total public health burden of U.S. data centers in 2030 is valued at up to more than $20 billion per year, double that of U.S. coal-based steelmaking and comparable to that of on-road emissions of California. Further, the public health costs unevenly impact economically-disadvantaged communities, where the per-household health burden could be 200x more than that in less-impacted communities. We recommend adopting a standard reporting protocol for criteria air pollutants and the public health costs of AI, paying attention to all impacted communities, and implementing health-informed AI to mitigate adverse effects while promoting public health equity.

1 Introduction

The rise of artificial intelligence (AI) has numerous potentials to play a transformative role in addressing grand societal challenges, including air quality and public health [1, 2]. For example, by integrating multimodal data from various sources, AI can provide effective tools and actionable insights for pandemic preparedness, disease prevention, healthcare optimization, and air quality management [1, 3]. However, the surging demand for AI — particularly generative AI, as exemplified by the recent popularity of large language models (LLMs) — has driven a rapid increase in computational needs, fueling the unprecedented expansion of energy-intensive AI data centers. According to McKinsey projections, under a medium-growth scenario [4], the U.S. data centers are anticipated to account for 11.7% of national electricity consumption in 2030, a substantial increase from their current share of less than 4% in 2023.

The growing electricity demand of AI data centers has not only created significant stress on power grid stability [5,6], but also increasingly impacts the environment through escalating carbon emissions [7,8] and water consumption [9]. These environmental impacts are driven primarily by the "expansion of AI products and services," as recently acknowledged by Google in its latest sustainability report [10]. To mitigate the challenges posed to both power grids and the environment, a range of strategies have been explored, including grid-integrated data centers [6, 11], energy-efficient hardware and software [12–14], and the adoption of carbon-aware and water-efficient computing practices [9, 15–17], among others.

The hidden toll of AI. While the environmental footprint of AI has garnered attention, the public health burden, a hidden toll of AI, has been largely overlooked. Across its entire lifecycle — from chip manufacturing to data center operation — AI contributes substantially to air quality degradation and public health costs through the emission of various criteria air pollutants. These include fine particulate matter ($PM_{2.5}$, particles measuring 2.5 micrometers or smaller in diameter that can penetrate deep into lungs and cause serious health effects), sulfur dioxide (SO_2), and nitrogen dioxide (NO_2). Concretely, the AI hardware manufacturing process [18], electricity generation from fossil fuels to power AI data centers, and the maintenance and usage of diesel backup generators to ensure continuous AI data center operation all produce significant amounts of criteria air pollutants. Moreover, the distinct spatial-temporal heterogeneities of emission

[1] Yuelin Han and Zhifeng Wu contributed equally and are listed alphabetically.
Corresponding authors: Adam Wierman (adamw@caltech.edu) and Shaolei Ren (shaolei@ucr.edu)

sources suggest that focusing solely on reducing AI's carbon footprints may not minimize its emissions of criteria air pollutants or the resulting public health impacts (Section 5).

Exposure to criteria air pollutants is directly and causally linked to various adverse health outcomes,[2] including premature mortality, lung cancer, asthma, heart attacks, cardiovascular diseases, strokes, and even cognitive decline, especially for the elderly and vulnerable individuals with pre-existing conditions [20–23]. Moreover, even short-term (hours to days) $PM_{2.5}$ exposure is harmful and deadly, accounting for approximately 1 million premature deaths per year from 2000 to 2019 and representing 2% of total global deaths [24].

Globally, 4.2 million deaths were attributed to ambient (i.e., outdoor) air pollution in 2019 [25]. Air pollution has become the second highest risk factor for noncommunicable diseases [26]. Notably, according to the latest Global Burden of Disease report [27], along with high blood pressure and high blood sugar, ambient particulate matter is placed among the leading risk factors for disease burden globally in every socio-demographic group.

While the U.S. has generally better air quality than many other countries, 4 in 10 people in the U.S. still live with unhealthy levels of air pollution, according to the "State of the Air 2024" report published by the American Lung Association [28]. In 2019 (the latest year of data provided by the World Health Organization, or WHO, as of November 2024), an estimate of 93,886 deaths in the U.S. were attributed to ambient air pollution [29]. In fact, even compliance with the U.S. Environmental Protection Agency (EPA) air quality standards does not necessarily guarantee healthy air that meets the WHO guidelines. Concretely, the EPA's recently tightened primary standard for $PM_{2.5}$ sets an annual average limit of 9 $\mu g/m^3$, considerably higher than the WHO's recommended level of 5 $\mu g/m^3$ [30,31]. In addition, the EPA projects that 53 U.S. counties, including 23 in the most populous state of California, would fail to meet the revised national annual $PM_{2.5}$ standard in 2032 [32].

Further, criteria air pollutants are not confined to the immediate vicinity of their emission sources; they can travel hundreds of miles through a dispersion process (i.e., cross-state air pollution) [33,34], impacting public health across vast regions — pollutants from the 2024 Canadian wildfires significantly degraded air quality across much of the U.S. and reached as far as Mexico and Europe [35].

Importantly, along with transportation and industrial activities, electricity generation is a major contributor to ambient air pollution with substantial public health impacts [26, 36, 37]. For example, a recent study [38] shows that, between 1999 and 2020, a total of 460,000 *excess* deaths were attributed to $PM_{2.5}$ generated by coal-fired power plants alone in the U.S. As highlighted by the U.S. EPA [36], despite years of progress, "fossil fuel-based power plants remain a leading source of air, water, and land pollution that affects communities nationwide." Moreover, according to the U.S. Energy Information Administration (EIA) projection [39], the coal consumption by the electricity sector in 2050 will still be about 30% of the 2024 level in the baseline reference case, and the number will exceed 50% in the high zero-carbon technology cost case. Indeed, the growing energy demands of AI are already delaying the decommissioning of coal-fired power plants and increasing fossil-fuel plants in the U.S. as well as around the world [6, 40, 41].

The public health outcomes of AI due to its emission of criteria air pollutants lead to various losses, such as hospitalizations, medication usage, emergency room visits, school loss days, and lost workdays. Moreover, these losses can be further quantified in economic costs based on epidemiology and economics research for the corresponding health endpoints [22,42]. In contrast, the environmental impacts of AI, e.g., carbon emission from fossil fuels and water consumption for data center cooling, often do not cause the same immediate health impacts. For instance, while anthropogenic carbon emissions could also pose risks to public health, such impacts are often second- or third-order effects through long-term climate change which can then threaten the human well-being by affecting the food people eat and facilitating the spreading of pests, among others [43]. Nonetheless, despite their immediate and tangible impacts on public health, the criteria air pollutants of AI have remained under the radar, entirely omitted from today's AI risk assessments and sustainability reports [10, 44, 45].

Quantifying the public health costs of AI. In this paper, we uncover and quantify the hidden public health impacts of AI. We introduce a general methodology to model the emission of criteria air pollutants

[2]While we focus on public health, we note that the impacts of criteria air pollutants extend beyond humans and include harms to environmentally sensitive areas, such as some national parks and wilderness areas which, classified as "Class 1 areas" under the Clean Air Act, require special air protection [19].

associated with AI tasks across three distinct scopes: emissions from the maintenance and operation of backup generators (Scope 1), emissions from fossil fuel combustion for electricity generation (Scope 2), and emissions resulting from the manufacturing of server hardware (Scope 3). Then, we analyze the dispersion of criteria air pollutants and the resulting public health impacts across different regions.

Our main results (Section 4) focus on the scope-2 health impacts of U.S. data centers and, specifically, LLM training.[3] Using the reduced-complexity modeling tool COBRA (CO-Benefits Risk Assessment) provided by the EPA [46], our screening analysis demonstrates that driven by the growing demand for AI, the U.S. data centers could contribute to, among others, approximately 600,000 asthma symptom cases and 1,300 premature deaths in 2030, exceeding 1/3 of asthma deaths in the U.S. each year [47]. The overall public health costs could reach more than \$20 billion, double that of the U.S. coal-based steelmaking industry [48], and rival or even top those of on-road emissions of the largest U.S. states such as California with $\sim$35 million registered vehicles [49]. Moreover, depending on the location, training an AI model of the Llama-3.1 scale can produce an amount of air pollutants equivalent to driving a car for more than 10,000 round trips between Los Angeles and New York City (LA-NYC), resulting in a health cost that even exceeds 120% of the training electricity cost.

Critically, the health costs are unevenly distributed across counties and communities, disproportionately affecting low-income counties (e.g., Meigs County, Ohio) where the per-household health burden could be equivalent to nearly 8 months of electricity bills and more than 200x compared to that in other counties.

In addition, to highlight the importance of scope-1 and scope-3 health impacts, we consider data center backup generators in Virginia (Scope 1) and semiconductor manufacturing plants in Arizona and Ohio (Scope 3). Our analysis shows that, assuming the actual emissions are only 10% of the permitted level, the data center backup generators registered in Virginia (mostly in Loudoun, Prince William, and Fairfax) could already cause 14,000 asthma symptom cases among other health outcomes and a total public health burden of \$220-300 million per year, impacting residents in multiple surrounding states and as far as Florida (Section 2.2.1). If these data centers emit air pollutants at the maximum permitted level, the total public health cost will become 10-fold and reach \$2.2-3.0 billion per year. The scope-3 health impact of AI is also substantial. For example, just a single semiconductor facility in Arizona can cause an annual public health cost of \$26-39 million, with \$14-21 million attributed to the facility's on-site emissions of criteria air pollutants (Section 2.2.2). Furthermore, relocating the same facility to a planned site in Ohio could almost quadruple the public health cost to \$94-156 million, with \$23-36 million resulting from on-site emissions.

Finally, we provide recommendations to address the increasing public health impact of AI (Section 5). Specifically, we recommend technology companies adopt a standard reporting protocol for criteria air pollutants and public health impacts in their AI model cards and sustainability reports, implement health-informed AI to proactively minimize the adverse health effects of AI data centers, pay attention to all impacted communities, and prioritize reducing the health impact on disadvantaged communities to promote public health equity.

To summarize, our study sheds light on and quantifies the overlooked public health impact of AI. It can inform the public, policymakers, and technology companies in conducting a more comprehensive cost-benefit analysis. We also urge further research to comprehensively address the public health implications when developing powerful and truly responsible AI in the future, ensuring that the growth of AI does not exacerbate the health burden or outweigh the potential benefits AI can provide to improve public health.

2 Background on the Air Quality Impact of AI

This section presents an overview of AI's impact on air quality and contribution to criteria air pollutants throughout its lifecycle, beginning with background on criteria air pollutants and U.S. air quality policies.

2.1 Criteria Air Pollutants

Criteria air pollutants, including $PM_{2.5}$, SO_2 and NO_2, are a group of airborne contaminants that are emitted from various sources such as industrial activities and vehicle emissions. The direct emission of $PM_{2.5}$ is called

[3] Our study focuses on the 48 contiguous U.S. states plus Washington D.C. because the EPA data does not include other regions [46]. If located in countries with higher population densities or less strict air quality standards, the same AI task and data centers would likely contribute to significantly more deaths and other adverse health effects. We recommend further research on the public health impact of AI outside the U.S.

primary $PM_{2.5}$, while precursor pollutants such as SO_2, NO_x, and VOCs, can form secondary $PM_{2.5}$ and/or ozones [50]. These air pollutants can travel a long distance (a.k.a. cross-state air pollution), posing direct and significant risks to public health over large areas, particularly for vulnerable populations including the elderly and individuals with respiratory conditions [33, 34].

Long-term exposure to $PM_{2.5}$, even at a low level, are directly linked to numerous health outcomes, including premature mortality, heart attacks, asthma, stroke, lung cancer, and even cognitive decline [21, 22]. These health effects result in various losses, such as hospitalizations, medication usage, emergency room visits, school loss days, and lost workdays, which can be further quantified in economic costs based on public health research for various health endpoints [42]. In addition, short-term (hours to days) $PM_{2.5}$ exposure is also dangerous, contributing to approximately 1 million premature deaths per year globally from 2000 to 2019 [24].

Under the Clean Air Act, the U.S. EPA is authorized to regulate the emission levels of criteria air pollutants, reducing concentrations to comply with the National Ambient Air Quality Standards (NAAQS) [51]. For example, the NAAQS primary standards set the annual average $PM_{2.5}$ concentration at $9\mu g/m^3$ and the 98-th percentile of 1-hour daily maximum NO_2 concentration at 100 parts per billion by volume, both counted over three years [31]. In addition, state and local governments may set additional regulations on criteria air pollutants to strengthen or reinforce national standards [52].

While CO_2 is broadly classified by the EPA as an air pollutant following the U.S. Supreme Court ruling in 2007 [53] and contributes to long-term climate change, it often does not cause the same immediate health impacts as criteria pollutants. In the U.S., CO_2 and other greenhouse gases are subject to different EPA regulations from those for criteria air pollutants. Thus, for the sake of presentation in this paper, we use "air pollutants" to solely refer to criteria air pollutants wherever applicable.

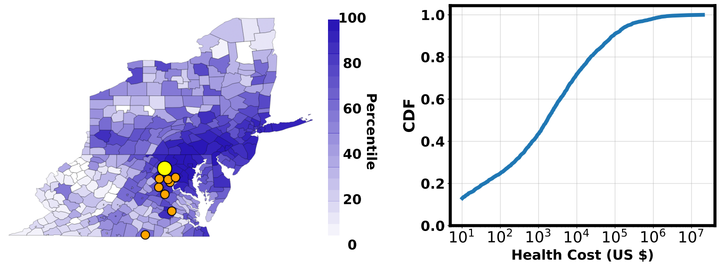
2.2 AI's Contribution to Air Pollutants

To understand the impact of AI on air quality, we focus on the three scopes over which AI contributes to criteria air pollutants as well as other toxic materials. The scoping definition in this paper parallels the well-established greenhouse gas protocol [54].

2.2.1 Scope 1

The scope-1 public health impact of AI primarily comes from the emission of operating on-site backup generators. Data centers are mission-critical facilities that are designed to operate with high availability and uptime guarantees. As a result, to maintain operation during emergencies such as grid outages, AI data centers require highly reliable backup power sources [10, 45]. Diesel generators are known to emit significant amounts of air pollutants and even hazardous emissions during operation. For example, they emit 200-600 times more NO_x than new or controlled existing natural gas-fired power plants for each unit of electricity produced [55]. Nonetheless, there is limited experience with cleaner backup alternatives that can provide comparable reliability in real-world settings, as highlighted by the U.S. Department of Energy in its recent recommendations regarding AI data center infrastructures [6]. Consequently, AI data centers, including those newly built by major technology companies, primarily depend on on-site diesel generators for backup power [6, 10, 45, 56]. For example, in northern Virginia (mostly in Loudoun, Prince William, and Fairfax), the number of permits for data center diesel generators has increased by about 70% since 2023 compared to the total number of permits issued between 2000 and 2022 [56].

While diesel generators need to comply with air quality regulations and typically do not operate over extended periods of time, regular maintenance and testing are essential to ensure their operational reliability. In addition, capacity redundancy is typically followed for diesel generator installations to ensure high availability [58]. Thus, diesel generators represent a major source of on-site air pollutants for data centers and pose a significant health risk to the public [59]. For instance, the total permitted annual emission limits for data centers in northern Virginia are approximately 13,000 tons of NO_x, 1,400 tons of VOCs, 50 tons of SO_2, and 600 tons of $PM_{2.5}$, all in U.S. short tons. Assuming that the actual emissions are only 10% of the permitted level, these backup generators could already cause 14,000 asthma symptom cases and 13-19 deaths each year among other health implications, resulting in a total annual public health burden of \$220-300 million throughout the U.S. This includes \$190-260 million in Virginia, West Virginia, Maryland, Pennsylvania, Delaware, New Jersey, New York, and Washington D.C. We show the county-level health cost and the top-10 counties in Figure 1, while deferring the details of calculations to Appendix A.3.



(*a*) *Health cost map* (*b*) *CDF of county-wide health cost*

State	County	Health Cost (million $)
MD	Montgomery	**19.9** (17.3, 22.4)
VA	Fairfax	**18.9** (16.6, 21.2)
MD	Prince Georges	**8.9** (7.5, 10.4)
MD	Baltimore	**8.3** (7.0, 9.6)
DC	District of Columbia	**7.6** (6.2, 9.0)
MD	Anne Arundel	**6.3** (5.5, 7.2)
MD	Baltimore City	**6.0** (4.8, 7.1)
VA	Loudoun	**5.4** (4.7, 6.1)
VA	Prince William	**5.0** (4.4, 5.7)
MD	Frederick	**4.6** (3.9, 5.2)

(*c*) *Top-10 counties by health cost*

Figure 1: *The county-level total scope-1 health cost of data center backup generators operated in Virginia (mostly in Loudoun County, Fairfax County, and Prince William County) [57]. The backup generators are assumed to emit air pollutants at 10% of the permitted levels per year. The total annual public health cost is $220-300 million, including $190-260 million incurred in Virginia, West Virginia, Maryland, Pennsylvania, New York, New Jersey, Delaware, and Washington D.C. (a) County-level health cost in Virginia, West Virginia, Maryland, Pennsylvania, New York, New Jersey, Delaware, and Washington D.C. Counties with data centers are marked in orange, except for Loudoun County (marked in yellow). (b) CDF of the county-level cost. (c) Top-10 counties by the total health cost.*

Moreover, due to power grid capacity constraints in many U.S. states, AI data centers are increasingly pressured to vary their loads subject to the grid's operating conditions, i.e., grid-integrated data centers [6,60]. This trend may necessitate extended reliance on backup generators, e.g., possibly 15 days per year [6]. Such prolonged usage of diesel generators could substantially elevate AI's scope-1 air pollution, creating even higher public health costs. Concretely, if the backup generators in northern Virginia emit air pollutants at the maximum permitted level, the total public health cost could reach $2.2-3.0 billion per year.

What further adds to the public health threat is that many data center generators in a region may operate simultaneously for demand response during grid capacity shortages, potentially resulting in a short-term spike in $PM_{2.5}$ and NO_x emissions that can be particularly harmful [6,24,31].

2.2.2 Scope 2

While technology companies have started implementing various initiatives — such as purchasing renewable energy credits and nuclear power from small modular reactors [5,10,61] — to lower their (market-based) carbon emissions, the vast majority of U.S. data centers remain directly powered by local power grids with a substantial portion of fossil fuel-based energy sources [10]. Thus, just as AI is accountable for scope-2 carbon emissions, it also contributes to scope-2 air pollution through its electricity usage.

The combustion of fossil fuels for electricity production is a major emitter of criteria air pollutants, releasing large amounts of $PM_{2.5}$, SO_2, NO_x, VOCs, and others.[4] Critically, the growing energy demands of AI are already delaying the decommissioning of coal-fired power plants and increasing fossil-fuel plants in the U.S. and other countries [6,40]. For example, in addition to keeping 2,099 MW coal generation capacity until 2039 (more than 80% of the 2024 level), Virginia Electric and Power Company plans to install 5,934 MW gas-fired plants to meet the growing energy demand driven by AI data centers [41]. At the national level, per the EIA's projection, [39], the 2050 natural gas consumption for U.S. electricity generation will be about 80% of the 2024 level in the baseline reference case, and even exceed the 2024 level by 20% if the zero-carbon technology cost is high; for coal consumption by the electricity sector in 2050, the numbers will also be considerably high, about 30% and over 50% of the 2024 level in the baseline reference case and in the high zero-carbon technology cost case, respectively. These projections were published by the EIA at the very beginning of the generative AI boom in early 2023. More recently, it has been reported that AI data centers could even be primarily powered by coal power plants in some countries [40]. As a result, AI's scope-2 air pollution is expected to remain at a high level for a substantially long time into the future.

We also note that the practice of using various credits to offset scope-2 carbon emissions [10] may not be

[4] Wet cooling towers, including those used by data centers [9,10] and carbon-free nuclear power plants, rely on water evaporation for heat rejection and produce $PM_{2.5}$ due to spray drift droplets [62,63]. Nonetheless, because of limited data available, we exclude the cooling tower $PM_{2.5}$ emission from our analysis unless other specified.

effective for mitigating the scope-2 public health impact. The reason is that the public health impact of using grid electricity is highly location-dependent, e.g., the impact in a populated region may not be mitigated by renewable energy generated elsewhere.

2.2.3 Scope 3

The surging demand for AI necessitates large quantities of computational hardware, including graphics processing units (GPUs), thus intensifying the supply chain requirements [64]. However, semiconductor manufacturing generates various criteria air pollutants, wastewater, toxic materials, and hazardous air emissions [18]. Moreover, the energy-intensive nature of semiconductor production further contributes to pollutants from power plants. Combined with other pollution sources such as transportation and electronic waste recycling [65], the supply chain activities form a large portion of AI's scope-3 impact on public health.

Although semiconductor manufacturing facilities are subject to air quality regulations [66], they still pose significant risks, affecting populations across large regions. Maricopa County, AZ, has been an EPA-designated non-attainment area for several years due to its failures to meet federal air quality standards [67]. The establishment of multiple semiconductor facilities in such areas could further exacerbate air quality issues. In 2023–2024, the estimated annual public health impact of a single semiconductor facility was $26-39 million, with $14-21 million attributed to direct on-site emissions of air pollutants from the facility, based on COBRA estimates [18, 46]. Moreover, relocating the facility to a planned site in Licking County, Ohio, could nearly quadruple public health costs to $94-156 million, with $23-36 million resulting from direct on-site emissions. This increase is partly due to Ohio's weather conditions and higher reliance on coal-based power [68]. The details of calculations are available in Appendix A.4. Importantly, the global demand for AI chips in 2030 is projected to be tens of times of the overall production capacity of this single facility [69], further magnifying the overall scope-3 public health impact of AI. It is also worth noting that additional pollutants, including hazardous air pollutants like hydrogen fluoride, may further elevate public health costs but are not included in this analysis.

3 Quantifying the Public Health Impact of AI

To quantify the public health impact of AI, we present a general methodology that quantifies AI's criteria air pollutants at the emission source, models its dispersed air pollutants at different receptors (i.e., destination regions), and finally obtains the public health impact and cost at each receptor.

For an AI task (e.g., AI model training), we consider M types of criteria air pollutants, N receptor regions of interest (e.g., all the U.S. counties), H types of public health impacts (e.g., mortality, asthma symptoms, school loss days, etc.). We use $p^s = (p^s_1, \cdots, p^s_M)$ and $p^r_i = (p^r_{i,1}, \cdots, p^r_{i,M})$ denote the quantities for M types of air pollutants attributed to the task at the emission source and at the receptor i, respectively, for $i = 1, \cdots, N$. Additionally, we use $h_i = (h_{i,1}, \cdots, h_{i,H})$ and $c_i = (c_{i,1}, \cdots, c_{i,H})$ to denote the incidences and economic costs associated with H types of health impacts at receptor i, respectively, for $i = 1, \cdots, N$. With a slight abuse of notations, we reuse these symbols when modeling AI's public health impacts across the three different scopes.

3.1 Criteria Air Pollutants at the Source

We first model AI's criteria air pollutants at the source across the three different scopes in Section 2.2.

3.1.1 Scope 1

On-site backup diesel generators are sized based on the data center power capacity and routinely tested to ensure a high availability of the entire data center. Thus, the overall scope-1 air pollutants should be attributed to each computing task based on its power allocation and duration. Suppose that the overall scope-1 emission by an AI data center under consideration is $\bar{p}^s = (\bar{p}^s_1, \cdots, \bar{p}^s_M)$, for M types of air pollutants, over a timespan of $\overline{T}$ (e.g., one year). Considering an AI task that is allocated a fraction of $x \in (0, 1]$ of the overall data center power capacity and lasts for a duration of T, we express the scope-1 air pollutants attributed to the AI task as

$$p^s = \frac{x \cdot T}{\overline{T}} \cdot \bar{p}^s, \tag{1}$$

which attributes the overall emission $\bar{p}^s$ to the task in proportion to its allocated power and duration.

3.1.2 Scope 2

AI's scope-2 air pollutants come from its usage of electricity generated from fossil fuels. Suppose that the power grid serving the AI data center has an emission rate of $\gamma = (\gamma_1, \cdots, \gamma_M)$ for M types of air pollutants to produce each unit of electricity. In practice, the power grid consists of multiple interconnected power plants to supply electricity to many customers over a wide area (e.g., a balancing area [70]). Thus, similar to carbon footprint accounting [71], the air pollutant emission rate γ can be calculated based on either the weighted average emission rate of all the power plants (i.e., $\gamma = \frac{\sum_k \gamma_k \cdot b_k}{\sum_k \cdot b_k}$ where γ_k and b_k are the emission rate and electricity generation of the power plant k) or the emission rate of the marginal power plant (i.e., the power plant dispatched in response to the next electricity demand increment), which are referred to as average emission rate or marginal emission rate, respectively. The average emission represents a proportional share of the overall air pollutant emission by an electricity consumer, while the marginal emission is useful for quantifying the *additionality* of air pollutants due to a consumer's electricity usage.

Suppose that the electricity consumption by the AI task is e, including the data center overhead captured by the power usage effectiveness. Then, we can write the scope-2 air pollutants as

$$p^s = e \cdot \gamma, \tag{2}$$

which is either based on either average attribution or marginal attribution. While the marginal emission is typically associated with a single marginal power plant, the average emission is spread across all the interconnected power plants within a wide area such as a power balancing area [70,71]. Thus, when considering the average attribution method, we split the energy consumption e over all the power plants in proportion to their contributions to the grid's supply and calculate the corresponding per-plant emission. In other words, each involved power plant is an individual pollution source, and the air pollutant emission at the k-th power plant is $p_k^s = e \cdot \frac{b_k}{\sum_k b_k} \cdot \gamma_k$, where b_k is the electricity generation of the k-th power plant.

Since both the average and marginal air pollutant emission rates vary over time and locations to meet the supply-demand balance, we can also refine the calculation of scope-2 air pollutants in (2) by considering the summation of air pollutants over multiple time slots over the AI task's duration.

3.1.3 Scope 3

Following the attribution method for scope-3 carbon emission and water consumption [9,13], we attribute the AI hardware's air pollutants during the manufacturing process to a specific task based on the task duration. Specifically, let the AI hardware's expected lifespan be $\overline{T}_0$ and the AI task lasts a duration of T. Considering that the M types of air pollutants for manufacturing the AI hardware are $\bar{p}_0^s = (\bar{p}_{0,1}^s, \cdots, \bar{p}_{0,M}^s)$ and excluding other miscellaneous pollutants (e.g., transportation), we obtain AI's scope-3 air pollutants as

$$p^s = \frac{T}{\overline{T}_0} \cdot \bar{p}_0^s. \tag{3}$$

As an AI server cluster includes multiple hardware components (e.g., GPU and CPU) manufactured in different locations, we apply (3) to estimate the scope-3 air pollutants for each component manufactured in a different location.

3.2 Air Quality Dispersion Modeling

Once emitted from their sources, criteria air pollutants can travel long distances, impacting multiple states along their paths. Unlike carbon emissions that have a similar effect on climate change regardless of the emission source locations, the public health impact of criteria air pollutants heavily depends on the location of the emission source. Generally, the closer a receptor is to the source, the greater the air quality impact. Furthermore, the dispersion of air pollutants is influenced by meteorological conditions, such as wind speed and direction.

The movement of air pollutants can be modeled using mathematical equations to simulate the atmospheric processes governing the dispersion, known as dispersion modeling. By incorporating emission data and meteorological inputs, dispersion modeling can predict pollutant concentrations at selected receptor locations [72]. We consider a general dispersion model $(p_1^r, \cdots, p_N^r) = D_\theta(p^s)$, which yields the amount of M types of air pollutants $p_i^r = (p_{i,1}^r, \cdots, p_{i,M}^r)$ at the receptor region $i = 1, \cdots, N$. The parameter θ captures the geographical conditions, emission source characteristics (e.g., height), and meteorological data if applicable [73]. We apply the dispersion model to each scope of air pollutants (Section 3.1) to estimate the corresponding pollutant concentrations at receptor regions.

In practice, many dispersion modeling tools are available, including AERMOD, CTDMPLUS, PCAPS and InMAP with a reduced complexity [22,72,74,75]. For example, PCAPS (Pattern Constructed Air Pollution Surfaces), an advanced reduced-complexity model that provides representations of both primarily emitted $PM_{2.5}$ and secondarily formed $PM_{2.5}$ and ozone, is used in COBRA as a quick assessment of otherwise lengthy iterations and simulations of various pollution scenarios in terms of the annual average $PM_{2.5}$ and seasonal average maximum daily average 8-hour ozone [22,75]. Even compared with state-of-the-science photochemical grid models, PCAPS provides similar prediction accuracies and can realistically capture the change in air pollution due to changing emissions [75]. More specifically, for electric power sectors and on-road/highway vehicle sectors (the two sectors we consider in Section 4), the prediction results of PCAPS compare very well with photochemical model predictions, with Pearson correlation coefficients of 0.92 and 0.94, respectively [22,75].

3.3 Converting Health Outcomes to Economic Costs

By assessing pollutant levels $p_i^r = (p_{i,1}^r, \cdots, p_{i,M}^r)$ and population size at each receptor region i, we can estimate the incidences of health outcomes $h_i = (h_{i,1}, \cdots, h_{i,H})$ and the corresponding public health cost $c_i = (c_{i,1}, \cdots, c_{i,H})$. The relations between p_i^r and h_i and between h_i and c_i can be established based on epidemiology research [22]. For example, the premature mortality rate can be modeled as a log-linear function in terms of the $PM_{2.5}$ level [23].

Further, by summing up the economic costs, we obtain quantitative estimates of the public health burden at both regional and national levels. It is important to note that the public health cost is not necessarily an out-of-pocket expense incurred by each individual, but rather reflects the estimated economic burden on a population to mitigate the adverse effects of pollutants within a specific region. Therefore, it is a quantitative scalar measure of the public health impact resulting from a particular pollutant-producing activity.

3.4 Implementation

We now briefly describe the specific implementation we use to study the public health impact of U.S. data centers and AI training. The details are available in Appendix A.

Due to the limited data available for scope-1 and scope-3 impacts, we mainly focus on the scope-2 health impacts from electricity consumption. To account for future uncertainties, we use the U.S. data center electricity consumption data provided by EPRI [5] and McKinsey [4] under various growth-rate scenarios, excluding cryptocurrency servers. Unless otherwise specified, we consider the average attribution method by default, i.e., attribute the overall health impact within an electricity region to data centers in proportion to their electricity consumption.

To model the air pollutant dispersion and quantify health impacts, we use the latest COBRA (Desktop v5.1, as of October 2024) provided by the U.S. EPA [46]. COBRA integrates reduced-complexity air dispersion modeling (including both primarily emitted $PM_{2.5}$ and secondly formed $PM_{2.5}$ and ozone [75]) with various concentration-response functions [22], offering a quantitative screening analysis particularly suitable for large-scale health impacts. The same or similar reduced-complexity modeling tools have been commonly used in the literature to examine the health impacts of various industries over a large area [74,76], including electric vehicles [77], bitcoin mining [78], and inter-region electricity imports [79], among others. While each health impact model used by COBRA considers 95% confidence intervals, the high-end and low-end estimates provided by COBRA are based on different models instead of the 95% confidence interval of a single model [22]. COBRA provides data for county-level population, health incidence, and valuation projections in 2030, but the baseline emissions are missing [46]. Thus, to account for model uncertainties, we estimate the 2030 baseline emission by extrapolating the COBRA data for 2016, 2023, and 2028 using three extrapolation methods (Linear, Exponential, and Unchanged) as detailed in Appendix A.1.

We only consider the contiguous U.S. and simply refer to it as the U.S. For consistency with COBRA, cities considered county-equivalents for census purposes are also referred to as "counties" in our paper. All our monetary values are for one year (or one AI task if applicable) and in 2023 U.S. dollars.

4 Results

We now present our estimates of the public health impacts caused by the U.S. data centers in aggregate and by training a large generative AI model at specific locations. Our results demonstrate that in 2030, the scope-2 pollutants of U.S. data centers alone could cause, among others, approximately 600,000 asthma symptom cases and 1,300 premature deaths, exceeding 1/3 of asthma deaths in the U.S. each year [47]. The overall public health costs of U.S. data centers could rival or even exceed those of on-road emissions of the largest U.S. states such as California. Moreover, depending on the locations, training an AI model of the Llama-3.1 scale can produce an amount of air pollutants equivalent to driving a passenger car for more than 10,000 LA-NYC round trips, resulting in a health cost that even exceeds 120% of the training electricity cost. Importantly, the health costs are disproportionately distributed across counties and communities, particularly affecting low-income counties that could experience more than 200x per-household health costs than others.

4.1 Public Health Impact of U.S. Data Centers in 2023

We first show in Table 1 the public health cost of U.S. data centers in 2023 as a reference.[5] Even at the beginning of the generative AI boom, the U.S. data centers have already resulted in a total public health cost of about $5.6 billion, or $39.7 per household, in 2023. This is equivalent to 43% of the data centers' total electricity cost. By considering marginal attribution, the U.S. data centers' public health cost increases to about $7.6 billion in 2023, due to the heavy reliance on fossil fuels by many marginal generators [70]. This suggests that, by powering the U.S. data centers using alternative energy sources (e.g., geothermal) off the main grid, the U.S. could have seen a public health benefit of $7.6 billion in 2023. Additional results can be found in Appendix B, including county-wide total and per-household health costs that demonstrate the uneven distribution of health impacts across different communities.

Table 1: *The public health cost of U.S. data centers in 2023.*

Attribution Method	Electricity (TWh)	Electricity Cost (billion $)	Mortality	Health Cost (billion $)	% of Electricity Cost	Per-Household Health Cost ($)	Months of Electricity Bill	% of CA On-road Health Cost
Average	152.1	13.0	**360** (270, 460)	**5.6** (4.2, 7.0)	43%	**39.7** (29.6, 49.8)	**0.29** (0.22, 0.36)	35%
Marginal	152.1	13.0	**490** (360, 620)	**7.6** (5.7, 9.4)	58%	**53.8** (40.5, 67.2)	**0.39** (0.30, 0.49)	47%

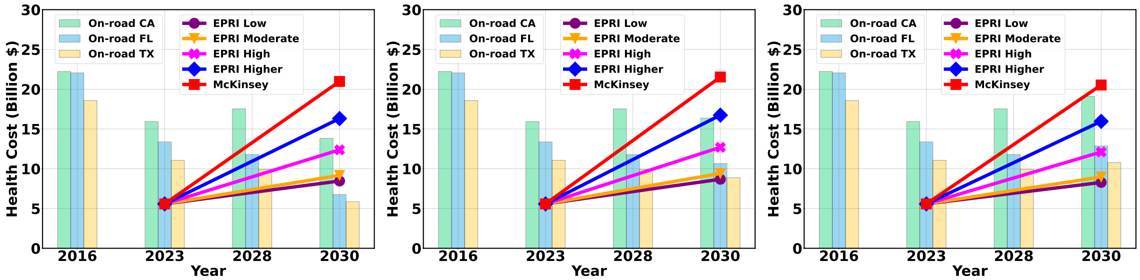
Mobile sources, including vehicles, marine engines, and generators, collectively account for more than half of the air pollutants in the U.S., with vehicles being a primary contributor [80, 81]. Thus, we contextualize the data centers' public health cost by comparing it to that of on-road emissions of California, which has about 35 million registered vehicles and exhibits the highest public health cost resulting from on-road emissions among all the U.S. states [46, 49]. On-road emissions are categorized as the "Highway Vehicles" sector in COBRA and include both tailpipe exhaust and tire and brake wear. The details of calculating on-road emissions and the corresponding health costs are available in Appendix A.1. We see from Table 1 that in 2023, the total public health cost of U.S. data centers exceeds 1/3 of that of California's on-road emissions.

4.2 Public Health Impact of U.S. Data Centers in 2030

This section presents our projections of the public health cost of the U.S. data centers in 2030.

We first show in Fig. 2 the health costs of U.S. data centers and compare them with top-3 state on-road emissions in 2030 by using different extrapolation methods. More detailed results are available in Table 2. Due to the tightening air pollutant regulations [82], the health costs of on-road emissions — a primary source of air pollutants in the U.S. — have generally decreased from 2016 to 2030. In contrast, the surging demand for AI data centers in the U.S. has outweighed the power plant emission efficiency improvement, potentially quadrupling the public health cost from 2023 to 2030. Under McKinsey's projection with a medium growth rate, the scope-2 pollutants of U.S. data centers in 2030 alone could cause, among others, approximately 600,000 asthma symptom cases and 1,300 deaths, exceeding 1/3 of asthma deaths in the U.S. each year [47]. Importantly, the public health costs of U.S. data centers could rival or even exceed those of on-road emissions of the largest U.S. states including California, suggesting a need for urgent attention to the health impact of U.S. data centers beyond on-road emissions.

[5] We use the "mid (low, high)" format to represent the midrange, low and high estimates offered by COBRA. When presenting a single value or a ratio (e.g., health-to-electricity cost ratio), we use the midrange by default.



(*a*) *Linear extrapolation* (*b*) *Exponential extrapolation* (*c*) *2028-to-2030 unchanged*

Figure 2: *The health costs of U.S. data centers and top-3 state on-road emissions from 2016 to 2030 based on different extrapolations for 2030 baseline emissions.*

Table 2: *The public health cost of U.S. data centers in 2030 based on EPRI's energy demand projection* [5]. *"†" denotes McKinsey's projection under a medium growth rate* [4].

Extrapolation Method	Projected Growth	Electricity (TWh)	Electricity Cost (billion $)	Mortality	Health Cost (billion $)	% of Electricity Cost	Per-Household Health Cost ($)	Months of Electricity Bill	% of CA On-road Health Cost
Unchanged	Low	196.3	16.8	**490** (360, 610)	**8.3** (6.3, 10.3)	49%	**55.3** (41.9, 68.8)	**0.40** (0.31, 0.50)	43%
	Moderate	214.0	18.3	**530** (390, 660)	**9.0** (6.8, 11.1)	49%	**59.9** (45.4, 74.5)	**0.44** (0.33, 0.54)	47%
	High	296.4	25.4	**710** (530, 890)	**12.1** (9.2, 15.1)	48%	**80.9** (61.3, 100.6)	**0.59** (0.45, 0.74)	63%
	Higher	403.9	34.6	**940** (700, 1180)	**16.0** (12.1, 19.8)	46%	**106.7** (80.8, 132.6)	**0.78** (0.59, 0.97)	84%
	Medium†	519.3	44.5	**1210** (900, 1510)	**20.5** (15.5, 25.5)	46%	**137.2** (103.9, 170.5)	**1.00** (0.76, 1.25)	107%
Linear	Low	196.3	16.8	**500** (370, 630)	**8.5** (6.4, 10.5)	50%	**56.5** (42.6, 70.5)	**0.41** (0.31, 0.51)	61%
	Moderate	214.0	18.3	**540** (400, 680)	**9.2** (6.9, 11.4)	50%	**61.3** (46.2, 76.3)	**0.45** (0.34, 0.56)	66%
	High	296.4	25.4	**730** (540, 920)	**12.4** (9.3, 15.4)	49%	**82.7** (62.4, 103.1)	**0.60** (0.46, 0.75)	90%
	Higher	403.9	34.6	**960** (710, 1210)	**16.3** (12.3, 20.3)	47%	**109.0** (82.2, 135.9)	**0.80** (0.60, 0.99)	118%
	Medium†	519.3	44.5	**1230** (920, 1550)	**21.0** (15.8, 26.1)	47%	**140.2** (105.7, 174.7)	**1.02** (0.77, 1.28)	152%
Exponential	Low	196.3	16.8	**510** (380, 640)	**8.7** (6.6, 10.8)	52%	**58.0** (43.8, 72.3)	**0.42** (0.32, 0.53)	53%
	Moderate	214.0	18.3	**550** (410, 700)	**9.4** (7.1, 11.7)	51%	**62.9** (47.4, 78.3)	**0.46** (0.35, 0.57)	57%
	High	296.4	25.4	**750** (560, 940)	**12.7** (9.6, 15.8)	50%	**84.9** (64.1, 105.7)	**0.62** (0.47, 0.77)	78%
	Higher	403.9	34.6	**990** (730, 1240)	**16.7** (12.6, 20.9)	48%	**111.9** (84.4, 139.4)	**0.82** (0.62, 1.02)	102%
	Medium†	519.3	44.5	**1270** (940, 1590)	**21.5** (16.2, 26.8)	48%	**143.9** (108.6, 179.2)	**1.05** (0.79, 1.31)	132%

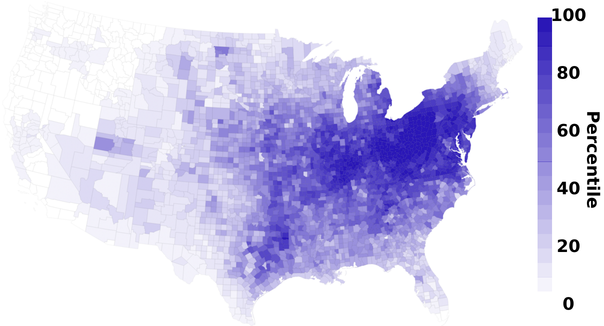
Next, we show in Fig. 3 the county-level per-household health cost of U.S. data centers in 2030 based on exponential extrapolation under McKinsey's medium-growth forecast. We see that the health cost is highly disproportionately distributed across different counties and communities, particularly affecting low-income communities. The ratio of the highest county-level per-household health cost to the lowest cost could be more than 200. Crucially, all the top-10 counties in the U.S. and 9 out of top-10 counties in Virginia (which has the largest concentration of data centers in the U.S. [4,5]) have lower median household incomes than the national median value. Moreover, many of the hardest-hit communities do not have large data centers or directly receive economic benefits from AI data centers such as tax revenues. Yet, compared to the national average of about 1 month of electricity bill per year, the households in these communities could each suffer from health impacts equivalent to up to $\sim$8 months of their electricity bills. The high degree of disparity across different communities in terms of the public health cost suggests that we must examine the local and regional health impacts of AI data centers and improve public health equity to enable truly responsible AI.

We also show the county-level total public health cost in Fig. 4. Compared to the per-household health cost distribution in Fig. 3, the county-level total health cost distribution is more aligned with the population distribution — despite the low per-household health cost, populous counties in California have a high total health cost. Nonetheless, some less populous counties (e.g., Hamilton County, Ohio) near coal and/or natural gas power plants are still significantly impacted and even more so than those (e.g., Loudoun County, Virginia) that have high concentrations of data centers.

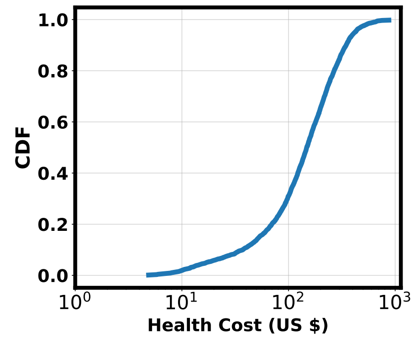
4.3 Public Health Impact of Generative AI Training

We now study the health impact of training a generative AI model. Specifically, we consider the training of an LLM and assume that the electricity consumption is the same as training Llama-3.1 recently released by Meta [84]. While we use Meta's Llama-3.1 training electricity consumption and U.S. data center locations as an example, our results should be interpreted as the estimated public health impact of training a general LLM with a comparable scale of Llama-3.1.

We show the results in Table 3. It can be seen that the total health cost can even exceed 120% of the



(*a*) *Per-household health cost map*



(*b*) *CDF of county-level per-household health cost*

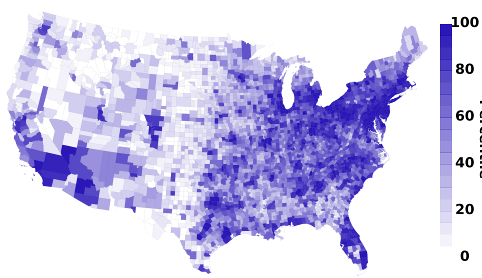
State	County	Per-household Health Cost ($)	Months of Electricity Bills	County-to-nation Income Ratio
WV	Mason	**986.4** (782.3, 1190.5)	**7.1** (5.6, 8.6)	0.71
OH	Meigs	**981.1** (744.5, 1217.7)	**7.9** (6.0, 9.8)	0.62
WV	Marion	**977.0** (783.2, 1170.9)	**7.1** (5.7, 8.5)	0.80
WV	Marshall	**974.0** (759.0, 1189.0)	**7.0** (5.5, 8.6)	0.77
OH	Gallia	**939.6** (710.7, 1168.6)	**7.5** (5.7, 9.4)	0.74
WV	Taylor	**890.1** (722.9, 1057.2)	**6.4** (5.2, 7.6)	0.70
PA	Fayette	**874.9** (694.0, 1055.7)	**6.1** (4.8, 7.4)	0.74
WV	Brooke	**861.6** (660.5, 1062.7)	**6.2** (4.8, 7.7)	0.69
PA	Greene	**837.9** (687.2, 988.5)	**5.9** (4.8, 6.9)	0.88
WV	Jackson	**753.2** (610.5, 895.9)	**5.4** (4.4, 6.5)	0.73

(*c*) *Top-10 counties by per-household health cost*

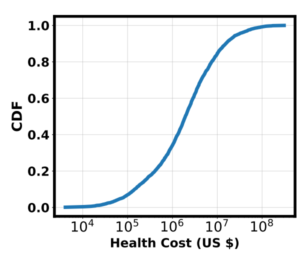
County	Per-household Health Cost ($)	Months of Electricity Bills	County-to-nation Income Ratio
Emporia City	**510.4** (369.2, 651.6)	**3.6** (2.6, 4.6)	0.55
Lancaster	**509.5** (405.5, 613.6)	**3.6** (2.9, 4.3)	0.83
Staunton City	**502.7** (386.3, 619.2)	**3.5** (2.7, 4.4)	0.79
Buena Vista City	**490.5** (378.8, 602.3)	**3.5** (2.7, 4.3)	0.65
Highland	**466.0** (367.9, 564.1)	**3.3** (2.6, 4.0)	0.76
Buchanan	**463.2** (362.3, 564.0)	**3.3** (2.6, 4.0)	0.53
Fairfax City	**462.8** (344.9, 580.8)	**3.3** (2.4, 4.1)	1.71
Dickenson	**454.0** (354.2, 553.9)	**3.2** (2.5, 3.9)	0.53
Tazewell	**441.8** (344.8, 538.8)	**3.1** (2.4, 3.8)	0.62
Colonial Heights City	**435.5** (340.3, 530.7)	**3.1** (2.4, 3.7)	0.96

(*d*) *Top-10 counties in Virginia by per-household health cost*

Figure 3: *The county-level per-household health cost of U.S. data centers in 2030 based on exponential extrapolation of baseline emissions (McKinsey's medium-growth forecast). The income data is based on the 2018-2022 American Community Survey 5-year estimates provided by [83].*



(*a*) *Health cost map*



(*b*) *CDF of county-level health cost*

State	County	Health Cost (million $)
IL	Cook	**309.6** (214.4, 404.7)
PA	Allegheny	**266.4** (204.7, 328.1)
TX	Harris	**262.0** (182.9, 341.1)
MI	Wayne	**171.8** (123.0, 220.6)
PA	Philadelphia	**169.4** (118.0, 220.8)
OH	Hamilton	**166.5** (127.3, 205.7)
NY	Kings	**165.2** (105.2, 225.2)
OH	Franklin	**152.0** (112.2, 191.8)
OH	Cuyahoga	**151.1** (110.6, 191.5)
NY	Queens	**138.6** (90.7, 186.5)

(*c*) *Top-10 counties by total health cost*

Figure 4: *The county-level total health cost of U.S. data centers in 2030 based on exponential extrapolation of baseline emissions (McKinsey's medium-growth forecast).*

Table 3: *The public health cost of training an AI model of the Llama-3.1 scale in Meta's U.S. data centers.*

Location	Electricity Price (¢/kWh)	Electricity Cost (million $)	Health Cost (million $)	% of Electricity Cost	Emission (Metric Ton)		
					PM2.5 (LA-NYC)	**NOx** (LA-NYC)	**SO2**
Huntsville, AL	7.11	2.1	**0.70** (0.54, 0.87)	33%	0.61 (13800)	2.80 (2500)	2.72
Stanton Springs, GA	6.88	2.0	**0.85** (0.65, 1.04)	41%	0.69 (15500)	3.37 (3000)	3.35
DeKalb, IL	8.20	2.4	**1.92** (1.41, 2.42)	79%	1.25 (28100)	7.31 (6600)	7.83
Altoona, IA	6.91	2.1	**2.51** (1.84, 3.17)	122%	1.52 (34000)	11.78 (10600)	14.76
Sarpy, NE	7.63	2.3	**1.54** (1.16, 1.92)	68%	1.13 (25300)	13.5 (12200)	18.51
Los Lunas, NM	5.75	1.7	**0.73** (0.56, 0.90)	43%	0.78 (17500)	8.36 (7500)	9.84
Forest City, NC	7.15	2.1	**1.07** (0.85, 1.30)	50%	0.72 (16200)	5.72 (5200)	3.27
New Albany, OH	7.03	2.1	**1.61** (1.20, 2.03)	77%	1.13 (25200)	5.15 (4600)	4.44
Prineville, OR	7.52	2.2	**0.23** (0.19, 0.28)	10%	0.59 (13300)	4.67 (4200)	2.40
Gallatin, TN	6.23	1.9	**0.32** (0.24, 0.40)	17%	0.41 (9200)	1.21 (1100)	0.93
Fort Worth, TX	6.60	2.0	**0.51** (0.38, 0.65)	26%	0.47 (10500)	3.02 (2700)	3.81
Eagle Mountain, UT	6.99	2.1	**0.24** (0.19, 0.29)	12%	0.60 (13300)	4.82 (4300)	2.52
Henrico, VA	8.92	2.7	**1.61** (1.20, 2.03)	61%	1.13 (25200)	5.15 (4600)	4.44

electricity cost and vary widely depending on the training data center locations. For example, the total health cost is only $0.23 million in Oregon, whereas the cost will increase dramatically to $2.5 million in Iowa due to various factors, such as the wind direction and the pollutant emission rate for electricity generation [70]. Additionally, depending on the locations, training an AI model of the Llama-3.1 scale can produce an amount of air pollutants equivalent to more than 10,000 LA-NYC round trips by car.

The results highlight that the public health impact of AI model training is highly location-dependent. Combined with the spatial flexibility of model training, they suggest that AI model developers should take into account potential health impacts when choosing data center locations for training.

5 Our Recommendations

We provide our recommendations to address the increasing public health impact of AI.

Recommendation 1: Standardization of Reporting Protocols

Despite their immediate and tangible impacts on public health, criteria air pollutants have been entirely overlooked in AI model cards and sustainability reports published by technology companies [10, 44, 45]. The absence of such critical information adds substantial challenges to accurately identifying specific AI data centers as a key root cause of public health burdens and could potentially pose hidden risks to public health. To enhance transparency and lay the foundation for truly responsible AI, we recommend standardization of reporting protocols for criteria air pollutants and the public health impacts across different regions. Concretely, criteria air pollutants can be categorized into three different scopes (Section 2.2), and reported following the greenhouse gas protocol widely adopted by technology companies [10, 45, 85].

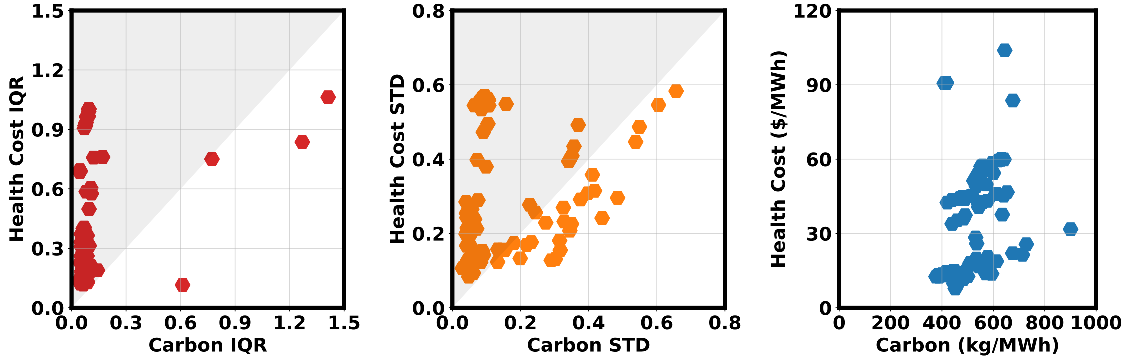
Just as addressing scope-2 and scope-3 carbon emissions is important for mitigating climate change, it is equally crucial to address scope-2 and scope-3 criteria air pollutants to promote public health throughout the power generation and hardware manufacturing processes in support of AI. For instance, power plants are dispatched based on real-time energy demand to ensure grid stability. As a result, only focusing on regulating scope-2 air pollutants at the power plant level fails to address the root cause — electricity consumption — and overlooks the potential of demand-side solutions. In contrast, recognizing scope-2 air pollutants and their associated public health impacts enables novel opportunities for health-informed AI, which, as detailed below, taps into demand-side flexibilities to holistically reduce AI's adverse public health impacts.

Recommendation 2: Health-informed AI

Data centers, including those operated by major technology companies [10, 45], predominantly rely on grid electricity due to the practical challenges of installing on-site low-pollutant and low-carbon energy sources at scale. However, the spatial-temporal variations of scope-2 health costs (Fig. 5) open up new opportunities to reduce the public health impact by exploiting the high scheduling flexibilities of AI training and inference workloads. For example, as further supported by EPRI's recent initiative on maximizing data center flexibility for demand response [11], AI training can be scheduled in more than one data center, while multiple AI models with different resource-performance tradeoffs are often available to serve AI inference requests. To date, the existing data centers have mostly exploited such scheduling flexibilities for reducing electricity costs [86], carbon emissions [15], water consumption [87], and/or environmental inequity [88]. Nonetheless, the public health impact of AI significantly differs from these environmental costs or metrics.

Concretely, despite sharing some common sources (e.g., fossil fuels) with carbon emissions, the public health impact resulting from the dispersion of criteria air pollutants is highly dependent on the emission source location and only exhibits a weak correlation with carbon emissions. For example, the same quantity of carbon emissions generally results in the same climate change impacts regardless of the emission source; in contrast, criteria air pollutants have substantially greater public health impacts if emitted in densely populated regions compared to sparsely populated or unpopulated regions, emphasizing the importance of considering spatial variability.

To further confirm this point, we analyze the scope-2 marginal carbon intensity and public health cost for each unit of electricity generation across all the 114 U.S. regions between October 1, 2023, and September 30,



(*a*) *Normalized IQR (110)*

(*b*) *Normalized STD (90)*

(*c*) *Average*

Figure 5: *Analysis of marginal scope-2 carbon emission rates and public health costs over 114 U.S. regions between October 1, 2023 and September 30, 2024 [71]. (a) In 110 out of the 114 U.S. regions (96%), the normalized IQR of marginal health cost is higher than that of marginal carbon intensity. (b) In 90 out of the 114 U.S. regions (79%), the normalized standard deviation of marginal health cost is higher than that of marginal carbon intensity. (c) The Pearson correlation between the per-region yearly average marginal health cost and carbon intensity is 0.292.*

2024, provided by [71].[6] The time granularity for data collection is 5 minutes. We show in Fig. 5a the region-wise normalized interquartile ranges (IQR divided by the yearly average) for both public health costs and carbon emissions. The normalized IQR measures the spread of the time-varying health and carbon signals. Specifically, in 110 out of the 114 U.S. regions (96%), the normalized IQR of health cost is higher than that of the carbon intensity for each unit of electricity consumption. Moreover, the normalized IQR for carbon emissions is less than 0.2 in most of the regions. This implies that health costs exhibit a greater temporal variation than carbon emissions in 110 out of the 114 U.S. regions. Likewise, in Fig. 5b, the greater temporal variation of health costs is also supported by its greater normalized standard deviation (STD divided by the yearly average) in 90 out of the 114 U.S. regions (79%). Next, we show in Fig. 5c the weak spatial correlation (Pearson correlation coefficient: 0.292) between the yearly average health cost and carbon intensity across the 114 regions. Furthermore, the normalized IQR of the health cost spatial distribution is 3.62x that of carbon emission spatial distribution (1.05 vs. 0.29), while the health-to-carbon ratio in terms of the spatial distribution's normalized STD is 3.37 (0.64 vs. 0.19). In other words, the health cost has a greater spatial spread than the carbon emission.

These findings highlight that leveraging spatial-temporal variations in a health-aware manner could significantly reduce AI's public health costs while still maintaining climate benefits. As a result, we advocate for a new research direction — health-informed AI. Specifically, decisions regarding the siting of AI data centers and the runtime scheduling of AI tasks should explicitly address their public health impacts. By judiciously accounting for and exploiting the spatial-temporal diversity of health costs, AI data centers can be optimized to minimize adverse public health impacts while supporting sustainability goals.

Additionally, as the public health awareness serves as an effective implicit incentive (e.g., as demonstrated in the context of residential energy conservation [89]), AI data center operators can also leverage this approach by informing end users about the public health impacts of their AI usage. This may help extract additional user-side demand flexibilities as part of the recent efforts to maximize the overall data center load flexibility [11].

Recommendation 3: Attention to All

Counties and communities located near AI data centers or supplying electricity to them often experience most significant health burdens. Nonetheless, these health impacts can extend far beyond the immediate vicinity, affecting communities hundreds of miles away [33, 34]. For example, the health impact of

[6] The health cost signal provided by [71] only considers mortality from $PM_{2.5}$, while COBRA includes a variety of health outcomes including asthma, lung cancer, and mortality from ozone, among others [22].

backup generators in northern Virginia can affect several surrounding states (Fig. 1a) and even reach as far as Florida.

While the health impact on communities where data centers operate is increasingly recognized, there has been very little, if any, attention paid to other impacted communities that bear substantial public health burdens. This disconnect leaves those communities to shoulder the public health cost of AI silently without receiving adequate support. To fulfill their commitment to social responsibility, we recommend technology companies holistically evaluate the *cross-state* public health burden imposed by their operations on all impacted communities, when deciding where they build data centers, where they get electricity for their data centers, and where they install renewables.

Additionally, to quantify the health effects on impacted communities with greater accuracy for potential regulatory actions, we recommend further interdisciplinary research such as cross-state air quality dispersion, health economics, and health-informed computing.

Recommendation 4: Promoting Public Health Equity

The public health impact of AI is highly unevenly distributed across different counties and communities in the U.S., often disproportionately affecting low-income communities and potentially exacerbating socioeconomic inequities [37, 90]. For example, as shown in Table 3c and 3d, all the top-10 counties in the U.S. and 9 out of top-10 counties in Virginia have lower median household incomes than the national median value. The ratio of the highest county-level per-household health cost to the lowest cost could be more than 200. Critically, minimizing the total health cost without considering equity can even reinforce existing inequities, similar to the way environmental inequities have been amplified [88]. Therefore, it is imperative to address the substantial health impact disparities across communities and ensure that AI fosters public health equity rather than exacerbating inequities.

6 Conclusion

In this paper, we uncover and quantify the overlooked public health impact of AI. We present a general methodology to model air pollutant emissions across AI's lifecycle, from chip manufacturing to data center operation. Our findings demonstrate that under McKinsey's projection with a medium-growth scenario, the U.S. data centers in 2030 could contribute to nearly 1,300 deaths annually, resulting in a public health burden of more than $20 billion which could even exceed that of on-road emissions of California. Importantly, these public health costs are unevenly distributed and disproportionately impact low-income communities, where the per-household health burden could be equivalent to nearly 8 months of electricity bills and 200x compared to other less-impacted counties. We recommend adopting a standard reporting protocol for criteria air pollutants and public health costs, paying attention to impacted communities, and implementing health-informed AI to mitigate these effects while promoting public health equity.

Our study provides novel insights for the public, policymakers, and technology companies, enabling a more comprehensive cost-benefit analysis of AI's impacts on society. We also call for further research to fully address the public health implications when developing powerful and responsible AI in the future. It is crucial to prioritize public health and ensure that the growth of AI does not exacerbate health burdens or negate the potential benefits AI can bring in improving public health.

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Appendix

A Implementation Details

We describe the evaluation methodology used for our empirical analysis. We use the latest COBRA (Desktop v5.1, as of October 2024) provided by the U.S. EPA [46] to study the public health impact of U.S. data centers in both 2023 and 2030. While COBRA uses a reduced-complexity air quality dispersion model based on a source-receptor matrix for rapid evaluation, its accuracy has been validated and the same or similar model has been commonly adopted in the literature for large-area air quality and health impact analysis [74, 76, 78, 79]. We consider county-level air pollutant dispersion throughout the contiguous U.S., which is the area currently supported by COBRA [46]. Note that cities considered county-equivalents for census purposes are also referred to as "counties" in COBRA. Throughout the paper, we use "county" without further specification.

All the monetary values are presented in the 2023 U.S. dollars unless otherwise stated. We set the discount rate as 2% in COBRA as recommended by the EPA based on the U.S. Office of Management and Budget Circular No. A-4 guidance [46]. When presenting a single value or a ratio (e.g., health-to-electricity cost ratio) if applicable, we use the midrange of the low and high estimates provided by COBRA.

A.1 Estimation of 2030 Baseline Emissions

For estimates in 2030, COBRA provides data for county-level population, health incidence, and valuation, but the baseline emissions are missing [46]. Thus, we estimate the 2030 baseline emission by extrapolating the data for 2016, 2023, and 2028 provided by COBRA. Specifically, we consider three different extrapolation methods as follows.

• **Linear:** For each pollutant type (e.g., $PM_{2.5}$, SO_2, and NO_x) at each source, we apply a linear model $y = a \cdot t + b$, where t is the year, to fit the 2016, 2023, and 2028 values and use the linear model to estimate the 2030 value. We also calculate the coefficient of determination, or R^2 score for each linear model. If R^2 is less than 0.5, we set the predicted 2030 value equal to the 2028 value. In addition, if the value is missing for a pollutant type at a source for any of the three years (2016, 2023, and 2028), we directly use the 2028 value as the 2030 value.

• **Exponential:** The exponential extrapolation method is similar to the linear method. When the model $y = a \cdot (1 + r)^t$ shows an exponentially decreasing trend from 2016 to 2028 (i.e., $r < 0$), we apply the model to estimate the 2030 value. Nonetheless, when the trend from 2016 to 2028 is increasing (i.e., $r > 0$), we roll back to a linear model for conservative estimates to avoid over-estimates resulting from an exponential model.

• **Unchanged:** We directly apply the 2028 baseline emission data to 2030.

We show in Table 4 and Table 5 the estimated total baseline emissions of air pollutants for electricity generation and on-road traffic in 2030 using different extrapolation methods. We also show the baseline emissions for 2016, 2023, and 2028 as provided by COBRA [46]. By reducing a state's on-road emissions to zero in COBRA, we obtain the corresponding public health cost in that state.

Table 4: *U.S. electricity generation baseline emissions from 2016 to 2030*

Year	**Electricity Generation Emission** (Metric Ton)			
	NOx	SO2	PM2.5	VOC
2016	1100575.41	1369417.44	111604.62	30250.76
2023	711746.94	717409.25	110878.22	34311.54
2028	695495.34	733437.11	110279.40	34446.71
2030 (Linear)	682541.75	726267.77	119326.10	36903.77
2030 (Exponential)	707846.63	751245.61	120870.45	37488.27

On-road emissions are categorized as the "Highway Vehicles" sector in COBRA and include both tailpipe exhaust and tire and brake wear. Thus, following the EPA and U.S. Department of Transportation classification [22, 91], $PM_{2.5}$ resulting from road dust is not counted as emissions of highway vehicles in our study. If the $PM_{2.5}$ from paved road dust (categorized as "Miscellaneous → Other Fugitive Dust → Paved Roads" in COBRA) is considered, California is still projected to have the highest state-wide public health cost of on-road vehicles among all the U.S. states in 2030. For example, by assuming exponential extrapolation and

Table 5: *U.S. and California on-road baseline emissions from 2016 to 2030*

Year	**U.S. On-road Emission** (Metric Ton)				**California On-road Emission** (Metric Ton)			
	NOx	SO2	PM2.5	VOC	NOx	SO2	PM2.5	VOC
2016	3293579.05	25001.53	106828.36	1680342.17	202427.66	1438.07	10197.26	89087.60
2023	1588423.83	11325.07	65742.16	996965.92	98095.76	1280.27	8144.83	54141.57
2028	1130369.84	10616.37	53455.43	758508.40	86573.30	1154.27	8276.27	44586.45
2030 (Linear)	594848.10	6402.84	40555.54	545983.16	52560.36	1109.71	7583.01	33840.13
2030 (Exponential)	925971.64	9009.44	47978.65	653737.61	68881.37	1122.56	7910.51	38536.35

including \$7.6 billion attributed to paved road dust $PM_{2.5}$, California is projected to have a total health cost of \$23.9 billion. Nonetheless, even by including paved road dust $PM_{2.5}$, our finding still indicates that the public health cost of U.S. data centers (e.g., \$21.5 billion based on McKinsey's projection) could be comparable to that of California's on-road emissions in 2030.

A.2 Evaluation of AI's Public Health Impact (Scope 2)

Due to the limited data available for scope-1 and scope-3 impacts, we mainly focus on the scope-2 health impacts unless otherwise specified. Thus, the locations of emission sources depend on the power plants supplying electricity to data centers. To evaluate the public health impacts of U.S. data centers, we consider both average attribution and marginal attribution methods for 2023. Nonetheless, since it is difficult, if not impossible, to obtain the marginal emission rate without knowing the actual dispatch decisions for the future, we only use the average attribution method for 2030. The two attribution methods are described as follows.

• **Average attribution:** We first calculate the total data center electricity consumption e_{DC} and the overall electricity consumption (including non-data center loads) e_{Total} within each electricity region. The U.S. electricity grid is divided into 14 regions following the AVoided Emissions and geneRation Tool (AVERT, the latest version v4.3 as of October 2024) provided by the EPA [70]. We use the state-level electricity consumption data for 2023 and 2030 provided by EPRI [5], and distribute state-level electricity consumption to relevant electricity regions following the state-to-region electricity apportionment used by AVERT. Note that the actual state-to-region electricity apportionment in 2030 may vary from the assumption in AVERT. Thus, we also consider an alternative apportionment to further evaluate the public health impact of U.S. data centers. Specifically, we consider a state-level electricity apportionment scenario in which each state is viewed as an electricity region. The evaluation results are shown in Appendix C and further reinforce our key finding that the health impact of U.S. data centers could rival that of on-road emissions in some of the largest U.S. states such as California.

We calculate the percentage $x\% = \frac{e_{DC}}{e_{Total}}$ of the data center electricity consumption with respect to the overall electricity consumption for each electricity region. The relationship between the health impact and emission reduction in COBRA is approximately linear. Thus, we apply a reduction by $x\%$ to the baseline emissions of all the power plants within the respective electricity region in COBRA and estimate the corresponding county-level health impacts, including health outcomes and costs.

When assessing the health impact of generative AI training, we follow the same approach, except for changing the total data center electricity consumption to the AI model training electricity consumption.

Assuming a medium growth rate, McKinsey projects that the U.S. data center electricity demand (excluding cryptocurrency) will reach 606 TWh, or 11.7% of the U.S. national electricity demand, in 2030 [4]. When using McKinsey's projection, we only use its projected percentage of 11.7%. That is, we consider the EPRI's projection of non-data center loads and scale up the EPRI's projection of data center electricity demand to match the percentage of 11.7%. As a result, the 2030 U.S. data center electricity demand is 519 TWh, instead of 606 TWh, in our study under McKinsey's projection. Nonetheless, as we apply a reduction by $x\%$ to the baseline emissions in COBRA, what matters most is the percentage, rather than the absolute electricity consumption by data centers.

• **Marginal attribution:** We only consider marginal attribution for 2023. Specifically, we use the state-level data center electricity consumption [5] and run AVERT to calculate the resulting county-level marginal air pollutant reduction [70]. AVERT allows a maximum of 15% electricity reduction within an electricity region during each hour. For regions where the data center electricity demand exceeds the 15% reduction threshold for certain hours in 2023, we cap the reduction at 15%, which results in a conservative estimate (i.e., the actual health impact of data centers is slightly higher). The county-level emission reduction data provided by AVERT is then applied to COBRA to estimate the county-level health outcomes and costs.

Electricity price. When estimating the electricity cost for data centers in 2023 and 2030, we use the state-level average price for industrial users in [92]. The projected U.S. nominal electricity price for industrial users remains nearly the same from 2023 to 2030 (24.96 $/MMBtu in 2023 vs. 23.04 $/MMBTu in 2030) in the baseline case per the EIA's Energy Outlook 2023 [39]. Thus, our estimated health-to-electricity cost ratio will be even higher if we further adjust inflation. Similarly, to estimate the household electricity bills, we use the state-level average price for residential users and county-level average household electricity consumption in [92].

Location-based emission. There are two types of scope-2 carbon emissions associated with electricity consumption: location-based and market-based [10]. Specifically, location-based carbon emissions refer to the physical carbon emissions attributed to an electricity consumer connected to the power grid, while market-based carbon emissions are net emissions after applying reductions due to contractual arrangements and other credits (e.g., renewable energy credits). In this paper, similar to location-based carbon emissions commonly studied in the literature [8], we focus on criteria air pollutants for AI data centers without considering market-based pollution reduction mechanisms.

While data centers, including large technology companies, often use various credits to reduce their market-based carbon emissions [10], it is likely less effective to apply this practice to mitigate the public health impact. The reason is that, unlike carbon emissions that have a similar effect on climate change regardless of the emission source locations, the public health impact of criteria air pollutants heavily depends on the location of the emission source. For example, the public health impact of using grid power from a populated region may not be effectively mitigated by the renewable energy credits generated elsewhere.

A.3 Public Health Impact of Backup Generators in Virginia

Virginia has issued a total of 174 air quality permits for data center backup generators as of December 1, 2024 [56]. More than half of the data center sites are within Loudoun County. We collect a dataset of the air quality permits: permits issued before January 1, 2023, from [57], and permits issued between January 1, 2023 and December 1, 2024, from [56]. The total permitted site-level annual emission limits are approximately 13,000 tons of NO_x, 1,400 tons of VOCs, 50 tons of SO_2, and 600 tons of $PM_{2.5}$, all in U.S. short tons. By assuming that the actual emissions are 10% of the permitted level, the data centers in Virginia could already cause approximately 14,000 asthma symptom cases and 13-19 deaths each year, among other health implications, resulting in a total annual public health burden of $220-300 million, including $190-260 million incurred in Virginia, West Virginia, Maryland, Pennsylvania, New York, New Jersey, Delaware, and Washington D.C., as estimated by COBRA under the "Fuel Combustion: Industrial" sector.

A.4 Public Health Impact of a Semiconductor Facility

We consider a semiconductor manufacturing facility located in Ocotillo, a neighborhood in Chandler, Arizona [93]. By averaging the rolling 12-month air pollutant emission levels listed in the recent air quality monitoring report (as of October, 2024) [18], we obtain the annual emissions as follows: 150.4 tons of NO_x, 82.7 tons of VOCs, 1.1 tons of SO_2, and 28.9 tons of $PM_{2.5}$. By applying these on-site emissions to COBRA under the "Other Industrial Processes" sector, we obtain a total public health cost of $14-21 million. Additionally, the total annual energy consumption by the facility is 2074.88 million kWh as of Q2, 2024 [93]. Assuming 84.2% of the energy comes from the electricity based on the company's global average [94], we obtain the facility's annual electricity consumption as 1746.63 million kWh. By using the average attribution method, we further obtain an estimated health cost of $12-17 million associated with the electricity consumption. Thus, the total health cost of the facility is $26-39 million.

By relocating the facility from Chandler, Arizona, to a planned site in Licking County, Ohio, and assuming the same emission level and electricity consumption, we can obtain the total health cost of $94-156 million, including $23-36 million attributed to direct on-site emissions and $70-120 million attributed to electricity consumption.

A.5 Energy Consumption for Training a Generative AI Model

We consider Llama-3.1 as an example generative AI model. According to the model card [44], the training process of Llama-3.1 (including 8B, 70B, and 405B) utilizes a cumulative of 39.3 million GPU hours of computation on H100-80GB hardware, and each GPU has a thermal design power of 700 watts. Considering Meta's 2023 PUE of 1.08 [45] and excluding the non-GPU overhead for servers, we estimate the total training energy consumption as approximately 30 GWh.

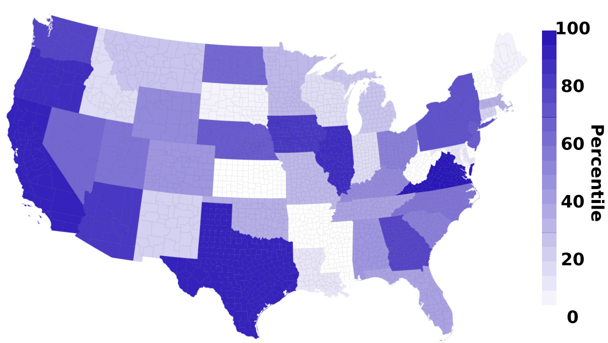
A.6 Average Emission for Each LA-NYC Round Trip by Car

We use the 2023 national average emission rate for light-duty vehicles (gasoline) provided by the U.S. Department of Transportation [91]. The emission rate accounts for tailpipe exhaust, tire wear and brake wear. Specifically, the average $PM_{2.5}$ emission rate is 0.008 grams/mile (including 0.004 grams/mile for exhaust, 0.003 grams/mile for brake wear, and 0.001 grams/mile for tire wear), and the average NO_x emission rate is 0.199 grams/mile for exhaust. We see that half of $PM_{2.5}$ for light-duty vehicles comes from brake and tire wear (0.004 gram/miles), which are also produced by other types of vehicles including electric vehicles. The distance for a round-trip between Los Angeles, California, and New York City, New York, is about 5,580 miles. Thus, the average auto emissions for each LA-NYC round trip are estimated as 44.64 grams of $PM_{2.5}$ and 1110.42 grams of NO_x.

B Public Health Impact of U.S. Data Centers in 2023

We show in Fig. 6 the state-wide data center electricity consumption in 2023 [5]. It can be seen that Virginia, Texas and California have the highest data center electricity consumption in 2023.

Next, we show in Fig. 7 the county-level per-household (scope-2) health cost caused by the U.S. data centers in 2023. We see that the health cost is highly disproportionately distributed across different counties and communities, particularly affecting low-income communities. The ratio of the highest county-level per-household health cost to the lowest cost is more than 100. Crucially, all the top-10 counties in the U.S. have lower median household incomes than the national median value. Moreover, by comparing Fig. 7 and Fig. 6, we see that many of the hardest-hit communities do not have large data centers or directly receive economic benefits from AI data centers such as tax revenues. We also show in Fig. 8 the county-level total health costs of U.S. data centers in 2023.



(*a*) *Electricity consumption map*

State	Electricity Consumption (TWh)	State	Electricity Consumption (TWh)	State	Electricity Consumption (TWh)
VA	33.85	OH	2.36	ID	0.15
TX	21.81	SC	2.02	WI	0.15
CA	9.33	WY	1.86	MD	0.10
IL	7.45	KY	1.62	LA	0.08
OR	6.41	CO	1.51	SD	0.07
AZ	6.25	AL	1.49	ME	0.03
IA	6.19	FL	1.38	NH	0.02
GA	6.18	TN	1.33	RI	0.02
WA	5.17	OK	1.23	KS	< 0.01
PA	4.59	MA	1.06	AR	< 0.01
NY	4.07	MO	0.97	DE	< 0.01
NJ	4.04	MN	0.82	DC	< 0.01
NE	3.96	MT	0.58	MS	< 0.01
ND	3.92	MI	0.53	VT	< 0.01
NV	3.42	NM	0.40	WV	< 0.01
NC	2.67	CT	0.26		
UT	2.56	IN	0.19		

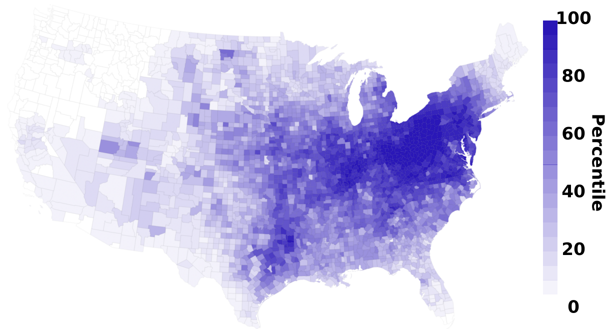
(***b***) *Electricity consumption by state (descending order)*

Figure 6: *State-level electricity consumption of U.S. data centers in 2023 [5].*

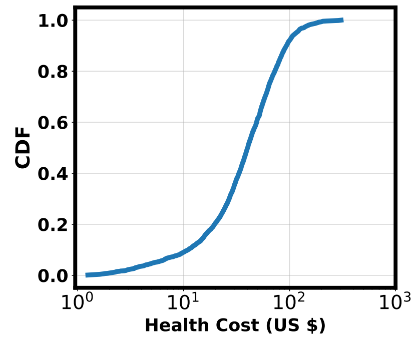
We show in Fig. 9 the per-household health cost of U.S. data centers in 2023 by considering the marginal attribution method. The health cost using marginal attribution means the public health burden resulting from the additional loads of the U.S. data centers connected to the grid in 2023. In other words, if the U.S. data centers had been powered using off-grid sources (e.g., on-site renewables) in 2023, the per-household public health benefit would be valued at up to \$319 and the total public health benefit would be \$7.6 billion.

C Public Health Impact of U.S. Data Centers in 2030 (State-level Electricity Apportionment)

AVERT [70] divides the U.S. electricity grid into 14 regions. Since the actual state-to-region electricity apportionment in 2030 may vary from the assumption in AVERT, we now consider an alternative apportionment



(*a*) *Per-household health cost map*

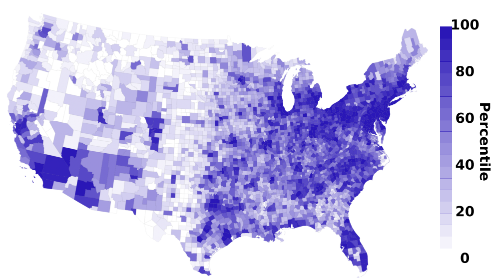


(*b*) *CDF of county-level per-household health cost*

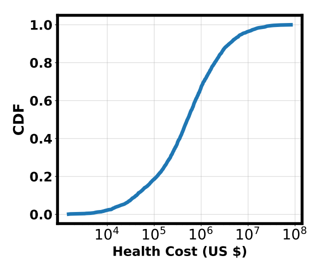
State	County	Per-household Health Cost ($)	Months of Electricity Bills	County-to-nation Income Ratio
WV	Marion	**306.0** (244.9, 367.1)	**2.2** (1.8, 2.6)	0.80
WV	Mason	**299.4** (235.6, 363.1)	**2.2** (1.7, 2.6)	0.71
OH	Meigs	**294.4** (220.0, 368.8)	**2.4** (1.8, 3.0)	0.62
OH	Gallia	**289.9** (216.5, 363.3)	**2.3** (1.7, 2.9)	0.74
WV	Marshall	**280.6** (215.6, 345.7)	**2.0** (1.6, 2.5)	0.77
WV	Taylor	**266.6** (215.4, 317.7)	**1.9** (1.6, 2.3)	0.70
PA	Fayette	**256.1** (201.9, 310.3)	**1.8** (1.4, 2.2)	0.74
PA	Greene	**245.4** (200.2, 290.5)	**1.7** (1.4, 2.0)	0.88
WV	Brooke	**235.7** (177.9, 293.5)	**1.7** (1.3, 2.1)	0.69
WV	Jackson	**227.1** (183.3, 270.9)	**1.6** (1.3, 2.0)	0.73

(*c*) *Top-10 counties by per-household health cost*

Figure 7: *The county-level per-household health cost of U.S. data centers in 2023.*



(*a*) *Health cost map*



(*b*) *CDF of county-level health cost*

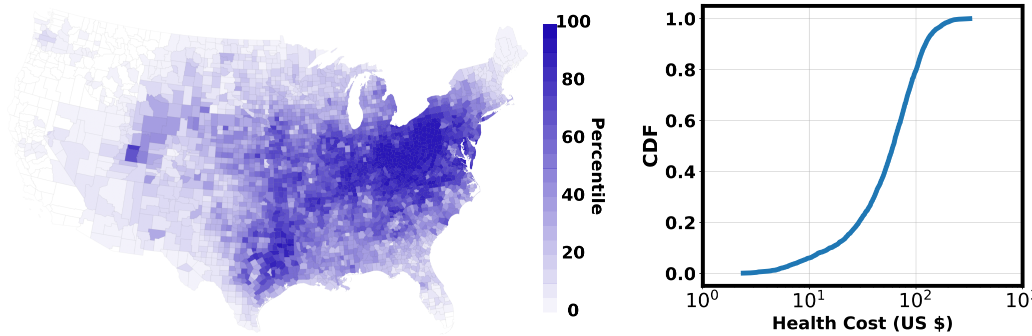
State	County	Health Cost (million $)
IL	Cook	**81.9** (55.8, 107.9)
PA	Allegheny	**80.1** (61.1, 99.2)
TX	Harris	**68.3** (46.4, 90.2)
OH	Hamilton	**49.0** (37.1, 60.9)
PA	Philadelphia	**48.1** (33.4, 62.7)
MI	Wayne	**46.8** (33.0, 60.6)
OH	Cuyahoga	**43.1** (31.1, 55.2)
NY	Kings	**41.7** (26.1, 57.3)
OH	Franklin	**41.5** (30.3, 52.7)
NY	Queens	**35.2** (22.5, 47.8)

(*c*) *Top-10 counties by health cost*

Figure 8: *The county-level health cost of U.S. data centers in 2023.*

Table 6: *The public health cost of U.S. data centers in 2030. "†" denotes McKinsey's projection under a medium growth rate (excluding energy consumption for cryptocurrency) [4]. State-level electricity apportionment.*

Extrapolation Method	Projected Growth	Electricity (TWh)	Electricity Cost (billion $)	Mortality	Health Cost (billion $)	% of Electricity Cost	Per-Household Health Cost ($)	Months of Electricity Bill	% of CA On-road Health Cost
Unchanged	Low	196.3	16.8	**370** (270, 460)	**6.3** (4.8, 7.8)	37%	**42.0** (31.8, 52.1)	**0.31** (0.23, 0.38)	33%
	Moderate	214.0	18.3	**400** (300, 500)	**6.8** (5.1, 8.4)	37%	**45.4** (34.4, 56.3)	**0.33** (0.25, 0.41)	36%
	High	296.4	25.4	**530** (400, 660)	**9.0** (6.9, 11.2)	36%	**60.4** (45.8, 75.0)	**0.44** (0.33, 0.55)	47%
	Higher	403.9	34.6	**690** (510, 860)	**11.8** (8.9, 14.6)	34%	**78.6** (59.6, 97.6)	**0.57** (0.44, 0.71)	62%
	Medium†	519.3	44.5	**890** (660, 1110)	**15.1** (11.5, 18.8)	34%	**101.0** (76.6, 125.4)	**0.74** (0.56, 0.92)	79%
Linear	Low	196.3	16.8	**370** (280, 460)	**6.3** (4.8, 7.8)	38%	**42.2** (32.0, 52.4)	**0.31** (0.23, 0.38)	46%
	Moderate	214.0	18.3	**400** (300, 500)	**6.8** (5.2, 8.5)	37%	**45.6** (34.5, 56.6)	**0.33** (0.25, 0.41)	49%
	High	296.4	25.4	**530** (400, 670)	**9.1** (6.9, 11.3)	36%	**60.7** (46.0, 75.5)	**0.44** (0.34, 0.55)	66%
	Higher	403.9	34.6	**690** (520, 870)	**11.8** (9.0, 14.7)	34%	**79.0** (59.8, 98.2)	**0.58** (0.44, 0.72)	86%
	Medium†	519.3	44.5	**890** (660, 1120)	**15.2** (11.5, 18.9)	34%	**101.6** (76.9, 126.2)	**0.74** (0.56, 0.92)	110%
Exponential	Low	196.3	16.8	**380** (290, 480)	**6.5** (4.9, 8.1)	39%	**43.6** (33.0, 54.2)	**0.32** (0.24, 0.40)	40%
	Moderate	214.0	18.3	**410** (310, 520)	**7.0** (5.3, 8.8)	38%	**47.1** (35.7, 58.5)	**0.34** (0.26, 0.43)	43%
	High	296.4	25.4	**550** (410, 690)	**9.4** (7.1, 11.7)	37%	**62.7** (47.5, 78.0)	**0.46** (0.35, 0.57)	57%
	Higher	403.9	34.6	**720** (530, 900)	**12.2** (9.2, 15.2)	35%	**81.6** (61.8, 101.4)	**0.60** (0.45, 0.74)	75%
	Medium†	519.3	44.5	**920** (690, 1160)	**15.7** (11.9, 19.5)	35%	**104.9** (79.4, 130.4)	**0.77** (0.58, 0.95)	96%



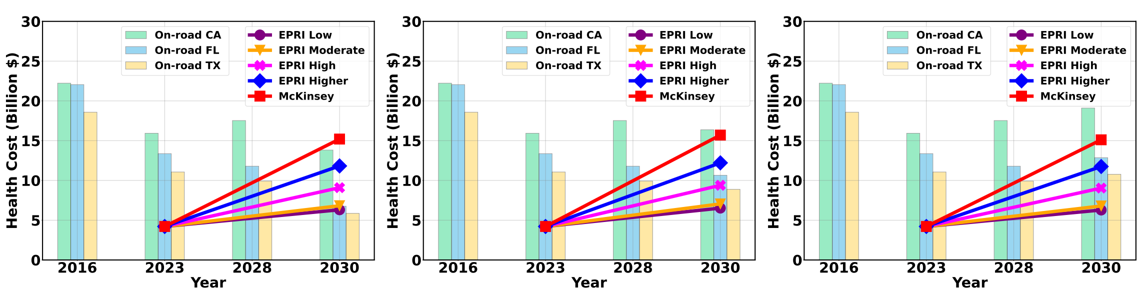
(*a*) *Per-household health cost map* (*b*) *CDF of county-level per-household health cost*

State	County	Per-household Health Cost ($)	Moths of Electricity Bills	County-to-nation Income Ratio
WV	Mason	**319.8** (258.1, 381.5)	**2.3** (1.9, 2.8)	0.71
OH	Meigs	**308.5** (235.2, 381.8)	**2.5** (1.9, 3.1)	0.62
OH	Gallia	**299.6** (229.0, 370.2)	**2.4** (1.8, 3.0)	0.74
WV	Brooke	**285.3** (213.3, 357.2)	**2.1** (1.5, 2.6)	0.69
WV	Marshall	**270.7** (204.2, 337.2)	**2.0** (1.5, 2.4)	0.77
PA	Fayette	**254.3** (195.8, 312.8)	**1.8** (1.4, 2.2)	0.74
WV	Marion	**252.8** (194.8, 310.8)	**1.8** (1.4, 2.2)	0.80
WV	Jackson	**252.2** (206.8, 297.7)	**1.8** (1.5, 2.1)	0.73
WV	Hancock	**252.1** (193.1, 311.1)	**1.8** (1.4, 2.2)	0.77
WV	Roane	**241.4** (196.8, 286.0)	**1.7** (1.4, 2.1)	0.55

(*c*) *Top-10 counties by per-household health cost*

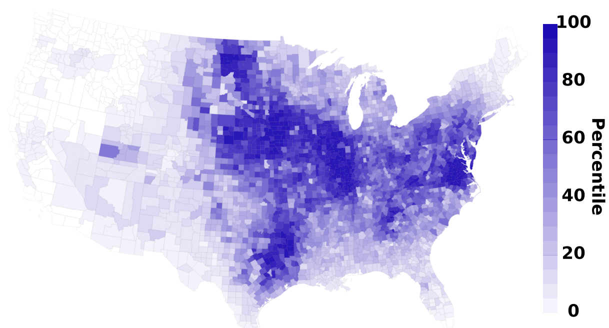
Figure 9: *The county-level per-household health cost of U.S. data centers in 2023. Marginal attribution.*

to further evaluate the public health impact of U.S. data centers in 2030. Specifically, we hypothesize a state-level electricity apportionment scenario in which each state is viewed as an electricity region (i.e., data centers are powered by in-state electricity). We show the results in Table 6, Fig. 10, and Fig. 11. While the actual values slightly differ from those in Section 4.2, the key message remains the same: the health impact of U.S. data centers could rival that of on-road emissions in some of the largest U.S. states such as California, and disproportionately affect low-income communities. As we consider in-state electricity to power data centers, 9 out of 10 most-effected counties in terms of the per-household public health burden are in Virginia which has the largest concentration of data centers [5].

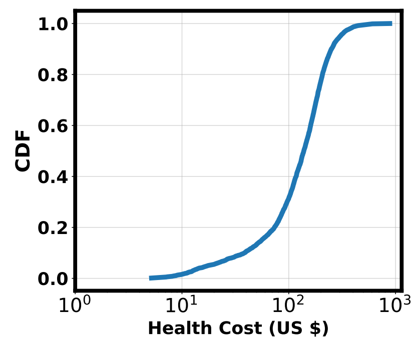


(*a*) *Linear extrapolation* (*b*) *Exponential extrapolation* (*c*) *2028-to-2030 unchanged*

Figure 10: *The health costs of U.S. data centers and top-3 state on-road emissions from 2016 to 2030 based on different extrapolations for 2030 baseline emissions. (State-level electricity apportionment.)*



(*a*) *Per-household health cost map*



(*b*) *CDF of county-level per-household health cost*

State	County	Per-household Health Cost ($)	Months of Electricity Bills	County-to-nation Income Ratio
VA	Emporia City	882.6 (623.3, 1141.8)	6.2 (4.4, 8.1)	0.55
VA	Colonial Heights City	661.4 (516.2, 806.5)	4.7 (3.6, 5.7)	0.96
VA	Brunswick	621.2 (441.8, 800.6)	4.4 (3.1, 5.7)	0.70
VA	Greensville	607.1 (408.1, 806.1)	4.3 (2.9, 5.7)	0.69
VA	Hopewell City	603.8 (466.9, 740.7)	4.3 (3.3, 5.2)	0.67
VA	Hanover	593.7 (455.7, 731.6)	4.2 (3.2, 5.2)	1.39
VA	Lancaster	580.3 (465.9, 694.7)	4.1 (3.3, 4.9)	0.83
VA	Petersburg City	576.0 (429.3, 722.7)	4.1 (3.0, 5.1)	0.62
ND	McLean	565.7 (451.1, 680.2)	4.8 (3.8, 5.8)	1.07
VA	Sussex	563.1 (397.7, 728.4)	4.0 (2.8, 5.1)	0.79

(*c*) *Top-10 counties by per-household health cost*

Figure 11: *The county-level per-household health cost of U.S. data centers in 2030 based on exponential extrapolation of baseline emissions (McKinsey's medium-growth forecast). The income data is based on the 2018-2022 American Community Survey 5-year estimates provided by [83]. (State-level electricity apportionment.)*

Location	Pearson Correlation	Normalized IQR			Normalized STD		
		Health	Carbon	$\frac{\text{Health}}{\text{Carbon}}$ Ratio	Health	Carbon	$\frac{\text{Health}}{\text{Carbon}}$ Ratio
Loudoun County, VA	0.427	0.158	0.065	2.409	0.131	0.059	2.222
Central Ohio, OH	0.479	0.160	0.065	2.441	0.137	0.066	2.064
The Dalles, OR	0.326	0.957	0.099	9.614	0.546	0.103	5.296
Douglas County, GA	0.756	0.507	0.093	5.418	0.293	0.075	3.913
Montgomery County, TN	0.760	0.289	0.067	4.320	0.195	0.046	4.236
Papillion, NE	0.736	0.748	0.840	0.891	0.487	0.553	0.881
Storey County, NV	0.584	0.178	0.057	3.132	0.168	0.042	4.004
Ellis County, TX	0.474	0.196	0.082	2.384	0.232	0.361	0.641
Berkeley County, SC	0.416	0.156	0.054	2.911	0.105	0.044	2.405
Council Bluffs, IA	0.361	0.185	0.111	1.671	0.129	0.311	0.415
Henderson, NV	0.584	0.178	0.057	3.132	0.168	0.042	4.004
Jackson County, AL	0.760	0.289	0.067	4.320	0.195	0.046	4.236
Lenoir, NC	0.240	0.176	0.059	2.982	0.129	0.046	2.800
Mayes County, OK	0.617	0.122	0.049	2.495	0.171	0.222	0.772

Table 7: *Correlation analysis of marginal carbon emissions and health impacts for Google's U.S. data center locations between October 1, 2023, and September 30, 2024 [71]. According to the region classification of WattTime [95], the two data centers in Storey County, NV, and Henderson, NV, belong to the same power grid region, and so do those in Jackson County, AL, and Montgomery County, TN.*

D Health-informed AI

We now provide additional results to highlight the importance of health-informed AI.

D.1 Correlation Analysis of Marginal Carbon Intensity and Health Impact for Google's U.S. Data Center Locations

In addition to the analysis in Section 5, we study the scope-2 marginal carbon intensity and public health cost for each unit of electricity generation across Google's U.S. data center between October 1, 2023, and September 30, 2024, provided by [71]. The health cost signal provided by [71] only considers mortality from $PM_{2.5}$, while COBRA includes a variety of health outcomes including asthma, lung cancer, and mortality from Ozone, among others [22]. The time granularity for data collection is 5 minutes.

We present the results Table 7, further confirming that carbon intensities and health impacts are not always aligned and that health impacts vary more significantly than carbon intensities in almost all the locations. This suggests that, by judiciously accounting for and exploiting the spatial-temporal diversity of health costs, AI data centers can be optimized to minimize adverse public health impacts while supporting sustainability goals.

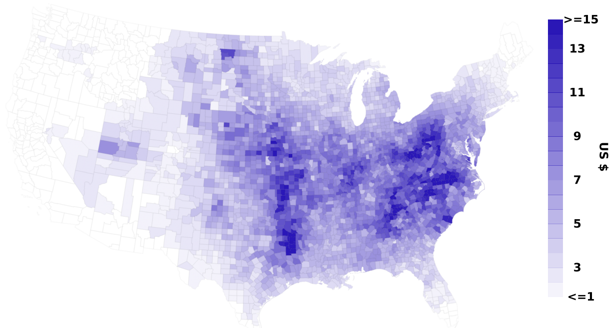
D.2 Location-dependent Public Health Impact

We now show the location-dependent public health impacts of two technology companies based on Google's and Meta's U.S. data center locations in 2023, excluding their leased colocation data centers whose locations are proprietary. Due to the lack of information about the per-data center electricity consumption, we uniformly distribute Google's North America electricity consumption over its U.S. data center locations based on Google's latest sustainability report [10]. Meta discloses its per-location electricity usage [45]. We consider criteria air pollutants without accounting for renewable energy credits these two companies apply to offset their grid electricity consumption (see "Location-based emission" in Appendix A.2). As a consequence, although we consider the U.S. data center locations of Google and Meta, our results should not be interpreted as a quantitative evaluation of these two specific companies' actual public health impacts. We also emphasize that our goal is to highlight the locational dependency of public health impacts and to motivate the need for health-informed siting of data centers. In our results, we refer to Google and Meta as Company A and Company B, respectively, to avoid potential misunderstandings.

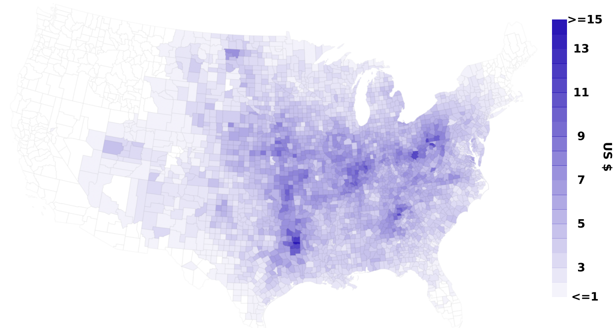
We first see from Table 8 that while the two companies have different public health costs due to their different electricity consumption, their health-to-electricity cost ratios are similar at the national level. Nonetheless, we notice from Fig. 12 that the two companies have significant differences in terms of the per-household health cost distribution and most-affected counties. This is primarily due to the two companies' different data center locations, and highlights the locational dependency of public health impacts. That is, unlike carbon emissions that have a similar effect on climate change regardless of the emission source locations, the public health impact of criteria air pollutants heavily depends on the location of the emission source.

Table 8: The public health costs based on two technology companies' U.S. data center electricity consumption in 2023.

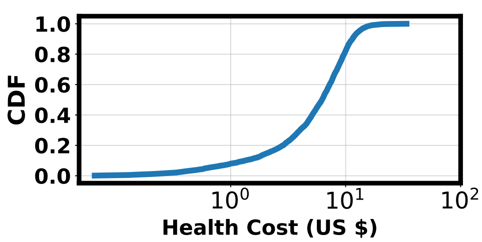
Company (Attribution)	Electricity (TWh)	Electricity Cost (billion $)	Health Cost (billion $)	% of Electricity Cost	Per-Household Health Cost ($)
A (Average)	18.5	1.4	**0.63** (0.47, 0.78)	45%	**4.5** (3.4, 5.5)
A (Marginal)	18.5	1.4	**0.97** (0.75, 1.20)	70%	**6.9** (5.3, 8.6)
B (Average)	10.6	0.8	**0.38** (0.29, 0.48)	51%	**2.7** (2.0, 3.4)
B (Marginal)	10.6	0.8	**0.53** (0.41, 0.66)	71%	**3.8** (2.9, 4.7)



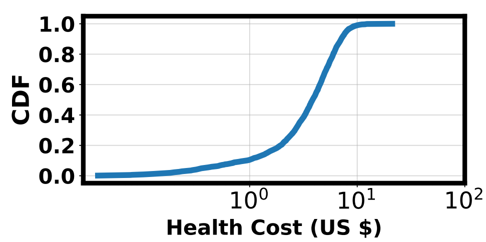
(*a*) *Per-household health cost (Company A)*



(*b*) *Per-household health cost (Company B)*



(*c*) *CDF of per-household health cost (Company A)*



(*d*) *CDF of per-household health cost (Company B)*

State	County	Per-household Health Cost ($)	County-to-nation Income Ratio
TX	Marion	**33.8** (27.2, 40.4)	0.64
VA	Mecklenburg	**23.7** (19.3, 28.1)	0.68
VA	Halifax	**23.5** (18.8, 28.1)	0.65
NC	Person	**23.5** (19.4, 27.6)	0.81
VA	Martinsville City	**22.5** (18.6, 26.5)	0.52
VA	Danville City	**21.7** (17.3, 26.1)	0.55
TX	Cass	**21.2** (16.5, 25.8)	0.72
GA	Pickens	**21.1** (17.3, 24.9)	0.97
WV	Marion	**20.5** (16.3, 24.6)	0.80
VA	Henry	**20.4** (15.9, 24.8)	0.58

(*e*) *Top-10 counties by per-household health cost (Company A)*

State	County	Per-household Health Cost ($)	County-to-nation Income Ratio
TX	Marion	**21.1** (17.0, 25.3)	0.64
TX	Cass	**13.3** (10.4, 16.3)	0.72
WV	Marion	**12.4** (9.9, 15.0)	0.80
GA	Pickens	**12.4** (10.1, 14.6)	0.97
WV	Marshall	**12.1** (9.2, 14.9)	0.77
WV	Mason	**12.0** (9.4, 14.6)	0.71
TX	Gregg	**12.0** (9.6, 14.5)	0.85
TX	Harrison	**12.0** (9.7, 14.3)	0.84
TX	Morris	**12.0** (9.3, 14.6)	0.69
OH	Gallia	**11.9** (8.9, 14.9)	0.74

(*f*) *Top-10 counties by per-household health cost (Company B)*

Figure 12: *The county-level per-household health cost of two companies in 2023. The income data is based on the 2018-2022 American Community Survey 5-year estimates provided by [83]. Average attribution.*

Thus, technology companies should account for public health impacts when deciding where they build data centers, where they get electricity for their data centers, and where they install renewables in order to best mitigate the adverse health effects while promoting equity.

From: Ben Hutchins <[redacted]>
Sent: Friday, March 21, 2025 11:21 AM
To: Planning Info <PlanningInfo@sanmarcostx.gov>
Subject: [EXTERNAL] Comment over City Council agenda items #11- ZC-25-02 and #12-PSA-25-01

To the San Marcos City Council,

Regarding the proposed AI Data Center, I'm writing to express my concern as a city resident of over 15 years. As you are well aware, this data center will use TOO MUCH water. The soul of our city, socially and economically is our water. But too much drought and increasing human use is putting it at risk. Current students at Texas State have never even seen the San Marcos River at average flow: it has been that long, and it is just getting worse. Comanche Springs is dry. Las Moras Springs is drying up, Jacob's Well is drying up. The writing is on the wall: if we don't actually advocate for water conservation, beyond empty lip service, the San Marcos River will follow suit. I support business in San Marcos, but this is absolutely not the place for a water hungry business. What is the point of designating the land as a "conservation/ cluster' area if we just change the designation at the request of a developer that doesn't know our community or our conservation issues? Please stop making decisions that continue to erode the environmental integrity of San Marcos.

Sincerely,

Ben Hutchins

123 E Sierra Circle,

San Marcos TX

Sin

From: Shirley Ogletree <[redacted]>
Sent: Sunday, March 23, 2025 11:09 AM
To: Planning Info <PlanningInfo@sanmarcostx.gov>
Subject: [EXTERNAL] Concerns about Data Center's Use of Water

Dear Planning and Zoning Members:

Thank you for your important service to our community.

As you know, we are experiencing a water shortage in San Marcos and other areas in Central Texas. According to the San Marcos River Foundation, the new Data Center, to be built largely in San Marcos, will require using a huge quantity of water. How will this impact other areas of development and current residents in the city? If the P&Z chooses to recommend this project to the San Marcos City Council, at the very least, **please require that the project reuse waste water.**

Thanks for your consideration,

Shirley Ogletree

812 Hillyer St.

San Marcos, TX 78666

From: Haley Popovich <[redacted]>
Sent: Monday, March 24, 2025 4:50 PM
To: P&Z Commissioners <PZCommission@sanmarcostx.gov>
Subject: [EXTERNAL] Data center proposed for 200-acre site in San Marcos, Texas

Hello,

I'm a citizen of San Marcos and I'm deeply concerned about the 199 acre AI data center that is potentially going to be built. I'm unable to attend the meeting tomorrow but I'm emailing to let you know I am very opposed. The data center would consume as much water as 4,000 people each day, and we are already on track to run out of water by 2047.

[San Marcos is on track to run out of water by 2047 if it doesn't take action](kut.org)

kut.org

Please do not let this project happen.

Thank you,

Haley Popovich

-----Original Message-----

From: Wolfa Dudley <[redacted]>

Sent: Tuesday, March 25, 2025 7:20 AM

To: Velasquez, Enrique <EVelasquez@sanmarcostx.gov>

Subject: [EXTERNAL] Citizen comment section

Good, whenever you find yourself reading this. This is a concern resident contacting you, in regards, to the AI center being built in San Marcos. This AI center would be detrimental to the water supply for both residents and the river (which as you know is very historical part to both the city and culture). As well as destroy acres of land that can be used for other beneficial projects (as well as simply left alone). Thank you for your time, as well your dedication.

From: Matt Payne <[redacted]>
Sent: Tuesday, March 25, 2025 1:38 AM
To: Council Members Mail Group <CouncilMembers@sanmarcostx.gov>; P&Z Commissioners <PZCommission@sanmarcostx.gov>
Subject: [EXTERNAL] San Marcos Council Must Deny Data Center Plan

Dear City Council Members,

I can not understand the benefits of building such an infrastructure in our community. Our water is being depleted at a hazardous rate simply with the increase in residency alone. While I hate to watch our river water levels drop every year, I'd leave this city with contempt for this council if that data center is built and depletes the water to a trickle. Droughts are uncontrollable, but reckless usage is unforgivable.

The use of acreage can be so much better utilized than what is being proposed with this AI data center. You should be thinking of this project similarly to a waste plant or landfill. Such a project depletes local land and resources without providing any beneficial use to the residents surrounding it. We would be selling out our beloved Gem of a place to live.

I know the council wants to develop growth plans and strategic projects to enrich San Marcos but this is not one to pursue. I ask you to please use wisdom and contemplate long term consequences to your decisions.

If its to any use, I would like to imagine our future city as one that has not paved and plundered in order to "keep up" with neighboring cities' planning. But instead, through conservation of our historical identity and natural beauty, has retained our charm and uniqueness. San Marcos can be a place set apart from the Austin/San Antonio Megaplex as a city that invested in its resources, sustained them, enriched its residents, and offers a refreshing retreat from sprawling neighbor communities.

As a proud San Marcos resident and voter, I strongly oppose the AI Data Center project. Please consider what I and many others are concerned about.

Think intently about your legacy and the potential troubles our community will face, as well as the ones we can avoid!

Thank You,

Matt Payne

From: Kirsten Bjornson <[redacted]>
Sent: Monday, March 24, 2025 7:21 PM
To: Planning Info <PlanningInfo@sanmarcostx.gov>
Subject: [EXTERNAL] Comments on Agenda Items #11- ZC-25-02 and #12- PSA-25-01

Hello,

I am writing to express my opposition to the proposed Agenda Items #11- ZC-25-02 and #12- PSA-25-01. I believe that we need to be more conscious of conservation of land and water in San Marcos and believe this development would negatively impact already scarce resources.

Furthermore, Page 110 of the adopted Vision SMTX Comprehensive Plan states that the existing Conservation/Cluster Place Type "identifies areas where development would be discouraged over the life of the Comprehensive Plan" and that " Development that does occur within conservation and reserve areas should be low impact to the natural environment by using a variety of development techniques and strategies".

The proposed agenda items #11 and #12 go directly against the Vision SMTX Comprehensive Plan. Therefore I will reiterate that I am AGAINST agenda items #11- ZC-25-02 and #12- PSA-25-01.

Thank you for your time.

Best,

Kirsten Bjornson

San Marcos, TX Resident

From: Tanya Link <[redacted]
Sent: Monday, March 24, 2025 6:35 PM
To: P&Z Commissioners <PZCommission@sanmarcostx.gov>
Subject: [EXTERNAL] Response to AI cooling towers proposal

Hello,

I am writing to express my extreme concerns for the proposal to build two large AI cooling towers in San Marcos and New Braunfels. Here are my reasons:

1. Texas is in a draught.

2. Jacob's well has been drastically low in water flow and therefore, inaccessible, for 2.5 years.

3. the city of San Marcos has already placed water use restrictions on individuals and corporations

3a. corporations only pay a fine when they overuse their allotted water. They are not stopped from overusing, and that compromises the availability for water for the rest of the county.

4. Within the next 20 years, the projected population growth rates for central Texas are so enormous that the water sources will not be able to accompany that level of water usage, at their current rate of use.

5. It is irresponsible to prioritize this project over the needs of the humans who already live here, and for those to come. Not to mention the health of our beloved San Marcos river is already in jeopardy. This AI tower project would further destroy the life of the delicate ecosystems that depend on the San Marcos river.

Please do not support this initiative as it is bad for humans and the environment.

Sincerely,

Tanya Link

San Marcos resident

From: Greg Brooks <[redacted]>
Sent: Monday, March 24, 2025 6:21 PM
To: Planning Info <PlanningInfo@sanmarcostx.gov>
Subject: [EXTERNAL] P&Z Commission Meeting March 25, 2025

Re: Agenda Items #11- ZC-25-02 and #12- PSA-25-01

Dear Commissioners:

I am writing to express my concern about the proposed zoning changes referenced above. It is my understanding that the changes would allow the development of the proposed data center.

While I do understand that the proposed development is far from the San Marcos River, the data center would use a considerable amount of water. As I am sure you are aware, we are seeing record low-flows from the river. ANY further burden on our water resources should be scrutinized.

While I am pro business development, I do not agree with the justification that bringing this development to San Marcos would be a benefit to the citizens of San Marcos in the long run.

Please seriously consider the ramifications of allowing this development to move forward. I respectfully urge you to deny the zoning request.

Sincerely,

Greg Brooks

512-799-8973

From: Lisa Arceneaux <[redacted]>
Sent: Monday, March 24, 2025 5:10 PM
To: Planning Info <PlanningInfo@sanmarcostx.gov>
Subject: [EXTERNAL] P&Z agenda items 3-25-25 #11 and #12 referencing a data center project

Dear P&Z members,

I served on the Comp Plan Stakeholders Committee for the latest City plan update and worked with the members and consultant for over two years.

I see on the Preferred Use Scenario Plan that the property in question is in the Conservation Cluster. I can see how changing it to Light Commercial would be conceivable given the power plant property designation adjacent.

During the development of the Preferred Use Scenario Map, the committee wanted to use conservation cluster areas to limit impervious cover and disturbance for land in watersheds that have already got impervious cover existing or planned. This land in question is in the Cottonwood Creek watershed and it is preferred that it be left undisturbed, or disturbed only with the use of low impact development techniques employed for stormwater infiltration, rainwater capture and reuse onsite.

If the area is rezoned for light commercial, I am very opposed to the use of the space for a Data Center due to the high water demand and energy demand such a facility puts on our strained resources. In the Comp Plan and in

water and energy planning, the basis for increasing water supply and energy is projected population growth. I'm not certain that incoming Data Centers to San Marcos was factored into those equations. Data Centers use energy to power the servers and to cool the rooms where they are stored. 100-degree summer heat in San Marcos exacerbates the problem of keeping them cool. Water is circulated in the backs of the servers and this water demand is also significantly higher than most light commercial industries. The large volume of water is sent to the wastewater treatment plant for treatment when the dissolved salt concentrations from cooling tower blowdown reaches trigger levels. I am uncertain if this new load will be manageable at the current or new wastewater treatment plan. Addition of a low organic carbon and high dissolved solids stream to the treatment plant could present unforeseen challenges for treatment, and curtain efforts underway to possible treat effluent to

potable water. (Texas State Researchers/Civil Engineers are working on this strategy to increase potable water supply for San Marcos)

San Marcos is in Stage 3 water conservation level that requires the city as a permitted water user to reduce water pumping by 40%. Stage 4 may be required as the drought persists. Data Centers need a consistent water supply 24/7, so this type of conservation scenario will not benefit the center or the city residents. Residents are called upon to reduce energy usage during the mid afternoons during 100 degree plus weather to minimize electric grid outages. Data Centers typically charge the utility if they have to reduce power. This scenario will not benefit the city residents or the utility.

In summary, changing the land use to light industrial is not the biggest issue for this project. However, adding a high energy and water dependent industry to an area like ours is not in the best interest of the current city residents, or its continued growth in population, in my opinion.

Thank you for considering these comments.

Lisa Arceneaux, P.E.

From: abigail lindsey <[redacted]>
Sent: Monday, March 24, 2025 6:25 PM
To: P&Z Commissioners <PZCommission@sanmarcostx.gov>; Velasquez, Enrique <EVelasquez@sanmarcostx.gov>; Council Members Mail Group <CouncilMembers@sanmarcostx.gov>; Hughson, Jane <JHughson@sanmarcostx.gov>
Subject: [EXTERNAL] Petition against PSA-25-01/ Data Center 904 Francis Harris Lane

Hello, I wanted everyone to have a copy of the petition against PSA-25-01. I plan to speak at all the meeting associated with this item. But I wanted you to know how upset the community is about this.

On a side note CloudBrust Data Center plans to build a Natural Gas Power Plant and a Data Center at 2955 Francis Harris Lane. This is outside the city limits of San Marcos but resides in both Hays and Guadalupe County it has also been removed from the ETJ of Hays County. CloudBurst will not be utilizing gas from Hays Power Plant on Francis Harris Lane.

That would mean two Data Centers on the same road only 2.9 miles from each other pulling water from Crystal Clear SUD which is supplied by Alliance Water. Hays Power Plant also uses Crystal Clear SUD as well.

This information is very concerning and I want to make sure everyone has all the information before a vote on this.

Please reach out if you have any questions.

Thank you

Abigail Lindsey

[redacted]

Petition to Stop the Data Center Development Located at 904 Francis Harris Lane, San Marcos, Texas 78666

To: San Marcos Planning and Zoning, San Marcos City Council, San Marcos City Mayor, Crystal Clear Special Utility District

From: Concerned Residents of Central Texas, Hays County, Comal County, Guadalupe County

Against the proposed change to the Preferred Scenario land designation being changed from "Conservation/Cluster" to "Commercial/ Employment Low" and to the proposed development of a Data Center located at 904 Francis Harris Lane, San Marcos, Texas 78666

We, the undersigned residents of Central Texas, Hays County, Comal County, Guadalupe County, strongly oppose the proposed development of the Data Center located at 904 Francis Harris Lane, San Marcos, Texas 78666. We believe this project poses significant risks and negative impacts on our community.

OUR CONCERNS:

1. Environmental Impact- The proposed data center will consume excessive amounts of water and electricity, straining local resources and increasing carbon emissions. Such facilities often contribute to air and noise pollution, further degrading our environment.

2. Strain on Local Infrastructure- The increased energy and water demand could lead to higher utility costs and shortages disproportionately affecting residents and small businesses. Additionally, construction and operational traffic will cause congestion and road wear.

3. Noise and Air Pollution- Large cooling systems and backup generators will produce constant noise and emissions, disrupting the peace of our neighborhoods and potentially harming public health. Rodriguez Elementary School is less than a mile away from the proposed Data Center.

4. Lack of Community Benefits- While the data center may create a few temporary construction jobs, it offers little in terms of long-term employment or economic benefits for our local workforce.

5. Potential for Future Expansion- Approving this development sets a precedent for further industrial expansion, increasing the risk of additional environmental and community disruptions.

6. General Provisions Relating to Cemetery-Approving this development could cause serious harm to the cemetery currently on the property. There seems to be a lack of oversight with the Tex. Health and Safety Code Ch. 711 with the current owner which may lead to oversight with the owner of the Data Center in regards to the cemetery.

OUR REQUEST:

We urge the Planning and Zoning Commission and City Council to vote no on PSA-25-01.

We call for:

*A vote of "No" on PSA-25-01

*Crystal Clear SUD to not supply water to the proposed Data Center located 904 Francis Harris Lane, San Marcos, Texas 78666

We, the undersigned, stand united in protecting our community and call for immediate action to halt the development of the Data Center located at 904 Francis Harris Lane, San Marcos, Texas 78666

Petition for
904 Francis Harris Lane
San Marcos, TX
78666

	Name	Address	Signature	Date	Optional Phone Number and/or Email
1	Lexi Morris	408 Moore St 78666	LMorris	3/18/25	[redacted]
2					
3					
4					
5					
6					
7					
8					
9					
10					

Petition for
904 Francis Harris Lane
San Marcos, TX
78666

	Name	Address	Signature	Date	Optional Phone Number and/or Email
1	Lauren Barrett	7575 cambridge st. Houston. tx	Lauren Barrett	3/16	
2	Lucy Allmand	612 Barbara DR San Marcos, TX		3/16	
3	Brian Allmand	612 Barbara DR San Marcos, TX		3/16	
4	Angie Ramirez	412 Barbara DR San Marcos, TX		3/16	
5	Carrie Bucklin	208 Calixto Ct SMTX 78666	Carrie Bucklin	3/17	[redacted]
6	Guadalupe Salsado	1988 coffee RD. SMTX		3/17	
7	Alexander Salgado	1988 coffee rd		3/17	
8	Lisa Guerra	112 Coers Dr. Apt. A SMTX 78666	Lisa Guerra	3/18	
9	cooper Stokes	1451 sadler drive Apt 5114		3/18	[redacted]
10					

Petition for
904 Francis Harris Lane
San Marcos, TX
78666

	Name	Address	Signature	Date	Optional Phone Number and/or Email
1	JERRY DELGADO	840 ALABAMA ST SAN MARCOS, TX	[illegible]	3/12/25	
2	Bill Walker	1717 Quail Run San Marcos, TX	[illegible]	3/12/25	
3	Georgia Clogston	808 W. bluebonnet Dr. San Marcos, TX	[illegible]	3/12/25	
4	Gibson Davis	↑ Same	[illegible]	3/12/25	
5	Sloan Rodgers	102 Wonder Wold Dr.	[illegible]	3/12/25	
6	Jennifer Flores	209 Valley Acres Dr New Braunfels 78130	[illegible]	3/14/25	
7	Brenda Underwood	209 Valley Acres Dr. New Braunfels, TX 78130	Brenda L. Underwood	3-14-25	
8	Simon Flores	209 Valley Acres New Braunfels TX 78130	[illegible]	3/14/25	
9	CINDY LINDER	301 Valley Acres DR. New BRAUNFels, TX 78130	Cindy M. Linder	3/14/25	
10					

Petition for
904 Francis Harris Lane
San Marcos, TX
78666

	Name	Address	Signature	Date	Optional Phone Number and/or Email
1	CASEY WILSON	1316 PROSPECT ~~ST~~ SAN MARCOS, TX	Casey Wilson	3/16/25	
2	DAVID WHITBECK	1316 PROSPECT ST. SAN MARCOS, TX	[illegible]	3/16/25	[redacted]
3	Christina Ausmus	911 N Bishop st San Marcos TX	[illegible]	3/17/25	[redacted]
4	Jordan Bucholz	911 N Bishop st San marcos TX	[illegible]	3/17/25	
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Petition for
904 Francis Harris Lane
San Marcos, TX
78666

	Name	Address	Signature	Date	Optional Phone Number and/or Email
1	John Henry Davis	445 Davis Ranch Rd. SM TX 78666	[signature]	3/17/2025	
2	TERI LYNN PETERSON	601 DAVIS RANCH RD SAN MARCOS 78666	[signature]	3/17/25	
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Petition for
904 Francis Harris Lane
San Marcos, TX
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	Name	Address	Signature	Date	Optional Phone Number and/or Email
1	D.T. Kelly	907 Deertrail	D.T. Kelly	3-15-25	[redacted]
2	Matt Barne	204 Harmons Way	[illegible]	3/15/25	
3	Valerie Medina	1747 FM 1101	Vale Medina	3/15/25	
4	Emily Eisel	520 Linda Drive	[illegible]	3/15/25	
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8					
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10					

Petition for
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	Name	Address	Signature	Date	Optional Phone Number and/or Email
1	Jordan Von Blohn	619 Columbia Ave San Marcos, TX 78666	[illegible]	3/15/25	[redacted]
2	Tom Purcell	403 Blanco St San Marcos TX 78666	[illegible]	3/15/25	[redacted]
3	Mindy Adams	1201 Oak Grove Rd San Marcos, TX 78666	[illegible]	3/15/25	[redacted]
4	Karl Toft	1319 W. San Antonio St San Marcos TX 78666	[illegible]	3/15/25	[redacted]
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Petition for
904 Francis Harris Lane
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	Name	Address	Signature	Date	Optional Phone Number and/or Email
1	[illegible]	330 wavell st	Monica L. Mabry-Toftemark	3/15/25	
2	Drew Zoch	121 Craddoch Ave	[illegible]	03/16/25	
3	Jeff Elber	7010 Centerpoint	Jeff Elber	3-20-25	
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10					

Petition for 904 Francis Harris Lane, San Marcos, Tx. 78666

Name	Address	Signature	Date	Optional/Phone Number/Email
Abigail Lindsay	308 Valley Acres Dr. New Braunfels, TX. 78130	Abigail Lindsay	3/12/25	
Lauren Hovey	300 Alpine Trl San Marcos, TX 78666	Lauren Hovey	3/12/25	
GREG LINDER	301 VALLEY ACRES Rd NEW BRAUNFELS, TX 78130	[illegible]	3/14/25	
GEORGE UNDERWOOD SR	209 VALLEY ACRES NEW BRAUNFELS TX 78130	[illegible]	3/14/25	
BARRY LINDSEY	312 VALLEY ACRES DR. NEW BRAUNFELS TX 78130	Barry Lindsey	3/14/2025	

Petition for
904 Francis Harris Lane
San Marcos, TX
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	Name	Address	Signature	Date	Optional Phone Number and/or Email
1	Lauren McEwan	1302 Delmar St.	[illegible]	3.15.25	
2	Joseph Sofial	228 Camino Way SMTX 78666	[illegible]	3/15/25	
3	Emily Watson	605 Clyde Ct. SMTX 78666	[illegible]	3/16/25	
4	JAIME WATSON	605 CLYDE CT SM TX 78666	[illegible]	3-16-25	
5	Niles Williamson	108 Riviera SMTX 78666	[illegible]	3/16/25	
6	Michelle Gold	171 Friendship Oaks SM 78666	[illegible]	3/16/25	[redacted]
7	Rebekah Porter	1103 EARLE ST. SM 78666	[illegible]	3/16/25	[redacted]
8	Daniel Reinhart	2018 Ridge View Dr SMTX 78666	[illegible]	3/16/25	
9	MICHAEL D. WHITE	810 PERKINS SMTX 78666	MDW	3.16.25	
10	Dorothy D. Adams	1201 Oak Grove Rd. SMTX 78666	[illegible]	Mar 16 2025	

Petition for
904 Francis Harris Lane
San Marcos, TX
78666

	Name	Address	Signature	Date	Optional Phone Number and/or Email
1	Taylor Leal	543 Lindsey	[signature]	3/15/25	
2	Kate Antoun	92 Crazy Cross Rd.	[signature]	3.15.25	[redacted]
3	Catherine Ramirez	112 E Holland St.	[signature]	3/15/25	
4	CHRISTINA Y. ORTA	227 KNOX ST SAN MARCOS, TX	[signature]	3/15/25	[redacted]
5	Amy Goldberg	233 Rock Bluff San marcos, TX	[signature]	3/15/25	
6	Amanda Anderson	130 Jackson ln apt A4 San Marcos TX	[signature]	3/15/25	[redacted]
7	Maia Clinkscales	703 Academy st, San Marcos, TX	[signature]	3/15/25	[redacted]
8	MICHAEL VILLARREAL	112 CORES DR APT A	[signature]	3/15/25	
9	Jen Thunderhawk	215 parker Drive San Marcos, TX	[signature]	3/15/25	
10	Sean Voight	1302 Delmar Street San marcos TX	[signature]	3/15/25	

Petition for
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	Name	Address	Signature	Date	Optional Phone Number and/or Email
1	SHAE LEWIS	204 HARMONS WAY SAN MARCOS, TX 78666		3/15/25	[redacted]
2	CJ WILLIAMS	1010 GIRARD ST. SAN MARCOS, TX 78666		03/15/2025	
3	VAL MOSHER	1010 GIRARD ST SAN MARCOS TX 78666		03/15 2025	[redacted]
4	Anastasiia Greider	525 W HOPKINS ST SAN MARCOS TX 78666		03/15/2025	[redacted]
5	Mike Lochman	217 CAMARO SAN MARCOS TX 78666		3/15/25	[redacted]
6	miguel guerra	291 S Main 78622 Fentress TX		3/15/25	
7	KEVIN HUFFAKER	520 Owl Hollow San Marcos TX 78666		3/15/25	[redacted]
8	Michael ~~Dylan~~ Showers	704 Harmons Way San marcos, TX 78666		3/15/25	
9	Geoffrey Treece	204 Harmons SAN MARCOS, TX 78666		3/15/25	
10	Jordy Greider	1105 Twisted Oak ct CANYON LAKE 78133		03/15/25	

Petition for
904 Francis Harris Lane
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	Name	Address	Signature	Date	Optional Phone Number and/or Email
1	Luke Orona	900 Peques Apt 301	[illegible]	3/12/25	[redacted]
2	Rebekah Resendez	911 Hillyer St	[illegible]	3/12/25	[redacted]
3	David Zambrano	721 Oak Meadows	[illegible]	3-12-25	[redacted]
4	Emily Jenkins	203 W Hillcrest	[illegible]	3/12/25	[redacted]
5	Emily McCuistion	701 Columbia Av. San Marcos, TX	[illegible]	3/12/25	[redacted]
6	Lauren Chappell, MSc Aquatic Bio	722 Thousand Oaks Loop	[illegible]	03/12/25	[redacted]
7	Erin Watson	205 Woodcreek Dr Wimberley 78676	[illegible]	3/12/25	[redacted]
8	Steve Anderson	1000 N Bishop St 78666	[illegible]	3/12/25	[redacted]
9	Mary Duffey	1000 N Bishop St 78666	[illegible]	3/12/25	[redacted]
10	Jeff Colasurd	1006 Barbara Dr. 78666	[illegible]	3/12/25	[redacted]

Petition for
904 Francis Harris Lane
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	Name	Address	Signature	Date	Optional Phone Number and/or [redacted]Email
1	Abby Wetzel	1717 Quail Run San Marcos	Abby Wetzel	3.12.25	[redacted]
2	Jennifer Lindsey	312 Valley Acres Dr New Braunfels (Hays County)	[illegible]	3.12.25	—
3	Cas Corbitt	1805 aquarena Springs San Marcos	Corbitt	3.12.25	—
4	ANDY GRUBBS ASPG	601 Owl Hollow RD San Marcos	[illegible]	5-12-25	
5	Rachel Kelly	5313 Indio Dr. Austin, TX 78745	Rachel K	3.12.25	—
6	Kendra Smith	1221 Conway Dr. San Marcos, TX 78666	[illegible]	3-12-25	[redacted]
7	Indica Smith	2110 Stonehaven San Marcos TX 78666	[illegible]	3-12-25	[redacted]
8	Corey Naredo	2110 Stonehaven San Marcos TX 78666	[illegible]	3-12-25	[redacted]
9	ARA SENEUIUENZA	2797 W13TH AVE #602 DENVER, CO 80204	[illegible]	3.12.25	
10	THOM CANADY	701 SETTLERS RD SAN MARCOS 78666	[illegible]	3-12-25	

Petition for
904 Francis Harris Lane
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	Name	Address	Signature	Date	Optional Phone Number and/or Email
1	Andy Villalpando	625 W. Hutchison St #102	Andrea Villalpando	3.12.25	[redacted]
2	Joshua Maltzahn	1044 Esplanade Pkwy	[illegible]	3/12/25	
3	Sengawiley Russell	1309 Baylor Ave	[illegible]	3/12/25	
4	Cameron Healy	827 Lewis St	C-Elise	3/12/25	[redacted]
5	CJ Ceting	421 W San Antonio St Apt K3	[illegible]	3/12/25	
6	Boone Graham	1111 Marlton St	[illegible]	3/12/25	
7	Trevor Smith	301 Saltillo St.	[illegible]	3/12/25	[redacted]
8	Diana Schennemsss	107 Blanco Street	[illegible]	3/12/25	
9	CARL JOHNSON	1011 W BLUEBONNET A SAN MARCOS TX 78666	[illegible]	3/12/2025	[redacted]
10	Shivani VanBlelen	619 columbia san marcos tx	Shivani VanBlelen	3.12.25	

Petition for
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	Name	Address	Signature	Date	Optional Phone Number and/or Email
1	JENNIFER CANADY	701 SETTLERS RD SMTX 78666	Jennifer Canady	3-13-25	
2	Timothy Wilkins	133 old ranch rd 12 Unit 2	Timothy Wilkins	3/12/25	[redacted]
3	ETHAN RAMIREZ	1005 INDIANA ST	[illegible]	3/12/25	
4	SCOTT MITCHELL	727 GEORGIA ST.	Scott Mitchell	3.12-25	
5	Misty Green	1009 Haynes St 78666	Misty Green	3/12/25	
6	Hayat Qurunful	1604 old RR12 78666	HQ	3.12.25	
7	David Leder	117 E Sierra Cir	[illegible]	3/12/25	
8	AUDREY CARTER	1654 POST ROAD	[illegible]	3/12/25	
9	Kenzi Gray	316 Trestle Tree	Kenzi Gray	3/12/25	[redacted]
10	William Stevens	~~[illegible]~~ 1304 Burleson Ave	[illegible]	3/12	

Petition for
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	Name	Address	Signature	Date	Optional Phone Number and/or [redacted] mail
1	Andy Howard	1004 Columbia	[illegible]	3.15.25	
2	Deborah Lane	560 S Old Bastrop Hwy	[illegible]	3-15-25	
3	Madeline Forta	3410 snell rd	[illegible]	3-16-25	
4	Scott Johnson	1309 Lazy Lane	[illegible]	3.16.25	
5	ERIKA WARREN	2859 ARROYO DOBLE	Erika Warren	3.16.25	
6	Allison Croft	332 River Ranch Circ.	[illegible]	3.16.25	
7	Jason Brazil	1606 Hamilton St. San Marcos	[illegible]	3.16.25	
8	Lori ~~[illegible]~~ Jenkins	205 Hunter Ridge Rd San Marcos Tx	Lori Jenkins	3/16/25	
9	Alaina Lee	461 Whispering hollow drive Kyle Tx	[illegible]	3/16/25	
10	Sara Milleson	390 Goddard Kyle, TX 78640	[illegible]	3/17/25	

Petition for
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	Name	Address	Signature	Date	Optional Phone [redacted]umber and/or Email
1	Sean McSorley	226 Chesterfield dr Kyle TX 78640	[illegible]	3/14	
2	Anthony Schumacher	San Marcos	[illegible]	3/14	[redacted]
3	Ethan Petersen	San Marcos	[illegible]	3/14	
4	Alexa Hughes	SAN MARCOS	[illegible]	3/14	
5	Fernanda Hernandez	San Marcos	[illegible]	3/14	[redacted]
6	Bailey Heatherly	San Marcos	[illegible]	3/14	
7	Diah Jantzen	925 Ridge Dr San Marcos	Diah Jantzen	3/15	[redacted]
8	Craig Jantzen	925 Ridge Dr San Marcos	Craig Jantzen	3/15/25	[redacted]
9	Elizabeth Emberson	503 Harvey St. 78666	[illegible]	3/15/25	[redacted]
10	BARRY LINDSEY	312 VALLEY ACRES DR. NEW BRAUNFELS TX 78130	Barry Lindsey	3/19/2025	

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	Name	Address	Signature	Date	Optional Phone Number and/or Email
1	Nikkye Vargas	918 Haynes St SM, TX 78666	Nikkye Vargas	3/14/25	[redacted]
2	Patricia Ray	900 Pequs St, Apt 701 SM, TX 78666	Patricia Ray	3/14/25	
3	Dillon Yruegas		Dillon Yruegas	3/14/25	
4	Lindsay Earnest			3/14/25	
5	Una Sheridan		Una Sheridan	3/14/25	
6	marissa morales	302 old settlers drive sm tx 78666		3/14/25	
7	Gabriella mercado	409 sparrow ln Kyle, tx 78640	Gabriella Mercado	3/14/25	
8	William Ellis	1250 Sadler Dr. #G31 San Marcos TX 78666		3/14/25	
9	Dellantino A. Greene	1740 old ranch rd 12, San marcos TX 78666	dellantino greene	3/14/25	
10	Mary Duttel			3/14/25	

Petition for
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	Name	Address	Signature	Date	Optional Phone Number and/or Email
1	Jillian Foletta	109 West Ave, San Marcos. TX	[illegible]	~~[illegible]~~3/14/25	[redacted]
2	Hillary Landau	805 Columbia SanMarcos, TX	[illegible]	3/14/25	
3	Sarah Miller	1230 N LBJ DR. SanMarcos TX	[illegible]	3/17/25	[illegible]
4	Avery May	205 Craddock Ave. San Marcos, TX	averyjMay	3/14/25	[redacted]
5	Nick Lochman	620 Rogers St San Marcos, TX	[illegible]	3/14/25	[redacted]
6	Leigh Mealey	322 Moore St San Marcos, TX	[illegible]	3/14/2025	[redacted]
7	AMANDA FRENCH	322 MOORE ST SAN MARCOS, TX	[illegible]	3/14/25	
8	Laura McBryar	205 S Mitchell San Marcos TX	MMcBryar	3.14.25	[redacted]
9	Addison Crump	1409 Lizzy Court	addison Crump	3/14/25	N/A
10	Molly LASSEN	226 Chesterfeild Dr Kyle TX	[illegible]	3/14/25	N/A

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	Name	Address	Signature	Date	Optional Phone Number and/or Email
1	Autumn Ewalt	524 W. Hopkins St.	[signature]	3/15/25	
2	Allyson Ingram	800 N. LBJ	[signature]	3/15/25	
3	Nicholas Patterson	165 S Guadalupe St	[signature]	3/15/25	
4	J. MIDORI KOBAYASHI	194 Villanova Dr.	[signature]	03/15/25	
5	Tessa Wendeburg	~~8~~ 1350 N LBJ	[signature]	march 15 2025	
6	Mason Stark	1410 W LBJ	M.S.	March 15 2025	
7	Karen Beaver	10700 Bois D. ~~AC~~ Arc Laporte Tx	Karen Beaver	"	
8	WAYNE SISSON	48 BROOKHOLLOW DR	[signature]	15 MAR 25	
9	Saja Carpenter	1413 Bergin Ct	[signature]	3/15/25	[redacted]
10	Kaysie Brown	6905 Circle S Rd.	[signature]	3/15/25	

Petition for
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	Name	Address	Signature	Date	Optional Phone Number and/or Email
1	Amanda McCorkle		[signature]	3/15	[redacted]
2	Jeff Cornell		[signature]	3/15	
3	Colin Zicko	190 Andesite Trl Buda, TX	[signature]	3/15	
4	DUANE EDWARDS	190 ANDESITE TRL	[signature]	3/15	
5	Ethan Reach		[signature]	3/15	
6	Shannon mcgowen		[signature]	3/15	
7	Jim Barton		[signature]	3/15	
8	Sarah Standland	310 Pat Garrison San Marcos, TX 78666	[signature]	3/15	
9	Kylee Standland		[signature]	3/15	
10	John Gurenu		[signature]	3/15	

Petition for
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	Name	Address	Signature	Date	Optional Phone Number and/or Email
1	Zane liston	1898 creek road B dripping springs 78676	Zane Liston	3/12/25	
2	Zoë Schwartz	205 S. Mitchell St. Apt 4. San Marcos TX	Zoë S	3/12/25	
3	Joseph Morse	205 S. Mitchell st Apt 4 San Marcos TX	Joseph Morse	3/12/25	[redacted]
4	Jalina Stutte	1801 Quail Run Dr SMTX	JStutte	3/12/25	
5	Mai Huynh	619 Columbia St. San Marcos, TX	MaiHuynh	3/12/25.	
6	Christopher Paul Cardoza	230 W. Sessom Dr. San Marcos, TX 78666	CPC	3/12/25	
7	Sage Richardson	1605 lancaster st San Marcos 78666	Sage Richardson	3/12/25	
8	STEPHEN DOUGLAS	1309 BAYLOR AVE SAN MARCOS, TX 78666	[illegible]	3/12/25	
9	Allison Worley	1503 Clyde St San Marcos, TX 78666	Allison Worley	3/12/25	[redacted]
10	Venessa Oliven	701 S LBJ Dr #298 SanMarcos,TX 78666	VenOl	3/12/25	

Melissa Montes
125 Horsemint Way
San Marcos, TX 78666

[redacted]

[redacted]

Planning & Zoning Commission:
Planning and Development Services
630 East Hopkins
San Marcos, TX 78666
planninginfo@sanmarcostx.gov

Hello,

As a resident of the Trace Community who lives less than 2 miles away from where the AI Data Center is set to be built, I'm writing with concern regarding the proposed data center development at [904 Francis Harris Ln] as outlined in the recent proposal submitted by Armbrust & Brown, PLLC.

While I understand that data centers play an important role in supporting technological advancements and the local economy, I would like to formally request that soundproofing and noise mitigation measures be required as part of the development plans for the facility.

Data centers contain a significant amount of electrical and mechanical equipment, including cooling systems, HVAC units, and backup generators, all of which can produce considerable noise. In residential areas or neighborhoods close to the proposed site, this noise could become a source of disturbance and, potentially, a public safety concern, especially during evening and nighttime hours when ambient noise levels are lower.

To ensure the well-being of residents and the overall quality of life in the area, I respectfully request that the proposal for the data center include the following:

1. **Soundproofing Measures:** Use of acoustic panels, soundproof enclosures for noisy equipment, and sound-absorbing materials in walls and ceilings.

2. **Quieter Cooling and HVAC Systems:** Adoption of low-noise cooling methods, such as liquid cooling or low-speed fans, and the placement of noisy equipment away from sensitive areas.
3. **Vibration Dampening:** Installation of vibration-dampening systems to minimize the transmission of sound from equipment to surrounding areas.
4. **Backup Power Systems:** Use of quiet, enclosed backup generators, or the use of alternative energy sources that reduce noise during power outages.
5. **Noise Barriers:** The inclusion of noise barriers, such as landscaping or walls, to block sound from escaping the building and impacting surrounding residential areas.

The incorporation of these noise reduction measures will not only ensure compliance with local regulations but also help maintain a peaceful and safe environment for residents in the vicinity. I kindly request that these considerations be addressed in the final approval process for the proposed data center.

Thank you for your attention to this important issue. I look forward to your response and am happy to provide any additional information or collaborate further on this matter.

Sincerely,

Melissa Montes

From: Hunter Tedford <[redacted]>
Sent: Tuesday, March 25, 2025 8:47 AM
To: Velasquez, Enrique <EVelasquez@sanmarcostx.gov>
Subject: [EXTERNAL] Planning and zoning

Hello,

My name is Hunter Tedford, and I am citizen of San Marcos, Texas. It has come to my attention that a proposed AI center is to be built here in San Marcos. This would be majorly detrimental to the citizens and the natural inhabitants of this town. The state county and city are already facing a water scarcity crisis in building an AI data center will only fuel that crisis. The springfed San Marcos river runs right through town, which is home to numerous endangered and threatened species like the Texas blind salamander, Fountain Darter, Comal Springs riffle beetle, Comal Springs drypoid beetle, Pecks Cave amphipod, and San Marcos salamander. These species are already endangered and threatened due to the lack of spring flow, dropping water levels, and pollution entering into the river. All of these species will face further danger if another facility is built in town that requires a lot of water like AI data centers. For the health of the endangered, threatened, and endemic species that inhabit San Marcos and the Edwards aquifer, as well as the citizens of San Marcos, who rely on the water for drinking and recreational use, the best option is to not build the AI data center. I thank you for your time and consideration.

Hunter Tedford

From: Jennifer S <[redacted]>
Sent: Tuesday, March 25, 2025 9:34 AM
To: citizencomment <citizencomment@sanmarcostx.gov>; Cleary, Julia <JCleary@sanmarcostx.gov>; Planning Info <PlanningInfo@sanmarcostx.gov>
Subject: [EXTERNAL] Case number ZC-25-02 Trace resident comment

As a resident of Trace Subdivision I am very concerned about the proposed data center development (904 Francis Harris LN). I am requesting serious consideration be given to the noise these data centers can create and how it may affect the residents who live close by as well as existing wildlife. I understand the value of these data centers and the need for progress, but I am respectfully requesting that mandatory noise mitigation requirements be included in the proposal. This will be essential for the health and well being of the surrounding community. I hope this can be considered as a non-negotiable item in the discussions which would show the residents in the surrounding areas who have chosen to call San Marcos home are prioritized in the consideration of the city's growth.

Thank you,

Jennifer Sanderson

Sent from my iPad

From: Elizabeth Riley <[redacted]>
Sent: Tuesday, March 25, 2025 9:38 AM
To: Velasquez, Enrique <EVelasquez@sanmarcostx.gov>
Subject: [EXTERNAL] Opposition to PSA-25-01

Good morning,

I am emailing to register my deep opposition to the proposed zoning change on PSA 25-01. San Marcos can not support any additional building with our current and future projections of our water needs. An AI data center (the eventual result of the zoning changes) would use an ungodly amount of water while San Marcos is currently in the middle of an extensive multi year drought. This directly endangers both the city water supply and our precious natural San Marcos River. While I realize that growth is inevitable, we CAN be smart and intentional with how growth is projected. Please understand that I intend to both advocate at city hall and within my own extensive personal and professional circles against this change. It is to our extreme detriment with no genuine benefit for San Marcos either in tax revenue or job creation (in fact, AI is detrimental to job creation as a whole) to promote options for an AI data center.

Thank you,

Elizabeth Riley

San Marcos Resident

[redacted]

From: Michelle Rimmel <[redacted]>
Sent: Tuesday, March 25, 2025 9:44 AM
To: Velasquez, Enrique <EVelasquez@sanmarcostx.gov>
Subject: [EXTERNAL] Upcoming Data Center Meeting Today

Hello,

I've been made aware that there is a meeting for an upcoming data center in Hays County. I'm unable to make this meeting but have major concerns about the data center and its water consumption. We are in a major draught and our water tables/aquifers are extremely low. It would be environmentally, economically, and socially irresponsible to welcome a data center to Hays County without them bringing in their own water as this is a beyond a strain on our infrastructure and environmental needs. Your public can't even water their grass/yards, on a basis to sustain their own home slabs.

The data center should not be allowed to tap into our water systems nor drill a water well to sustain their needs. If Hays County is considering allowing them to do this, then I strongly encourage Hays county to refuse the data center.

Please let me know if there is anything else I can do.

Best,

Michelle

From: jennifer wheeler <[redacted]>
Sent: Tuesday, March 25, 2025 9:46 AM
To: Velasquez, Enrique <EVelasquez@sanmarcostx.gov>
Subject: [EXTERNAL] Opposed to PSA-25-01

I am emailing today regarding the approval of rezoning PSA-25-01 200 acres of land at 904 Francis Harris Lane.

Water levels are at an all time low and hays county can not handle the burden the rezoning of this land would cause on our water levels.

Have you driven by Sewell park in the past year, water is at an all time low. Our rivers habitats can not handle more strain that this rezoning could cause.

I have lived in San Marcos for over 30 years and have not seen our water am areas this low

With all the new building in San Marcos, this town can not handle another source that would require that much water usage per day.

I am all for growth in San Marcos but what would this rezoning actually add to our city?

Against the rezoning of PSA-25-01

Sincerely,

Jennifer Crumpton

From: Whitney <[redacted]>
Sent: Tuesday, March 25, 2025 9:50 AM
To: Velasquez, Enrique <EVelasquez@sanmarcostx.gov>
Subject: [EXTERNAL] Data Centers

Hello,

I am a long term resident of San Marcos and Hays county. I own a home and work here, participate in the local community and produce agricultural products. I have chosen to raise my children here, but I am gravely concerned for future of our water supply. I know that the city is working towards long term water security. Only just this morning community impact published the following: “ In the 2017 plan, San Marcos was projected to have enough water supply to meet the demand of 57.38 acre-feet, or ac-ft, per day.

However, after updated population projections, San Marcos now anticipates requiring 102.8 ac-ft per day by 2075, according to San Marcos Utilities Director Tyler Hjorth’s update at a City Council work session Jan. 21.

With the new projections, the amount of water residents would need could exceed the city’s supply by 2050.”

The article goes on to read that along with diversifying water sources, San Marcos is focused on conservation.

I do not think that Data Centers are the most conservative choice for development in our area concerning water use. I especially feel that any zoning change from conservation land or open land/ag evaluation to industrial zoning would be irresponsible and not in-line with the city or county’s stated goals or best interests.

I sincerely hope to see P&Z give this thorough consideration and make the best choice possible on behalf of our future generations and their water here.

Thank you,

Whitney Waller, and on behalf of

Ellen Waller

William Waller

Annette Waller

Joshua Moore

And Michael McLeod

along with 3 young children

From: Josh DeCamp <[redacted]>
Sent: Tuesday, March 25, 2025 10:10 AM
To: Velasquez, Enrique <EVelasquez@sanmarcostx.gov>
Subject: [EXTERNAL] PSA-25-01

Hello,

I am writing to urge you to do your part to decline the proposal that would change zoning to allow an AI data center to be built in this location (PSA-25-01). These kinds of businesses are incompatible with the flourishing of the people and natural resources of the area. Water resources are already under heavy strain in all of central Texas because of unrestrained development that puts the profits of developers over the wellbeing of people and the lands we inhabit. Data centers use enormous amounts of water for cooling and provide little to no benefit to the local economy. If we don't do what we can now to push back against proposals like this there is a serious risk that our rivers will run dry in all but the wettest years and we will lose a huge part of what makes this such a great place to live.

Thank you for your time and attention.

Sincerely,

Joshua DeCamp

From: Jade Gibbs <[redacted]

Sent: Tuesday, March 25, 2025 11:00 AM

To: Velasquez, Enrique <EVelasquez@sanmarcostx.gov>

Subject: [EXTERNAL] AI Data Center

Good morning,

I am writing to oppose the construction of an AI data center here in San Marcos. Building this will deeply affect the life of many endangered species here as well and all of the citizens on this city. We have been in a drought for about 3 years now and are expected to go into a La Niña which will greatly increase the effects of the drought. We will not have water to live and if we don't have that then we do not have any water to spare for development. Water and life is a priority over urban development and I truly hope you understand the consequences this data center will have on our community, river, and overall lives.

Sincerely,

Skylar Gibbs

-----Original Message-----

From: Christopher L <[redacted]>

Sent: Tuesday, March 25, 2025 11:29 AM

To: Velasquez, Enrique <EVelasquez@sanmarcostx.gov>

Subject: [EXTERNAL] Opposition to Ai data center

I currently understand that the Data Center John Maberry is associated with is not the CloudBurst Artificial Intelligence Data Center planned for 2955 Francis Harris Lane. However, there are important similarities. The timeline is the same. In addition, Cloudburst describes a 200-acre site on their website, which meshes with the 199.49 acre site referenced on the City Council Agenda. Also, CloudBurst has a contract with Transfer Energy LP to provide natural gas to the site, consistent with the presence of a natural gas-fueled electrical power station adjacent to the site of the proposed Data Center, which Maberry confirmed was an important feature for the Data Center's interest in this location.

In addition to the inherent risks imposed by natural gas pipelines, Energy Transfer has a particularly shoddy track record. Approximately 3 years ago, Energy Transfer was convicted of criminal charges for extensive groundwater pollution related to the construction of pipelines in Pennsylvania.

The company is also the subject of a class action lawsuit led by investors:

“The Energy Transfer class action lawsuit alleges that, throughout the Class Period, defendants made false and misleading statements and failed to disclose that: (i) Energy Transfer had inadequate internal controls and procedures to prevent contractors from engaging in illegal conduct with regards to drilling activities, and/or failed to properly mitigate known issues related to such controls and procedures; (ii) Energy Transfer, through its subsidiary Rover Pipeline, LLC, hired third-party contractors to conduct Horizontal Directional Drilling Activities (“HDD”) for the Rover Pipeline Project, whose conduct of adding illegal additives in the drilling mud caused severe pollution near the Tuscarawas River when a large inadvertent release took place on April 13, 2017; and (iii) Energy Transfer continually downplayed its potential civil liabilities when the Federal Energy Regulatory Commission (“FERC”) was actively investigating Energy Transfer’s wrongdoing related to the April 13 release and consistently provided it with updated information about FERC's findings on this matter." Businesswire.com, June 15, 2022.

Energy Transfer also aggressively opposes freedom of speech. It has launched its own $300 million dollar lawsuit against Greenpeace in retaliation for its protests against Energy Transfer's Dakota Access Pipeline.

To my knowledge, John Mabry has not revealed the name of the data center he plans to sell his property to, but claims it is not an artificial intelligence data center and is not affiliated with Cloudburst. However, the AI Cloudburst Data Center planned for 2955 Francis Harris Lane in New Braunfels was also not originally affiliated with Cloudburst. It was purchased under the name of Data Center LB on February 7. Later, on the same day, February 7, Data Center LB entered an agreement with Cloudburst. This is the kind of thing I consider highly possible with the Data Center proposed by Maberry for 904 Francis Harris Lane. It may not be an artificial intelligence center related to Cloudburst at the moment of purchase, but that doesn't mean it can't establish that affiliation 30 minutes later.

According to a recent New York Times article, "Residents rarely learn how data centers may affect their lives until it's too late. Big tech operators are aggressively deploying nondisclosure agreements to force local officials, construction workers and others to keep these projects under wraps."

Data centers, and especially AI data centers, consume a lot of water and a huge amount of energy, pollute the environment and accelerate climate change. The City would not have any control over what these Centers do or don't do. Also, in this time of massive dismantling of environmental regulation, the results could be particularly devastating. The risks are extremely serious. I urge the Commission to vote no on PSA-25-01 and ZC-25-02.

Sent from my iPhone

From: Candice M <[redacted]>
Sent: Tuesday, March 25, 2025 11:35 AM
To: P&Z Commissioners <PZCommission@sanmarcostx.gov>
Cc: Velasquez, Enrique <EVelasquez@sanmarcostx.gov>; citizencomment <citizencomment@sanmarcostx.gov>
Subject: [EXTERNAL] Concerns - ZC-25-02 (904 Francis Harris Ln Light Industrial)

Good morning,

I hope this email finds you well. As a resident of the Trace neighborhood, less than two miles from the proposed data center at 904 Francis Harris Ln, I am writing to express my strong concerns regarding the recent zoning change application. The proposal to rezone the property submitted by Armbrust & Brown, PLLC raises significant concerns that could be detrimental to the well-being of our community.

Unfortunately, I am unable to attend the meeting tonight in person, but this issue is too important to remain unaddressed. While I understand the need for development and technological growth, this project has severe environmental implications. Data centers require enormous amounts of energy and water for their operation and cooling systems, often relying on non-renewable energy sources. According to the University of Illinois Urbana-Champaign (https://cee.illinois.edu/news/AIs-Challenging-Waters), a single data center can consume over 500,000 gallons of water per day, placing tremendous pressure on our already strained water supply. Considering we are currently sitting in stage 3 drought restrictions, this added strain would cause harm to agriculture, wildlife, and the well-being of residents of San Marcos and its surrounding areas who rely on our already limited resources.

I urge you to reconsider this zoning change and the proposed development to ensure that environmental sustainability, resource management, and community welfare are at the forefront of any decisions made.

Thank you for your time and consideration on this extremely important matter.

Respectfully,

Candice Mongellow

From: Jessica Allen <[redacted]
Sent: Tuesday, March 25, 2025 11:36 AM
To: Velasquez, Enrique <EVelasquez@sanmarcostx.gov>
Subject: [EXTERNAL] PSA-25-01

Enrique Velasquez,

I am concerned about the appeal to Planning and Zoning of San Marcos to change the zoning of the 200 acres of land at 904 Francis Harris Lane, so the land owners can build a data center.

This data center would be pulling water from Crystal Clear Special Utility District and be pulling power from Pedernales Electric. Crystal Clear is where San Marcos, Martindale, Kyle and Buda get their water.

Data Centers, especially ones for AI, use a lot of water. Between 500,000 to 18,000 gallons of water A DAY. We don't know what size this one would be classified as.

We are in a terrible drought and should not allow this industry in Central Texas. The San Marcos is at record lows, the lowest since 1956, Jacobs Well is dry, Canyon Lake is at record lows. All of this water is connected.

We need to protect our water resources.

Thank you for your time and consideration.

Sincerely,

Jessica Allen

1412 Schulle Dr, San Marcos, TX 78666

Dear Planning and Zoning Commission,

I am writing to request that you value the communities voice by upholding the preferred scenario map that was drafted through a public process. Amending 904 Francis Harris Lane from conservation to commercial/employment would be a dishonor to your constituents. Additionally I ask that the zoning change is not granted for the aforementioned address.

The data center use is not sustainable, regardless of the closed water system. The strain on our power grid would be immense.

Sincerely,
A concerned resident
Emmanuel Hernandez

From: Dan Wolff <[redacted]>
Sent: Tuesday, March 25, 2025 11:44 AM
To: Velasquez, Enrique <EVelasquez@sanmarcostx.gov>
Subject: [EXTERNAL] PSA-25-01

Enrique Velasquez,

I am concerned about the appeal to Planning and Zoning of San Marcos to change the zoning of the 200 acres of land at 904 Francis Harris Lane, so the land owners can build a data center.

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We need to protect our water resources.

Thank you for your time and consideration.

Sincerely,

Dan Wolff

1412 Schulle Dr, San Marcos, TX 78666

From: Shannon Brown <[redacted]>
Sent: Tuesday, March 25, 2025 12:13 PM
To: Velasquez, Enrique <EVelasquez@sanmarcostx.gov>
Subject: [EXTERNAL] Opposition to AI Data Center (PSA-25-01)

Hi,

I'm writing to communicate that as a San Marcos resident, and someone who moved here, started a business here, and intends to live here the rest of my life, I strongly oppose an AI Data Center in San Marcos.

We simply don't have enough water to support this type of industry. Crystal Clear Special Utility District uses water from the Edwards Aquifer, San Marcos River and Lake Dunlap. With the Guadalupe River (that flows into Lake Dunlap) drying up, and spring flow from the aquifer at historic lows, approving this data center would be a terrible mistake that threatens the soul of San Marcos: the San Marcos River.

The reason people choose to visit or live in San Marcos is because of the River. If the river dries up, that's the end of life in San Marcos as we know it.

As hard as it is to imagine the San Marcos River drying up, it is possible, especially at the upper areas in town. All you have to do is look at the Blue Hole and Brackenridge Park in San Antonio to know that over-pumping can make even highly-productive springs go dry and river parks unswimmable.

It is unconscionable to ask citizens to conserve water constantly, and then approve an AI facility that will use anywhere from 18,000 to 500,000 gals of water per day. When the average homeowner typically uses 250 gals of water per day. There's no amount of citizen conservation that could make up for the gross misuse of massive quantities of water at an AI data center.

This is not the right location for that facility. Our natural resources are worth far more than whatever the AI data center could ever try to offer the city.

Thank you for your time and consideration,

Shannon

--

Shannon Brown, Founder

Ecosystem Regeneration Artisans

ERAnativeland.com