The Potential of Data Center Waste Heat Recovery for Greenhouse Food Production in the U.S.: Ramifications for Sustainable AI

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Abstract

The rapid rise of AI has caused concerns about increased energy consumption and concomitant greenhouse gas emissions (GHG) and climate destabilization. To help address the environmental impact of AI and the need for sustainable agricultural practices, this study explores the potential to reuse waste energy from U.S. data centers (DC) to grow food crops in greenhouses. The total cooling load of DCs is estimated from their power consumption and the efficiency of cooling equipment. A location-dependent thermal model of greenhouses is then employed to determine the minimum cooling load required to match the maximum heating demand of tomato greenhouses, thereby defining the greenhouse dimensions. By simulating the annual heating requirements of greenhouses, the study evaluates the actual reduction in cooling power consumption of DCs, the mitigation of fossil fuel use in both DCs and greenhouses, and the potential for food production. The results based on the dataset of 6.6 GW of DCs and scaled them to the entire U.S. DC fleet of 40GW (in 2024) found DC waste heat could supply greenhouse areas between 30,085-45,448 hectares. Even the more modest areas of 6GW of currently studied DCs could support the production of 2.7–5.3 million tonnes of tomatoes, meeting the 84-166% of U.S.'s requirements, exceeding the domestic fresh tomato production. This approach would also substantially offset natural gas use 747-995 million m³ of natural gas and reduce electricity usage by 1.9 to 2.5 TWh annually making a major impact on GHG emissions for AI.

Keywords : green computing; data center; AI; sustainable AI; waste heat recovery; greenhouses; energy efficiency

1. Introduction

The rapid advancement of digitalization and artificial intelligence (AI) has driven unprecedented investment in data centers (DCs) worldwide. The United States (U.S.) currently leads globally, with nearly 5,400 facilities, accounting for approximately 45% of the global total [1,2]. As of recent estimates, there are over 11,800 DCs worldwide, with demand continuing to rise due to AI's computational and storage requirements [3,4]. AI-ready data center capacity is anticipated to grow at an average rate of 33% per year through 2030, with 70% of global DC capacity projected to support advanced AI workloads by then [5]. This growth, however, comes at a significant environmental cost, including increased energy consumption and greenhouse gas (GHG) emissions. Google, for instance, reported a 48% rise in GHG emissions above its 2019 baseline due to its expanding AI infrastructure [9,10].

Sustainable AI has emerged as a subfield to address the environmental impact of AI development, focusing on aligning AI innovation with sustainability goals [1]. One promising approach is waste heat recovery from DC operations, which could transform an environmental liability into a resource for critical industries like agriculture [2,3]. This study explores the potential to reuse waste energy from U.S. DCs to grow food crops in greenhouses, addressing two global challenges: the environmental impact of AI and the need for sustainable agricultural practices. By repurposing waste heat, this approach aligns with principles of sustainability and offers a pathway to mitigate the carbon footprint of AI-driven infrastructure [4]. For this, total cooling load of DCs is estimated first by considering their power consumption and the average efficiency of cooling equipment. A location-dependent greenhouse model is then employed to determine the minimum cooling load required to match the maximum heating demand of tomato greenhouses, thereby defining the greenhouse dimensions. By simulating the annual heating requirements of greenhouses, the study evaluates the actual reduction in cooling power consumption of DCs, the mitigation of fossil fuel use in both DCs and greenhouses, and the potential for food production in th U.S.

2. Background and Context

As digitalization and AI have gained momentum, there has been an unprecedented increase in investment in data centers worldwide over the past few years with projections to increase even further in the coming decade [5,6]. Currently, the U.S. tops the list of countries with the most DCs, with nearly 5,400 facilities, accounting for approximately 45% of the global total [7,8]. Germany is a distant second with 521 DC facilities, the UK is 3rd with 514, and China is 4th with 449 DCs as of March 2024 [8]. According to the 2024 McKinsey report, the demand for

AI-ready data center capacity is expected to increase at an average rate of 33 percent per year between 2023 and 2030, assuming a midrange scenario. The report additionally signifies that approximately 70 percent of the total global demand for DC capacity will be for DCs equipped to host advanced-AI workloads by 2030[1][9]. The surge in data center investment is closely linked to the rapid expansion of AI technologies, particularly in the wake of generative AI (Gen AI). In 2023, the U.S. witnessed a considerable surge in AI investments, reaching a total of $67.2 billion. This figure represents a significant increase compared to other major investors, with China, the second-largest investor in this field, having invested approximately 8.7 times less [10]. In 2023, the combined capital investments of the three industry leaders in AI adoption and DC installation; Google, Microsoft, and Amazon, surpassed those of the entire U.S. oil and gas industry. The total amount invested by these three companies equaled approximately 0.5% of the U.S. GDP [5].

Despite advances in hardware and software efficiency, however, large-scale AI developments have contributed to a sharp rise in overall energy consumption [5,6,11]. The rise in energy consumption is particularly notable in the operation of large foundational models such as ChatGPT, which, despite being optimized for efficiency, still require immense computational resources that are supported by energy-intensive DC operations [12]. For instance, Google has revealed that the increased electricity demand driven by AI and its expanding DC infrastructure has resulted in a 48% surge in greenhouse gas (GHG) emissions above the company's 2019 baseline [13,14]. Thus, Jevons paradox emerges[2]: although individual DCs and AI models are achieving greater energy efficiency [5], the growing number and scale of deployments is driving up overall energy consumption. In addition, the growth of DCs could put significant strain on local power grids, exacerbated by the huge mismatch between the rapid pace of DC construction and the often slower pace of grid expansion and generation capacity [5].

2.1 Sustainable AI and Waste Heat Recovery

Based on several studies showing the rapidly growing energy consumption and environmental impact of AI development [12,16–18], high-profile media outlets have increasingly covered the environmental costs associated with AI technologies [13,14,19]. The energy consumption of

[1] Currently, the fastest-growing advanced-AI use case is Generative AI (Gen AI), which will account for approximately 40 percent of the total [9].

[2] As systems become more efficient, their reduced cost or increased utility may lead to greater use, ultimately increasing overall resource consumption. Also known as the “rebound effect”[15].

AI development demonstrates how the rapid growth of AI technologies has brought with it not only transformative capabilities, but also significant environmental and social costs. In response to the accelerated pace of global AI innovation, a growing subfield of AI ethics, known as Sustainable AI, is identifying and addressing these and other hidden costs, exploring ways to align AI development with broader sustainability goals [20–24]. Within the Sustainable AI discourse, one approach contextualizes AI as a critical infrastructure of modern society that requires care and ongoing repair [25]. In this context, the term "repair" is not merely an act of restoring functionality but also serves to mend social relations and uphold values. Rather than reinforcing existing structures, repair as transformation encourages deliberate change [25]. Hence, instead of continuing to criticize AI, which rarely results in a significant reduction in its widespread use, this study explores ways to improve the wasteful and currently very resource-intensive industry. This is an important consideration, especially since it seems unrealistic to remove existing AI infrastructures that support so many of today's society's functions [26].

As a first measure, the environmental impact that has been the subject of most Sustainable AI research, namely carbon emissions, can be addressed. Carbon emissions from DCs are due to 1) the consumption of substantial electrical energy to provide computational power, but also results in 2) the production of a considerable amount of heat. DC rooms are functioning best within a moderate temperature range of 20-21°C [27] and thus as a result, a considerable amount of energy , i.e. 33-42% [28–32] of the energy consumed in a DC, is allocated to cooling the server rooms in order to maintain a temperature that ensures the continued functioning of the computers and AI algorithms [27]. If the global AI infrastructure is to be sustainable, then industry and academics should be looking for ways to reduce and/or reuse the energy associated with cooling the DCs. It follows that there is thus an opportunity to re-use the waste heat from the DCs by waste heat recovery which also reduces the cooling load [33,34]. This approach is already in use across various energy-intensive industries that generate substantial heat during their operations, such as the cement industry [35], and the iron and steel industry [36]. One core challenge that has been identified in the field of waste heat recovery from DCs is the absence of benchmark data on high performance computing heat generation and waste heat profiles [37]. Despite this challenge, a comprehensive review by Yuan et al. on waste heat recovery from various sources within a DC (e.g., exhaust air, circulating water, and coolants) validates its feasibility and applicability, in terms of their technical, energy, exergy, environmental and economic analysis, across diverse energy applications [34]. These include heating supply, district heating supplementation, cooling and electricity generation, as well as industrial and agricultural processes. Several operational cases confirm and demonstrate the feasibility and effective utilization of waste heat from commercial DCs in surrounding residential areas and facilities. For instance, the Equinix data center in France transfers excess heat into a heating network that serves about 60,500 households and supplies heating for the Olympic aquatic center, which hosted events during the 2024 Paris Olympics [38]. Similarly, in Sweden, the EcoDataCenter2 project has been launched, with the first phase of the DC expected to be operational in 2026. The project is distinguished by its deliberate design for circularity and aims to use waste heat to support "a large area" of food production [39].

2.2 Sustainable AI serving food industry

Although limited, some studies have explored the potential of utilizing waste heat from DCs to support the food industry. Researchers have explored novel energy recovery systems to decarbonize the agricultural sector by repurposing waste heat from already existing DCs for farming applications, such as heating cowsheds, greenhouses, and drying rooms [40]. In these systems, low-temperature water absorbs heat via an air source heat pump, becoming high-temperature water, which is then stored or distributed for agricultural use. Excess heat is stored in a water tank and used when DC heat supply is insufficient [40]. A case study of a Chinese DC (9.6 MW capacity) demonstrated that this approach could save 764 MWh of electricity annually, reducing coal consumption by 230 tons and CO_2 emissions by 168 tons [40].

In this study the reuse of waste energy of U.S. DCs, totaling a 6,561MW capacity, is investigated for growing food crops in greenhouses to enhance food security, thereby partially mitigating their carbon emissions and environmental impact. This approach aligns with principles of sustainability by transforming an environmental liability into a resource for critical industries. By redirecting waste heat to greenhouses, this approach could potentially address two pressing global challenges simultaneously: the environmental impact of AI and the need for more sustainable agricultural practices. In an experimental study conducted in Helsinki, Finland, waste heat from a server rack was used to extend the chili pepper growing season in a rooftop greenhouse [41]. A separate modeling study [42] demonstrated that a 1 MW data center could fully meet the heating requirements of a greenhouse measuring 4 m in height and 17 m in length, even under extreme ambient temperatures of −30 °C. Additionally, simulations in Northern Sweden [43] examined the performance of two greenhouse sizes (2,000 m² and 10,000 m²) under two production scenarios: partial-year cultivation without grow lights and year-round production with artificial lighting. The findings showed that the larger greenhouse was more cost-effective, as it could recover a greater amount of waste heat, leading to lower tomato production costs. Being similar to DCs, a cryptocurrency mining system was experimentally assessed for its heating potential [44]. In parallel, a quasi-steady-state thermal model was developed to simulate the thermal interactions between a greenhouse and its surrounding environment, allowing for the estimation of heating and cooling demands. By incorporating experimental waste heat data into the thermal model, the heat generated by three different cryptocurrency mining setups (1, 50, and 408 miners) was evaluated for use in optimally sized greenhouses across six locations in Canada and the U.S.: Alberta, Ontario, Quebec, California, Texas, and New York.

3. Methods

This study aims to investigate the potential of U.S. DCs to provide heating for food production greenhouses while simultaneously minimizing their cooling loads. The common approach to sizing heating, ventilation, and air conditioning (HVAC) systems for buildings involves conducting a thermal loss/gain analysis under worst-case scenarios to determine the maximum heating and cooling loads required [45,46]. Similarly, HVAC systems for greenhouses must be sized based on their peak thermal load. In this study, the heating load of the greenhouse is calculated using the comprehensive greenhouse model developed by Asgari et al. [44,47]. The heating load calculation component of this model has been updated and extensively validated with a <3% error against actual data provided by the Ontario Greenhouse Vegetable Growers (OGVG) [48]. This model is applied to estimate the heating load of the greenhouse, which is proposed to be supplied using the waste heat generated by U.S. DCs. The heat exchange process can be facilitated by employing heat exchangers, enabling the dissipation of DC cooling loads as heat transferred to the greenhouse as shown in Figure 1.

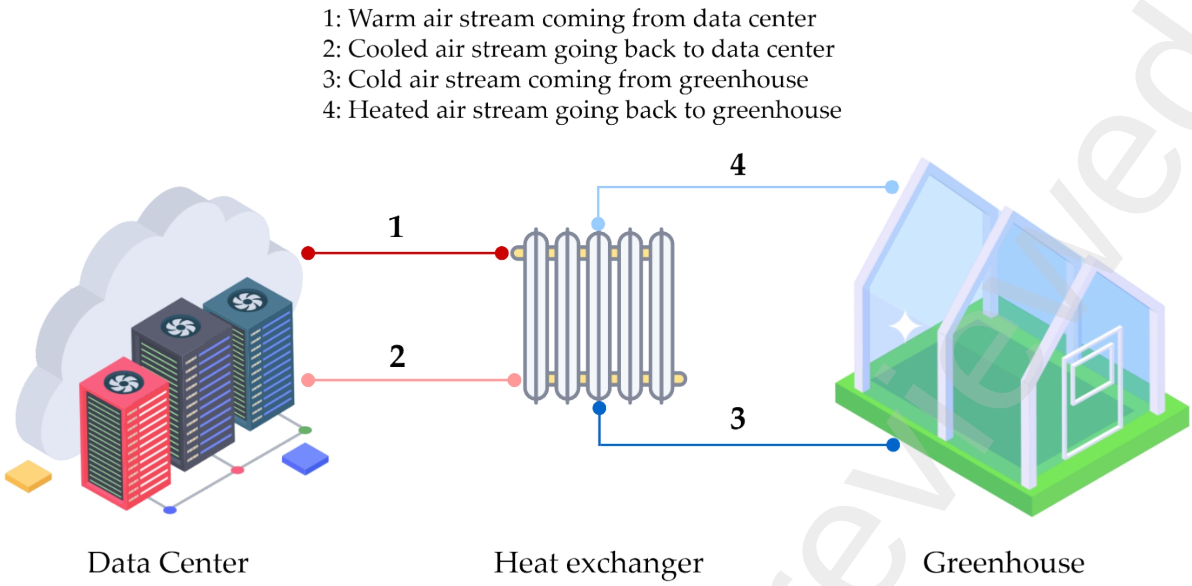

Figure 1. The schematic of the greenhouse waste heat recovery (WHR) system for heat generated in DCs

A list of the 84 significant DCs in the United States has been compiled based on data from the Aterio platform [49]. These DCs are distributed across various states, as illustrated in Figure 2. They are categorized according to their size, represented by total power consumption, as detailed in Table 1.

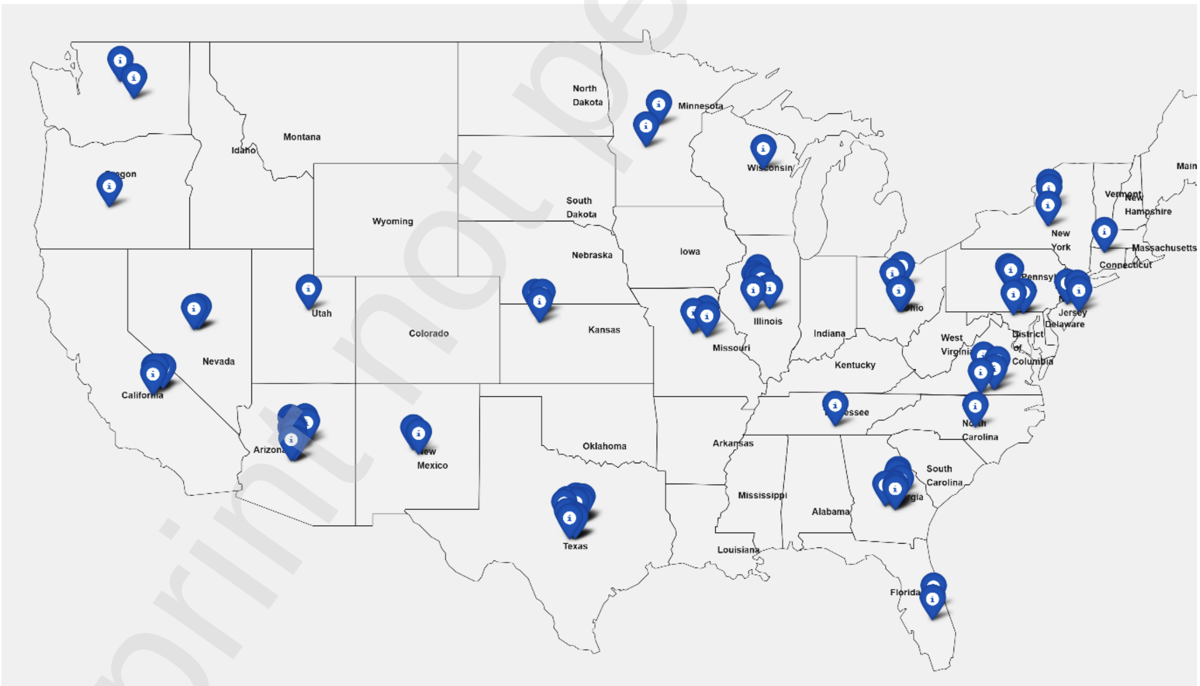

Figure 2. The location of DCs distributed across the U.S. *[49]*

Table 1. DCs across the U.S. categorized by their power consumption and location *[49]*.

Data center size	*Power consumption (MW)*	*Total count*	*Involved states*
Mega	> 50	20	AZ, VA, CA, UT, TX, OH, NV, NJ, MN, MD, GA, WA
Large	10 - 50	28	NJ, VA, WI, AZ, GA, MA, NY, TX, IL, OH, MO, NM, CA, FL, CO, MI

Medium	1 - 10	33	PA, CO, IL, MA, MO, TX, TN, MI, OH, GA, CA, NY, NM, CT, AZ, NV, FL, MN, OR, WA, NC
Small	< 1	3	MI, MD, NY

After information technology (IT) equipment, cooling systems contribute the most to the total power consumption of DCs, typically accounting for 33–42% of the total operational power [28–32]. According to the 2024 U.S. Data Centers Energy Usage Report, the operational power of AI-based data centers fluctuates between 60% and 80% of the rated capacity [50]. One of the most common cooling technologies employed is computer room air conditioners (CRACs), which are used to maintain the temperature of IT equipment. As newer data center designs reach power densities that exceed the cooling capacity of CRAC systems alone, however, alternative cooling techniques have been introduced. These include direct and indirect water-based cooling systems integrated with computer room air handlers (CRAHs) [33]. All these systems operate based on thermodynamic refrigeration cycles. While novel cooling technologies demonstrate improved performance efficiencies, the most widely adopted systems generally exhibit coefficients of performance (COP) in the range of 2–4 [31–33,51–53]. Using the total power consumption of DCs, the proportion of energy attributed to cooling systems ($P_{cooling}$) in kW (or MW) is determined, enabling the calculation of the minimum cooling load ($Q_{cooling}$) in kW (or MW) using Equation 1.

$$Q_{cooling} = P_{cooling} \times COP \tag{1}$$

Upon completing the sizing procedure, the accumulative total annual heating demand of the designed greenhouse will be calculated in kWh (as shown in Figure 3 for a sample greenhouse [47]). This demand is intended to be met by utilizing waste heat from DCs. Consequently, the potential annual power savings due to the cooling load minimizations in the DCs, will be calculated and reported in kWh.

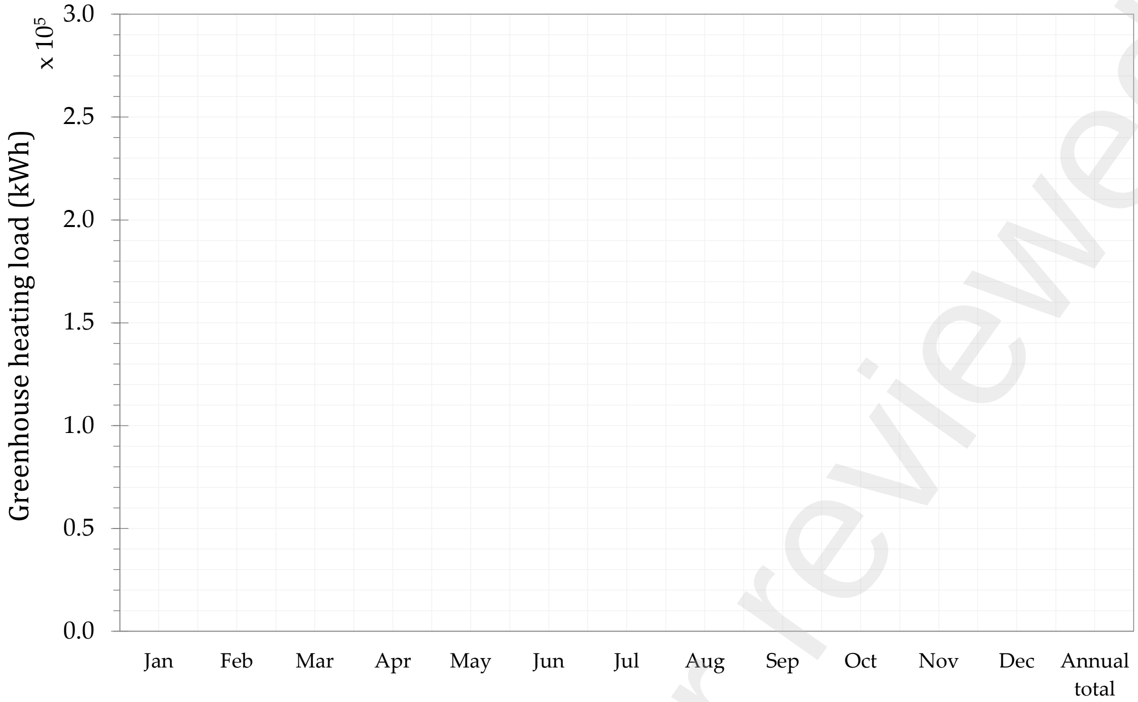

Figure 3. Monthly and accumulative annual heating demand of a sample greenhouse studied by Asgari et al. [47].

Additionally, potential direct and indirect NG savings will be estimated. Direct NG savings arise from replacing conventional heating systems in greenhouses with the heat recovered from DCs. The average heating value of NG in the United States is 38.5 MJ/m³ [54]. Indirect NG savings, on the other hand, result from the reduction in energy consumed for cooling DCs, as this energy would otherwise be supplied by the power grid, which is predominantly powered by NG plants [55]. According to the U.S. Energy Information Administration [56], approximately 0.21 m³ of NG is required to generate 1 kWh of electrical energy in power plants.

For illustration purposes, in this study, greenhouses are designed for tomato cultivation. Based on surveys and simulations, the average annual yield of American tomato greenhouses ranges from 48 to 71 kg/m² [57,58].

The National Renewable Energy Laboratory (NREL) database [59] is utilized alongside the parametric analysis feature of the System Advisor Model (SAM) [60] to extract meteorological data and solar radiation on the tilted surfaces of greenhouses. A Python script was developed and is available in the Open Science Framework [61] under GNU GPL v3 to automate the execution of the greenhouse model across all U.S. locations, incorporating site-specific meteorological data and technical assumptions.

4. Results

The findings of the parametric analysis on prospective sustainable savings in U.S. DCs are reported for both lower and upper bound estimates. These estimates are derived from the documented actual power consumption levels and the mean annual productivity of American tomato greenhouses. The minimum level of food production and environmental savings will be calculated for 60% capacity factor and 48 kg/m^2 of the tomato production, and the maximum potential savings will be reported for 80% capacity factor and the tomato yield of 71 kg/m^2.

Table 2 presents the minimum level of potential power and NG savings, along with the total land area of greenhouses that could potentially be used for tomato production in the U.S. The substantial benefits of waste heat recovery from several major DCs in the U.S. are highlighted by the significant values provided in Table 2.

Table 2. Minimum level of potential productions and savings by managing the waste heat (cooling loads) of the U.S. data centers in heating the greenhouses.

DC No	*State*	*Rated Capacity (MW)*	*Heated greenhouse area (hectares)*	*Potential tomato production (tonne/year)*	*Potential power saving in DC (MWh)*	*Direct NG saving (10,000 m^3)*	*Indirect NG saving (10,000 m^3)*
1	FL	2	7.4	3,528	27	0.5	0.6
2	FL	12	26.4	12,672	1,334	25.0	28.0
3	TX	84	60.6	29,088	15,201	284.3	319.2
4	TX	200	137.4	65,952	36,928	690.6	775.5
5	VA	326	272.4	130,752	49,022	916.8	1,029.5
6	TX	26	29.6	14,220	6,050	113.1	127.0
7	TX	26	18.8	9,000	4,505	84.3	94.6
8	TX	4.5	3.2	1,548	772	14.4	16.2
9	TX	30	18.0	8,640	6,066	113.4	127.4
10	TX	200	101.4	48,672	41,987	785.2	881.7
11	TX	6.2	3.0	1,422	1,290	24.1	27.1
12	TX	20	9.4	4,500	4,510	84.3	94.7
13	TX	13.5	6.4	3,168	3,180	59.5	66.8
14	AZ	9	10.5	5,040	2,176	40.7	45.7
15	AZ	36	45.6	21,888	9,156	171.2	192.3
16	AZ	1,800	2,475.0	1,188,000	446,807	8,355.9	9,383.0
17	AZ	300	378.0	181,440	77,989	1,458.5	1,637.8
18	AZ	11	14.4	6,912	2,896	54.2	60.8
19	AZ	176	240.6	115,488	45,153	844.4	948.2
20	AZ	280	355.8	170,784	78,666	1,471.2	1,652.0
21	AZ	3.6	3.9	1,872	785	14.7	16.5
22	AZ	5.8	7.0	3,348	1,694	31.7	35.6
23	AZ	69	73.5	35,280	14,944	279.5	313.8
24	GA	4	1.8	882	958	17.9	20.1
25	GA	28.8	14.2	6,804	7,610	142.3	159.8
26	GA	324	148.5	71,280	84,215	1,574.9	1,768.5

27	GA	15	6.9	3,294	3,912	73.2	82.2
28	GA	5.4	2.4	1,170	1,404	26.3	29.5
29	GA	4	1.8	882	1,031	19.3	21.7
30	CA	6	12.6	6,048	1,515	28.3	31.8
31	GA	12	5.5	2,628	2,900	54.2	60.9
32	CA	27	42.3	20,304	9,673	180.9	203.1
33	NM	6	3.1	1,476	2,438	45.6	51.2
34	NM	20	10.4	4,968	8,137	152.2	170.9
35	NC	10	5.9	2,808	3,105	58.1	65.2
36	TN	3	0.9	432	654	12.2	13.7
37	NV	100	92.3	44,280	32,878	614.9	690.4
38	NV	9	8.0	3,852	2,839	53.1	59.6
39	CA	77	95.4	45,792	34,172	639.1	717.6
40	CA	6	7.4	3,564	2,671	49.9	56.1
41	OH	60	18.5	8,856	16,657	311.5	349.8
42	VA	800	423.0	203,040	322,398	6,029.3	6,770.4
43	MO	20	6.5	3,132	6,653	124.4	139.7
44	MO	8	2.2	1,044	2,210	41.3	46.4
45	MO	3.9	1.1	522	1,245	23.3	26.1
46	VA	42	14.0	6,696	13,904	260.0	292.0
47	VA	105	34.7	16,632	34,213	639.8	718.5
48	MD	264	101.3	48,600	100,948	1,887.9	2,119.9
49	MD	0.8	0.2	86	240	4.5	5.0
50	CO	5	1.3	630	1,743	32.6	36.6
51	CO	14.4	5.1	2,448	6,578	123.0	138.1
52	PA	10	2.9	1,404	3,078	57.6	64.6
53	OH	27	6.6	3,168	8,638	161.5	181.4
54	PA	7.2	2.3	1,080	2,296	42.9	48.2
55	OH	8	2.0	936	2,625	49.1	55.1
56	NJ	30	9.8	4,716	10,443	195.3	219.3
57	UT	200	76.5	36,720	70,146	1,311.8	1,473.1
58	NY	0.7	0.2	94	241	4.5	5.1
59	NY	6.75	2.1	1,008	2,363	44.2	49.6
60	NJ	80	28.8	13,824	30,091	562.7	631.9
61	NJ	33	11.9	5,724	11,796	220.6	247.7
62	NY	24	8.3	3,960	9,624	180.0	202.1
63	CT	4	1.3	630	1,524	28.5	32.0
64	OH	10	2.5	1,188	3,123	58.4	65.6
65	IL	10	2.6	1,242	3,638	68.0	76.4
66	IL	24	3.9	1,854	6,155	115.1	129.3
67	IL	1.72	0.4	202	615	11.5	12.9
68	IL	36.4	5.6	2,664	8,821	165.0	185.2
69	IL	32	5.0	2,376	7,908	147.9	166.1
70	IL	10.8	1.7	792	2,671	50.0	56.1
71	MA	3	0.8	367	977	18.3	20.5
72	MA	15	3.7	1,764	4,414	82.5	92.7
73	MA	16	3.8	1,818	4,838	90.5	101.6
74	MI	1.5	0.4	169	566	10.6	11.9
75	MI	1	0.2	108	380	7.1	8.0

76	MI	20	5.0	2,376	7,409	138.6	155.6
77	MA	10	2.4	1,134	3,007	56.2	63.2
78	MA	1.5	0.3	158	457	8.6	9.6
79	WI	12	2.5	1,206	4,297	80.4	90.2
80	MN	4.8	0.8	367	1,707	31.9	35.8
81	MN	200	32.9	15,768	70,597	1,320.2	1,482.5
82	OR	5.3	3.3	1,584	2,515	47.0	52.8
83	WA	89	26.1	12,528	33,242	621.7	698.1
84	WA	5	3.3	1,566	2,561	47.9	53.8
Total	--	6,561	5,624	2,699,860	1,880,804	35,173	39,497

Figure 4 maps the ten largest data centers across among the listed DCs of the United States, with capacities ranging from 200 to 1800 MW. Arizona hosts some of the largest DCs, including DCs 16, 17, and 20, which are among the most significant facilities as 16 alone represents the power requirements of all the DCs out of the top ten combined.

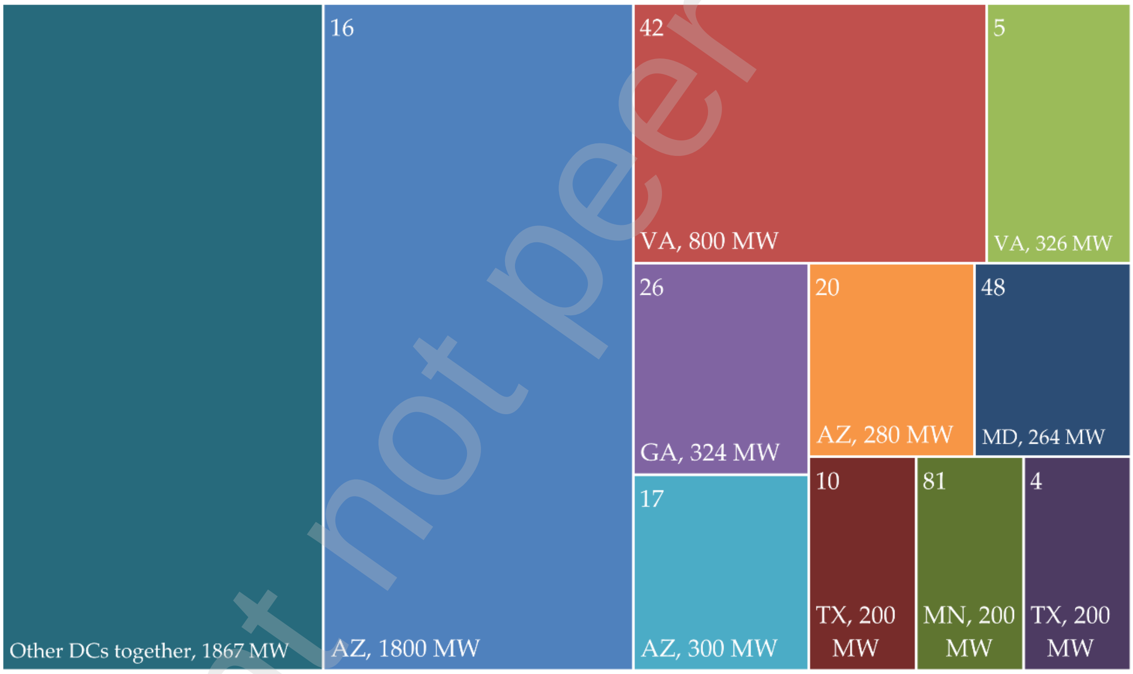

Figure 4. The ten largest DCs in the studied US dataset, along with their states of establishment and respective rated capacities.

The land area of greenhouses that can potentially be heated by the waste heat from DCs is illustrated for the top ten selected facilities in Figure 5. The largest tomato greenhouse area, (in a minimum and maximum range of approximately 2,475-3,300 hectares), corresponds to DC number 16 in Arizona, the largest DC in terms of rated capacity in the dataset studied. The third-largest greenhouse area, however, is attributed to DC number 17 in Arizona, which is not the third-largest DC according to Figure 4. This highlights the importance of climatic conditions and year-round solar flux at each location. For example, as shown in Figure 5, the size of the greenhouse heated by DC numbers 5 and 19 is approximately same at the range of 241-363 hectares. The capacity of DC 19, however, is nearly half that of DC 5, emphasizing the combined influence of DC rated capacity and local meteorological conditions on greenhouse sizing. Table 3 further expresses the total tomato production potential across all studied states, accounting for both available waste heat and regional climatic conditions. Arizona, Virginia, and Texas, distinguished by the largest DC capacities and the most favorable climatic conditions, have the greatest potential to contribute significantly to food security in the U.S.

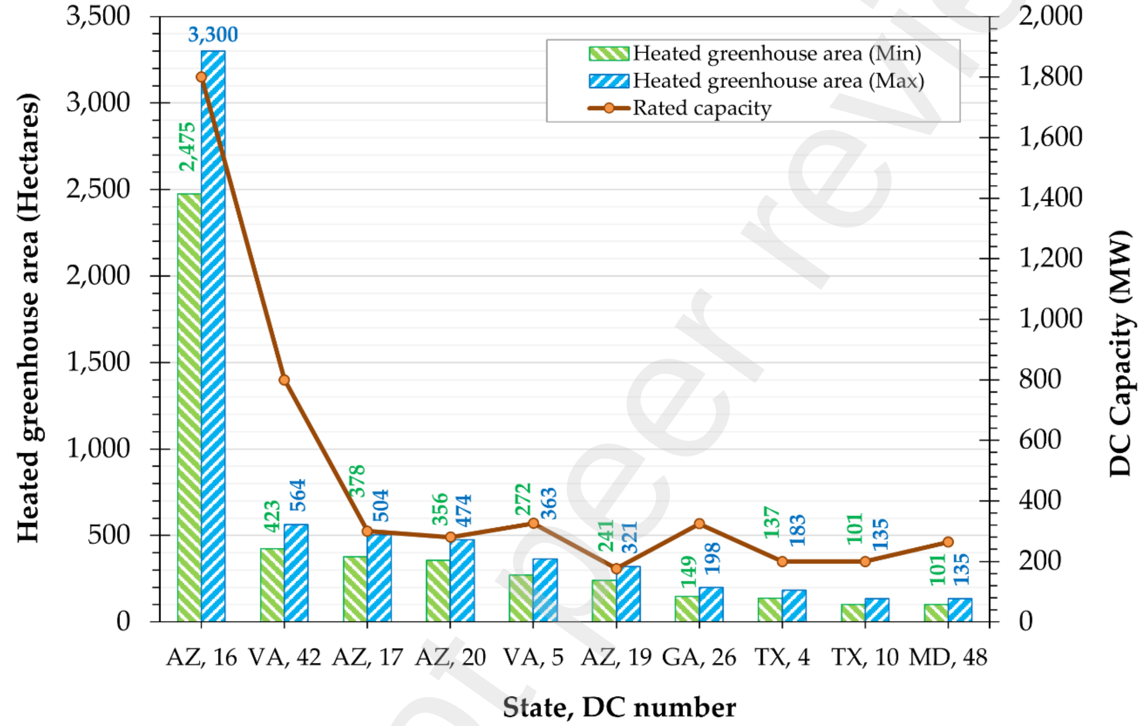

Figure 5. Ten largest heated greenhouses vs the corresponding DCs capacities.

Table 3. Potential year-round tomato production capacity of DC-heated greenhouses located at different states.

State	*Potential tomato production (tonne/year)*	
	Minimum	*Maximum*
AZ	1,730,052	3,412,100
VA	357,120	704,338
TX	186,210	366,893
GA	86,940	171,465
CA	75,708	149,313
MD	48,686	96,026
NV	48,132	94,998
UT	36,720	72,420
NJ	24,264	47,819
FL	16,200	31,844
MN	16,135	31,817
OH	14,148	27,930
WA	14,094	27,823
IL	9,130	18,142
NM	6,444	12,727
MA	5,242	10,373
NY	5,062	9,984

MO	4,698	9,266
CO	3,078	6,071
NC	2,808	5,538
MI	2,653	5,245
PA	2,484	4,899
OR	1,584	3,115
WI	1,206	2,396
CT	630	1,225
TN	432	852
Total	2,699,860	5,324,617

How much power savings can be achieved by managing the cooling loads of DCs for food production purposes? The primary goal of this nationwide study is to identify the significant savings potential in the total power consumption of DCs while contributing to the sustainable food production across the United States. These savings could help protect electrical grids from overloading or be redirected toward other sustainable objectives, such as electric vehicle charging and hydrogen generation. Power savings are directly linked to the heating demands of greenhouses, which are expected to be met by the waste heat from DCs. This reduces the electrical loads required for cooling equipment in AI-based data centers. By implementing the waste heat recovery strategies under the capacity factor varying between 60% and 80%, electricity usage management could range from 1.9 TWh to 2.5 TWh annually, as provided in Table 4. Similarly, it is logically demonstrated in Table 4 that electricity savings in DCs, both directly and indirectly, contribute to a substantial reduction in natural gas consumption. This reduction applies to heating food production greenhouses and power generation by NG-fired power plants. As shown in Table 4, approximately 747-995million m³ of NG consumption could be mitigated by establishing a symbiotic relationship between DCs and controlled food production environments in the U.S. It is important to note that this estimate is based on data from a limited number of DCs in the country (84 out of 5,390 DCs [62]). The aggregate rated capacity of DCs operating across the country was approximated at 40 GW, as outlined in the 2024 U.S. Data Center Energy Usage Report [50]. In contrast, the total rated capacity of the dataset under consideration in this study amounts to 6.6 GW.

Table 4. Power electricity and NG savings due to the waste heat recovery in DCs for greenhouse heating purposes.

State	*Potential power saving in DC (MWh)*		*Direct NG saving (10,000 m³)*		*Indirect NG saving (10,000 m³)*	
	Minimum	*Maximum*	*Minimum*	*Maximum*	*Minimum*	*Maximum*
AZ	680,267	907,015	12,722	16,962	14,286	19,047
VA	419,536	559,351	7,846	10,461	8,810	11,746
TX	120,488	160,421	2,253	3,000	2,530	3,369
GA	102,031	135,992	1,908	2,543	2,143	2,856
MD	101,188	134,900	1,892	2,523	2,125	2,833
MN	72,304	96,346	1,352	1,802	1,518	2,023
UT	70,146	93,516	1,312	1,749	1,473	1,964

NJ	52,331	69,685	979	1,303	1,099	1,463
CA	48,031	64,029	898	1,197	1,009	1,345
WA	35,803	47,741	670	893	752	1,003
NV	35,716	47,649	668	891	750	1,001
OH	31,043	41,384	581	774	652	869
IL	29,808	39,935	557	747	626	839
MA	13,694	18,251	256	341	288	383
NY	12,229	16,268	229	304	257	342
NM	10,575	14,100	198	264	222	296
MO	10,108	13,443	189	251	212	282
MI	8,356	11,116	156	208	175	233
CO	8,320	11,065	156	207	175	232
PA	5,374	7,141	101	134	113	150
WI	4,297	5,753	80	108	90	121
NC	3,105	4,134	58	77	65	87
OR	2,515	3,334	47	62	53	70
CT	1,524	1,990	28	37	32	42
FL	1,362	1,813	25	34	29	38
TN	654	863	12	16	14	18
Total	1,880,804	2,507,236	35,173	46,889	39,497	52,652

5. Discussion: Transforming AI and Food Systems for a Sustainable Future

Historically, data center location has been driven by two primary factors: the availability of low-cost energy and proximity to reliable infrastructure [63]. In contrast, almost none of the world's DCs have been purposefully sited near greenhouse infrastructure or other infrastructure that could use waste heat. This highlights an underexplored opportunity to rethink site selection criteria by integrating sustainability into decision-making processes. DCs can be located at existing greenhouses and new DCs have the opportunity to co-develop with greenhouses on the same site. Environmental considerations, such as the waste heat recovery, have been largely overlooked in the site selection process. This oversight reflects a gap in the integration of sustainable design principles, which considers the broader environmental and societal impacts of infrastructure decisions. For instance, as a result of the current research, as demonstrated in Table 5, the current dataset of data centers with a total rated capacity of 6.6 GW has the potential to support a greenhouse area ranging from 5,624 to 7,499 hectares. Scaling this to the entire U.S., the total rated capacity of DCs in 2024, estimated at 40 GW, could supply greenhouse areas between 30,085 and 45,448 hectares. By 2028, with the projected growth of DC capacity to 74–132 GW, the corresponding greenhouse areas could expand significantly, ranging from 63,057 to an impressive 149,980 hectares. These figures underscore the vast potential for integrating waste heat recovery from DCs into agricultural production, providing a clear pathway to enhance food security and promote sustainable resource use.

Table 5. Estimated greenhouse areas that can be supported by waste heat recovery from data centers in the U.S., based on rated capacities for the current dataset, total 2024, and 2028 total projections.

	Rated capacity (GW)	*Minimum land area of supplied greenhouse (hectares)*	*Maximum land area of supplied greenhouse (hectares)*
Current dataset	6.6	5,624	7,499
U.S. total, 2024	40	30,085	45,448
U.S. total, 2028	74-132	63,057	149,980

The approach used in this research also directly supports the United Nations Sustainable Development Goal (SDG) of zero hunger. By repurposing waste heat to sustain greenhouse operations, food production efficiency and resilience are enhanced, while mitigating the environmental impacts of the food production sectors. For instance, the integration of waste heat recovery in DCs can significantly reduce the reliance on NG for greenhouse heating. Considering that 1 m^3 of natural gas emits 1.94 kg of CO_2 [64], the current number of DCs alone could save between 747 and 995 million m^3 of NG (1.45-1.93 billion kg CO_2), while nationwide adoption in 2024 could result in savings of 4,527–6,030 million m^3 (8.78-11.7 billion kg CO_2). Given that a typical passenger vehicle emits approximately 4.6 metric tons of CO_2 annually [65], these savings correspond to the CO_2 emissions produced by approximately 1.9 to 2.5 million fossil fuel-powered vehicles. This is equal to 1.3-1.7% of total agricultural emissions in 2021 in the U.S. [66]. These reductions represent a significant step toward decarbonizing both the energy and agricultural sectors. Implementing waste heat recovery from DCs to support greenhouse operations presents one major challenge, concerning CO_2 supplementation essential for optimal plant growth. Greenhouses typically require CO_2 enrichment to enhance photosynthesis and improve crop yields. Approximately, 0.18 kg/hr of CO_2 is needed for every 100 m^2 of greenhouse space [67,68]. Given the potential scale of greenhouses supported by the current dataset, this translates to a substantial annual CO_2 requirement ranging from 0.89 to 1.2 billion kg (compared to 1.45-1.93 billion kg CO_2 savings), and for U.S. data centers projected in 2024, between 4.7 and 7.2 billion kg (compared to 8.78-11.7 billion kg CO_2 savings). Addressing this demand necessitates the integration of secondary technologies, such as CO_2 supply, carbon concentration or symbiotic systems like mushroom cultivation units that can co-produce CO_2. These additions introduce complexities in terms of infrastructure and operational management. This dependency means that 55–62% of the total anticipated CO_2 reductions (almost 100% of the direct CO_2 reductions) hinge on these supplementary technologies.

Waste heat recovery has been shown to be useful in other contexts for greenhouse growing of tomatoes [69]. Furthermore, the potential increase in tomato production enabled by this approach is noteworthy. With 9.2 kg of fresh tomatoes consumed per capita annually in the U.S. [70], total tomato demand of the American people will be 3.2 million tonnes annually [71]. The currently studied DCs could support the production of 2.7–5.3 million tonnes of tomatoes, meeting the 84-166% of U.S.'s requirements, exceeding the domestic fresh tomato production (1.27 million tonnes in 2019 [72]) and imported fresh tomatoes (2 million tonnes in 2023). These numbers illustrate the transformative potential of coupling AI infrastructure with greenhouse agriculture to enhance food security while reducing environmental impacts. The policy implications of this strategy are clear: governments should incentivize industries to collaborate on innovative solutions that link AI infrastructure to agricultural sustainability. Policies [73–75] to encourage waste heat recycling and provide support for greenhouse infrastructure retrofitting could be used to achieve these goals. While the European Union's Renewable Energy Directive (REDIII) provides the legal definition of waste heat, which plays a crucial role in aligning it with broader energy efficiency strategies and renewable energy goals, a legal analysis by Holzleitner-Senck et al. (2025), however, highlights ambiguities and inconsistencies of the regulation that can create uncertainty and hinder the implementation of waste heat initiatives [76].

When discussing the potential of AI to support SDGs, the focus often remains on AI applications in predictive analytics or resource management. This study demonstrates that AI can also contribute to sustainability goals, however, through transformative changes in its own life cycle. By coupling AI with the decarbonization of food systems, environmental and social goals can be advanced in tandem, laying the groundwork for a more integrated approach to achieving global sustainability. Efforts to decarbonize AI infrastructure present a unique opportunity to address not only the environmental challenges posed by AI, but also to contribute to the decarbonization of adjacent industries, such as food production.

This is, by redirecting waste heat from DCs to greenhouses, a "win-win- win" scenario advances sustainability across multiple sectors. First, this approach has the potential to reduce reliance on natural gas, which is traditionally used to heat greenhouses. Secondly, this supports the broader goal of decarbonizing the food delivery chain by reducing the need for importing food from other (possibly far away) countries to meet local demand. Third, a significant reduction in the power grid's load allocated to data center operations can be achieved, enhancing the environmental benefits of this approach by decreasing dependence on NG-based electricity. Starting with small- to medium-sized data centers, the implementation of sustainable projects becomes more accessible and feasible. Policymakers could prioritize smaller-scale AI-based infrastructures as a practical platform to realize the proposed sustainable ideas. For instance, avoiding mega-sized DCs, the total energy savings from DCs smaller than 50 MW is estimated to contribute 0.24–0.33 TWh, accounting for 13% of the total power demands of the current dataset. By strategically targeting smaller facilities, the adoption of such innovations can serve as a scalable model for broader application, ensuring incremental yet impactful progress toward sustainability by providing local food.

6. Conclusions

The rapid growth of AI-driven DCs leads to soaring energy consumption and greenhouse gas emissions, highlighting inefficiencies in their operations. One major challenge is the energy-intensive cooling systems, which consume 33–42% of the total rated power capacity of the DCs. To address this, this study suggested redirecting waste heat from DCs to greenhouses, supporting sustainable agricultural practices vital for global food security. The waste heat generated by the DCs was intended to meet the heating needs of the tomato greenhouse, for which a detailed model had been developed and validated in prior studies. The findings of a parametric analysis on prospective sustainable savings in U.S. DCs were reported, considering both lower and upper bound estimates derived from actual power consumption and the mean annual productivity of American tomato greenhouses. Minimum savings were calculated for a 60% capacity factor and 48 kg/m² tomato yield, while maximum savings were based on an 80% capacity factor and a yield of 71 kg/m².

The results demonstrated a substantial opportunity for both agricultural and energy savings by utilizing the waste heat from the 84 U.S. DCs for greenhouse heating. With a combined rated capacity of 6,561 MW, this system could heat 5,624 hectares of greenhouses, leading to a potential tomato production of 2,699,860 tonnes per year. Additionally, the DCs could achieve a total power saving of 1,880,804 MWh. This translated to direct NG savings of 35,173 m³ and indirect savings of 39,497 m³.

The analysis also revealed that the ten largest DCs in the U.S. dataset had capacities ranging from 200 MW to 1,800 MW. DC 16 in Arizona, the largest in capacity, could heat a greenhouse area between 2,475-3,300 hectares.

For the selected DCs in this study, the potential year-round tomato production capacity of DC-heated greenhouses across different states ranged from a minimum of 2,699,860 tonnes to a maximum of 5,324,617 tonnes.

Finally, implementing waste heat recovery strategies with a capacity factor between 60% and 80% could reduce electricity usage by 1.9 TWh to 2.5 TWh annually. This strategy also led to significant reductions in NG consumption for heating greenhouses and powering NG-fired plants, with an estimated mitigation of 747-995 million m^3 of natural gas. These estimates were based on data from 84 U.S. DCs out of a total of 5,390, with the national total rated capacity of 40 GW compared to the 6.6 GW considered in this study. This study conceptualized Sustainable AI as moving beyond maintaining current practices and instead implementing practical infrastructure changes that align AI infrastructure with sustainability goals. This approach offers a distinctive contribution to the AI *for* sustainability paradigm. It has the potential to guarantee not only the deployment of existing AI models for sustainability-related applications (i.e., in line with traditional AI for Sustainability approaches), but that the *development* of these models themselves can contribute to sustainability objectives.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All data and the code is available on the Open Science Framework under GNU GPL v3 at https://osf.io/97dhm/

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