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Data centre energy demand projections within shared socioeconomic pathways

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ABSTRACT

Widespread digital transformation and the rapid expansion of data centres for artificial intelligence (AI) pose growing challenges for electricity systems and global climate targets. Many studies project near-term data centre energy demand, but few extend beyond five years due to the high degree of uncertainty in technological trends and a lack of robust and widely accepted methodologies. This is a problem for climate mitigation research that covers plausible scenario envelopes over longer time horizons to assess carbon budgets and warming outcomes. In this study, we extend data centre energy demand projections to 2050 within the Shared Socioeconomic Pathways (SSP) framework, aligning with common approaches in climate scenario analysis. Our method draws on three main historical periods since 2010 marked by distinctive trends in data centre service demand growth or efficiency gains, combined with projected future trends in digital transformation levels. Across the five SSP scenarios, we find global data centre electricity demand ranges widely, reaching between 1,800 and 5,000 TWh by 2050. We also find that the average weighted carbon intensity of electricity consumed by data centres must fall to below 100 gCO_2/kWh from 2030 to remain compatible with 1.5°C climate targets. Unlike most SSP-based studies, we find that uncertainties in data centre energy demand growth as a result of within-sector development and efficiency dynamics are wider than uncertainties from the different socioeconomic development trajectories captured by variation across SSP storylines. Rather than subsuming data centres within the commercial buildings sector as currently, we argue that data centres should be differentiated as a separate end-use sector in global energy statistics and modelling to account for its unique growth characteristics and uncertainties. Our findings provide a structured, scenario-based extension of anticipated near-term data centre energy needs. Our characterisation of uncertainties informs strategies for managing long-term digital infrastructure growth in line with global climate goals.

1. Introduction

Digitalisation continues to reshape economies, industries, and societies amidst ongoing waves of innovation. Much of the current momentum behind digitalisation is from generative artificial intelligence (AI) and large language models [1]. Digitalisation holds significant potential to enhance efficiency, productivity, and convenience across energy demand and supply. In electricity, for example, it may support the transition to renewables by enabling the integration of intermittent sources into increasingly complex electricity networks. It also contributes to the energy transition by promoting greater investment in renewable energy infrastructure [2].

However, the narrative surrounding digitalisation and AI in the context of the supporting global energy transition is increasingly contested, as it raises concerns related to ethics, security, inequality, and the growing environmental impacts arising from various natural resource demands (materials [3], energy [4], water [5]) as well as indirect environmental impacts induced by the use of AI [6]. For the energy needs of data centres specifically, two key concerns are the extreme spatial concentration of demand and a mismatch between data centre and energy infrastructure build timelines. At the global level, and even at the national levels in some countries, overall changes in electricity demand appear relatively small; but they are far more geographically concentrated than demand from electric vehicles or other sources of

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electricity growth. Rapidly surging energy demand may outpace the expansion of clean energy, reinforcing dependence on fossil fuels and delays to the energy transition. Rebound effects can further compound this challenge. The potential of digitalisation to enable net-zero and other environmental targets lies in its ability to influence energy-intensive activity in buildings, transport and industry [7]. In this context, potentially adverse impacts should be minimised while maximising the enabling effects of digitalisation through informed planning, encompassing both policy interventions and public engagement [8].

Various assessments have been reported in scientific literature to quantify the energy consumption or carbon footprint of data centres, although the results are not always consistent and show significant variation, even for historical estimates [9]. Freitag et al. [10] summarises the studies estimating the carbon footprint of information and communication technologies (ICT) in 2015 and 2020, indicating that data centres account for approximately 18-41% of the total ICT footprint, which includes network and user devices. Among the different historical estimates and suggested growth of global data centre energy use, the work of Masanet et al. [11] is the most comprehensive and transparent in its accounting and assumptions. Bottom up or hybrid studies have also been conducted in assessing the environmental performance of data centres in the United States [12], Germany [13], as well as for individual data centre in the UK [14], and a tier 4 data centre in Türkiye [15].

The demand for digital services provided by data centres is not the only aspect experiencing significant growth; improvements in the energy efficiency of computation have also been remarkable [16]. As stated by Shehabi et al. [17], data centre growth does not direct translate into a corresponding rise in electricity consumption, as efficiency gains have outpaced service demand from overall energy use. However, whether efficiency improvements can keep pace with rising service demands in the long term remains unclear [18]. Table S1 summarises the main energy efficiency measures in data centres, covering hardware, computation, and facility upgrades.

Several studies have projected electricity demand of data centres, but most focus on the shorter-term (typically 5 years ahead, up to around 2030, or occasionally up to 10 years, to 2035) so do not explicitly inform long term climate mitigation or adaptation planning. Fig. 1 illustrates different energy projections for data centres, based on data from multiple reports. These projections range from those based on 2015-2021 data to more recent estimates starting from 2022 when the launch of ChatGPT triggered a surge in interest. Studies vary in their assumptions, methodologies and levels of transparency as well as their purposes and timelines. In the high energy scenario (lift off) outlined by the IEA, consumption may exceed 1,250 TWh by 2030 (Fig. 1, pink line). Much of this projected growth is attributed to AI accelerators, which account for the majority of data centre energy demand increases in the IEA analysis.

A recent study by Wijnhoven and Paccou [19,20] assesses the electricity consumption of AI (not included in Fig. 1, which covers data centres more broadly), starting at a lower initial estimate of 100 TWh in 2025. Their analysis projects an increase to 510–880 TWh by 2030 and a range of 190–1370 TWh by 2035, depending on four evaluated scenarios: limits to growth, sustainable AI, energy crunch, and abundance without boundaries. Information on data centre energy usage for different applications, such as AI versus non-AI workloads, is currently limited. This lack of detailed data makes in-depth analysis or projections challenging, prompting calls for greater transparency. Available US-based data suggests that less than a quarter of current data centre energy consumption is attributable to AI, but this share is expected to rise to around half by 2028 [21]. According to a recent assessment [22], if policy measures to improve data centre efficiency were implemented worldwide, electricity consumption could rise from 230 TWh in 2023 to 250–370 TWh by 2030. This represents a more optimistic outlook compared to most other scenarios and projections.

In general, growth expectations vary widely (Fig. 1). A more recent base year may align with higher forecasted demand due to technological breakthroughs, but outcomes ultimately depend on the methodology, assumptions, and scenario framing. An in-depth evaluation of data centre energy modelling approaches, their underlying assumptions, and a broader review of projection sources—including academic literature—can be found in the IEA 4E report [9]. Projecting the long-term electricity demand of data centres is inherently difficult, and many caution against making long-term projections. Koomey and Masanet [23] highlight that rapid innovation dynamics and pervasive

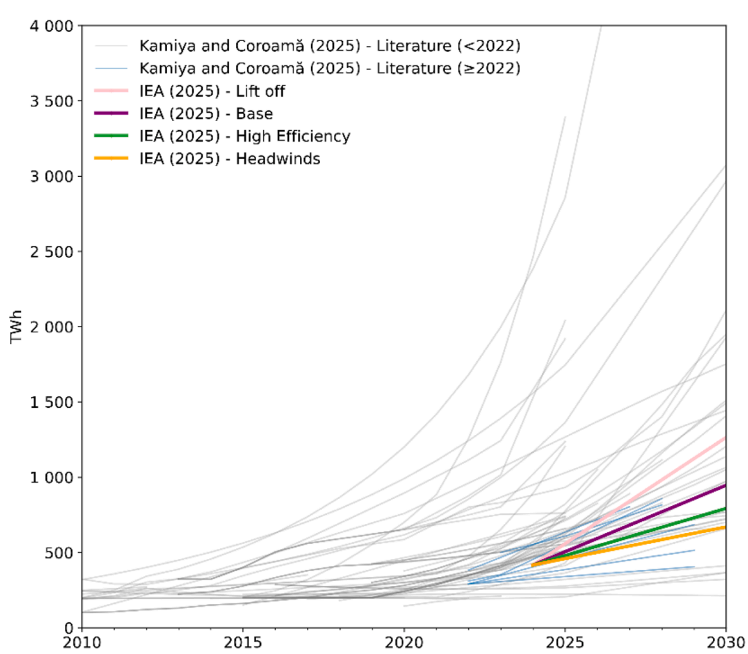

Fig. 1. Projected global electricity demand of data centres. References: IEA [24], many different studies reviewed by Kamiya and Coroamă [9]. One of the lines is truncated at 4000 TWh due to the y-axis limit; in the original publication it continues to almost 8000 TWh, but has been treated as an exploratory, extreme outlier scenario [9].

data gaps make accurate assessments difficult or even impossible, warning against averaging key parameters over long periods for fast-moving technologies like AI and data centres.

Near-term projections to 2030 inform energy system planners, network operators, and regulators to assess infrastructure needs and operational adequacy under different scenarios. Long-term projections to 2050 inform net-zero pathways, electricity system strategy, and climate policy to mitigate future lock-in effects. Longer-term climate targets are necessary due to the scale and complexity of decarbonisation efforts. Structural changes in energy systems and infrastructure unfold over decades, shaped by investment cycles, regulatory reforms, and broader societal transitions. Moreover, coordinated international action is a critical enabler given the global nature of climate change. Carbon budgets associated with global warming outcomes reflect these long-term dynamics, and national net-zero commitments are commonly framed for 2050 or beyond. Despite this, most data centre energy projections stop at 2030 (Fig. 1), given the challenges of looking even five years ahead. Our standpoint is that effective near-term climate mitigation strategies are complemented by a longer-term perspective. Our work analyses best available historical estimates and trends in digital transformation to explore potential future scenarios of data centre electricity demand within the Shared Socioeconomic Pathways (SSPs) framework through 2050. SSPs define various reference scenarios for global and regional socioeconomic development, based on five narratives that explore a range of plausible futures and examine potential barriers and opportunities for climate mitigation and adaptation.

In the context of climate mitigation, expanding the use of low-carbon energy is one of the primary strategies for reducing the greenhouse gas footprint of data centres. Here, both current and future outlook is mixed. On the one hand, data centres are enablers of greater investment in renewable energy infrastructure backed by ICT sector firms' emission-reduction commitments and balance sheets. On the other hand, rapid growth in demand has, at least in the short term, been powered by fossil fuel-based generation. In the United States, for instance, data centre electricity consumption has been estimated at around 50% higher carbon intensity than the grid average [25]. Meeting immediate needs has frequently led operators to rely on fossil-based capacity, particularly natural gas.

There are growing commitments to decarbonise the electricity used by data centres, particularly through procurement of renewable energy via power purchase agreements and energy certificates [26], as well as commitments under Climate Neutral Data Centre Pact [27]. More advanced, and often preferred, approaches include 24/7 carbon-free energy matching [28] and on-site renewable energy installations. Over the medium-term, alongside these renewable-based strategies, the possibility of small modular nuclear reactors powering data centres is also being actively explored by reactor manufacturers and major technology firms, enabled by government policy in the US, UK [29], and elsewhere. While these efforts signal a structural shift toward integrating low-carbon energy more systematically into data centre operations, progress remains uncertain, as some firms experiment with or pursue behind-the-meter gas generation [30]. This trend is driven by concerns over reliability, resilience, and delays in permitting or grid connections, and it can undermine the credibility of decarbonisation commitments.

Long-term projections of data centre electricity demand make it possible to analyse the extent to which renewable energy deployment have to be scaled to align digital infrastructure growth with climate goals. The current wave of data centre electricity consumption projections is being driven by the generative AI boom, anchored in bullish expectations for new data centre deployments and rising computational demands from widespread adoption of generative AI use cases. For example, the IEA's projections are driven by server shipments, which is a justifiable basis for short-term forecasting. However, there is a risk of falling into a 'hype cycle' [31] trap when making projections during a phase of rapid expansion especially in the context of long-term forecasts.

In this study, we contribute to bridging this gap in long-term data centre projections by developing a set of energy-demand pathways aligned with the SSP framework and common practice in climate scenario analysis.

Our first contribution is to develop historically calibrated projections, incorporating the disruptive impact of AI as identified by the IEA up to 2030. The historical calibration captures both service demand growth and efficiency trends observed in different periods. Our analysis is global in scope, with differentiation across world regions based on distinct socioeconomic or digital transformation characteristics.

Our second contribution is to align our projections with alternative long-term development pathways used in global climate change mitigation and adaptation. This is the first study to explicitly incorporate data centre energy uncertainties within the SSP framework.

The SSPs map socioeconomic pathways to 2050 and 2100 to support long-term net zero strategies and climate policy. We believe that extending projections, calibrated by historical trends and future digital transformation shaped by socioeconomic development can provide valuable insights for climate mitigation, while acknowledging the associated challenges and limitations. The SSP framework is closely integrated with climate models commonly used in IPCC reports and global climate mitigation pathways. Our purpose is not to predict the future, but to be prepared for what it may become. This macro perspective and extended projections enable analysis of how data centre energy demand could interact with long-term climate mitigation efforts.

2. Method

Our overall method for assessing the electricity demand of data centre projections up to 2050 within the Shared Socioeconomic Pathways (SSPs) framework can be divided into three major steps. The first step involves data collection and processing, which is particularly challenging due to the wide variation in estimates, including those for historical values. A critical review of source reliability conducted by Kamiya and Coroamă [9] is used as the basis for identifying representative values of electricity demand.

The second step uses an extrapolation method to project out to 2050. This is chosen over bottom-up or top-down approaches which require more specific assumptions and are less feasible for long-term projections. Bottom-up methods [32,33] are often considered more accurate, but required detailed data on future developments (e.g., server shipments, compute efficiencies, power usage effectiveness or PUE, a measure of non-ICT equipment related data centre efficiency). Top-down methods [32,33] are based on aggregate energy balances or reporting by government and companies. Both are challenging for long-term projections due to the rapidly evolving landscape and high levels of uncertainty, which can introduce subjectivity and susceptibility to hype issues discussed in the introduction.

In contrast, our extrapolations are guided by growth rates linked to levels of digital transformation under the five SSPs, and by the observed trade-off between digital service demand and efficiency improvements. The net effect of this relationship is historically characterised by two distinct phases, which serve as upper and lower bounds to data centre energy demand growth. Including lower bounds calibrated to a historical period in which efficiency gains dominated helps address one of the limitations of extrapolation approaches indicated by Kamiya and Coroamă [9], which is the tendency to produce exaggerated estimates. Further details are provided in Sections 2.1 and 2.2.

The third and final step assesses the CO_2 implications of electricity demand from data centres under different scenarios, according to the method outlined in Section 2.3. This assessment evaluates whether projected demand remains on track to meet the 1.5°C and 2°C climate targets, based on the allocated share of the assumed carbon budget for data centres.

2.1. Historical analysis: data and statistical modelling

We collect annual estimates of data centre electricity consumption from multiple sources, including Masanet et al. [11], IEA [24], and Kamiya and Coroamă [9], as summarised in Table 1. Years for which data in world regions, in addition to global totals, are inconsistent or missing are excluded from the assessment (i.e., 2019, 2021, and 2022).

To explore the relationship (or elasticity) between data centre electricity demand and digital transformation for use in our projections, we define two distinct phases: 2010–2017 and 2020–2024. The period from 2010 to 2017 is characterised as "efficiency-dominant", ending in 2017 in line with the IEA's observation [24] that "a sharp acceleration in data centre electricity consumption took place from around 2017 onward." During this time, despite exponential growth in service demand, electricity consumption remained relatively flat [34], attributed to significant improvements in PUE (e.g., from passive cooling systems), the shift toward hyperscale data centres, and advances in hardware and software efficiency. The period from 2020 to 2024 is characterised as "service demand-dominant" during which efficiency improvements continued, likely at a slower rate than before, but were outweighed by accelerating service demand (see Table S1), resulting in increasing electricity use. Certain years that are not directly assessed (Table 1), referred to as "fog years" for which it is unclear whether efficiency gains or demand growth dominate, are either omitted or represented using estimates to illustrate trends over time in the results. For example, adjacent years may be connected directly (e.g., 2020 to 2023), or, where appropriate, a central estimate from external sources such as Kamiya and Coroamă [9] may be used (e.g., for 2019).

We model the relationship between data centre electricity use and digital transformation, as measured by the e-government development index (EGDI) [35], based on observed dynamics across these two distinct periods during which either efficiency improvements or service demand growth are dominant. This EGDI serves as an aggregate proxy for the extent of a country's digital transformation, capturing not only ICT infrastructure but also digital skills and digital service provision. We use the EGDI to capture the underlying drivers of changes in data centre activity over time, since higher levels of digital transformation imply increased reliance on data-intensive services. Additional information on the rationale for using EGDI as a proxy is provided in Appendix 1. At the country level this proxy must be interpreted with caution, because countries that host a disproportionate share of global data centres or where data centres account for a high share of national electricity demand (e.g. Ireland) are not necessarily more digitalised in proportion to that share. In our analysis this issue is less pronounced because projections are conducted at aggregated world-region level, and a regional residual term is included.

To quantitatively assess this two-phase historical relationship, we first estimate elasticity coefficients (from a cross-sectional sample of 6 regions) that describe how a percentage change in digital transformation corresponds to a percentage change in the electricity consumption of data centres, controlling for region-specific variation (Eq. 1). These elasticities differ between phases and provide insight into the dominant dynamics at play. They are analysed based on logarithmic differences of data centre electricity consumption and digital transformation level between the start and end years of each period. This approach allows us to estimate how growth in electricity demand has responded to digital transformation historically. To enable consistent five-year interval comparisons, we extend the service demand-dominant phase (2020–2024) to 2025. For the efficiency-dominant phase, we use the average elasticity from the 2010–2015 and 2012–2017 periods, both of which cover five-year spans.

$$\Delta\ln(\mathrm{DCEnergy}_i) = \beta\cdot\Delta\ln(\mathrm{DigTrans}_i) + \varepsilon_i \tag{1}$$

Where:

- $\Delta\ln(\mathrm{DCEnergy}_i) = \ln\left(\mathrm{DCEnergy}_{i,\,t_{end}}\right) - \ln\left(\mathrm{DCEnergy}_{i,\,t_{start}}\right)$
- $\Delta\ln(\mathrm{DigTrans}_i) = \ln\left(\mathrm{DigTrans}_{i,\,t_{end}}\right) - \ln\left(\mathrm{DigTrans}_{i,\,t_{start}}\right)$
- $\mathrm{DCEnergy}_i$ is the electricity consumption of data centres in region i
- $\mathrm{DigTrans}_i$ is the digital transformation level in region i
- β is the global average elasticity across all 6 regions (a scenario construction parameters)
- ε_i is a region-specific residual, capturing local deviations from the global average relationship
- i denotes the region (i.e. Asia Pacific, Latin America, Middle East and Africa, North America, Europe)
- t_{start} = base/reference year (e.g., 2012)
- t_{end} = projection year (e.g., 2017)

We first estimate a single global elasticity coefficient β by fitting the model to pooled regional observations of digital transformation growth and data centre electricity consumption for each of the two phases. Underlying data on data centre electricity consumption $(\mathrm{DCEnergy}_i)$ for each region across the selected years, as summarised in Table 1, is provided in the Supplementary Data. The digital transformation level $(\mathrm{DigTrans}_i)$ is based on the e-government development index (EGDI) reported by the United Nations Department of Economic and Social Affairs [35], which is a composite measure of telecommunication infrastructure index, human capital index and online service index. Regional-level estimates were computed by aggregating country-level EGDI scores using population-weighted averages (see Supplementary Data). A total of 102 countries were included in the calculation, based on

Table 1
Historical estimates of data centre electricity consumption.

Source	Year	World Regions (R)	Notes on Use
Efficiency-Dominant Phase (Efficiency improvements offset growth in service demand)			
Masanet et al. [11]	2010-2018	Yes (6 R)	• Consistent and bottom-up historical estimate • Region (R) classification: Asia Pacific, Central and Eastern Europe, Latin America, Middle East and Africa, North America, Western Europe
Kamiya and Coroamă [9]	2019	No (Fog year)	• No consistent report available • Exclude from relationship assessment • Use for illustrative plotting, applying the middle range of estimates from the cited source that reviews available data
Service Demand-Dominant Phase (Growth in service demand exceeds efficiency improvements)			
IEA [24]	2020	Yes (6 R)	• Region (R) classification: North America, Central and South America, Europe, Africa, Middle East, Asia Pacific
Not available	2021-2022	No (Fog years)	• No consistent report available and not included in the IEA (2025) assessment • Not critical for the assessment, as it pertains to intermediate years • For illustrative plotting, an interpolation approach is applied
IEA [24]	2023-2024	Yes (6R)	• Region (R) classification: North America, Central and South America, Europe, Africa, Middle East, Asia Pacific

Note: "Fog years" refer to periods with limited or unclear data; these are excluded from elasticity estimation used for global scenario construction.

a reference set of 129 countries with data centres reported [36,37]. This coverage accounts for 98.7% of reported data centres' geographic distribution, with the remaining 1.3% not represented in the population-weighted regional estimates.

Once β is determined, we apply it to each region's log-difference data to compute a region-specific residual. This residual ε_i reflects unobserved local factors that influence energy demand independently of digital transformation growth. Due to limited region-specific data, we do not estimate individual elasticities for each region. This approach enables a consistent application of the global elasticity across all regions while still capturing regional variation through ε_i under the data limitation.

As the limited number of historical observations prevents us fitting a more conventional econometric model, our approach serves as a heuristic framework for future projections. The pooled regressions are used to derive elasticity estimates for scenario construction rather than for statistical inference and are not intended as models whose explanatory power is the focus of analysis. These elasticity estimates define the bounds of the growth rate scenarios used in our long-term projections described in Section 2.2. The residual ε_i is held constant for each region in future projections to account for persistent regional effects (e.g., electricity market and prices, policy and governance). Details of the underlying data and output for Eq(1) are provided in Supplementary Data. The derived elasticity estimates are phase-sensitive (Supplementary Data) and designed for projections up to 2050. Historical phases inform projections to 2050, while a separate "AI revolution" phase projected by IEA (see to Section 2.2) is used for the near term (2025-2030), where relationships may be less stable. This approach is not intended for very long-term projections (i.e. up to 2100), where longer-run average elasticity estimates for scenario construction may be more appropriate to avoid over-extrapolation.

2.2. Projections consistent with SSP scenarios

Since the IEA provides bottom-up projections for data centre electricity demand under four scenarios to 2030, our analysis builds on this foundation rather than duplicating it. To project data centre electricity demand beyond 2030, we used the elasticity coefficients and regional constant terms identified in Section 2.1. The model captures how changes in the level of digital transformation under different SSPs affect electricity demand. The IEA's 2035 projection is used as a benchmark for sense-checking and comparison against our extrapolation results. However, it is not used directly as the base year, as bottom-up projections beyond 2030 are also subject to significant uncertainties, as noted by the IEA [24]. In the main analysis, region-specific constant terms (Section 2.1) are carried forward unchanged, assuming the trends are continued. To assess the sensitivity of this assumption, we introduce alternative convergence specifications, which allows regional demand intensities to evolve toward the global average. Three cases are introduced in which convergence toward equity (based on population and GDP) and renewable energy development, is considered. These cases reflect a plausible scenario in which data centre electricity demand becomes less concentrated and more evenly distributed across regions, as it is increasing seen as critical infrastructure. In a separate case, demand (i.e. electricity consumed by data centre and associated built out) is progressively reallocated toward areas with lower-carbon electricity. Further details are provided in Appendix 2.

Projections include upper and lower bounds: the lower bound is calibrated to historical trends during the efficiency-dominant phase, while the upper bound reflects the service demand-dominant phase. The central estimate is benchmarked using the IEA base case value of around 1,200 TWh, with 700 TWh representing our lower bound (IEA's Headwinds scenario) and 1,700 TWh representing the upper bound (IEA's Lift-off scenario) in 2035. This means the central estimate lies slightly below halfway between the lower and upper bounds. An alternative central estimate, calculated as a simple mean of upper and lower bounds, is provided in the Supplementary Data.

For each region, we start with a base year value in 2030 using IEA's bottom-up estimate of data centre electricity consumption (see Supplementary Data) and the corresponding level of digital transformation. For each future time step and for every region–scenario pair, we calculate the log-difference in digital transformation relative to the previous time step. This process is repeated iteratively across the projection horizon, generating a time series of projected electricity demand for each region and SSP scenario.

The projected digital transformation levels applied in the model are based on a study by Fan et al. [38], which estimates these values under the five Shared Socioeconomic Pathways (SSPs), drawing on socioeconomic indicators such as GDP per capita, population, and R&D expenditure. SSP1 ("Sustainability") and SSP5 ("Fossil-fuelled Development") represent relatively optimistic trends, focusing on green growth and energy-intensive economic expansion, respectively. In contrast, SSP3 ("Regional Rivalry," a fragmented world of resurgent nationalism) and SSP4 ("Inequality," a world of increasing inequality) are more pessimistic. SSP2 ("Middle of the Road") offers a moderate pathway, where socioeconomic development trends largely follow historical patterns.

Regional classification differences between Masanet et al. [11] and the IEA [24] (see Table 1) were harmonised where necessary to ensure comparability, reducing the six regions to a consistent five regions classification). For example, the IEA uses "Europe" as a single world region, while Masanet et al. [11] distinguish between "Central and Eastern Europe" and "Western Europe." In our projections, the values for these subregions are summed to consistently represent Europe.

2.3. GHG implications and compatibility with 1.5°C and 2°C targets

To demonstrate one of the use cases for how our projections to 2050 can inform climate strategy, we assess the climate compatibility of future data centre electricity demand over the long-term. This analysis only covers operational electricity use of data centres and excludes embodied emissions associated with their manufacture.

We assume that 1% of the cumulative global carbon budget for different warming outcomes is pragmatically allocated to data centres, reflecting their estimated share of global emissions. The remaining 99% of the budget is reserved for all other sectors. This allocation is informed by estimates that data centres and data transmission networks account for approximately 1% of energy-related GHG emissions [39]. The allocation is normative and aligns with the underlying logic of the Science-Based Target initiative (SBTi), whereby future expected growth does not entitle a sector to a larger share of the remaining carbon budget. Instead, sectors with rapid demand expansion (in our case, data centre) are required to decarbonise more rapidly to remain consistent with the carbon budget. The 1% share therefore represents a deliberately stringent benchmark and is used here as a conservative benchmark. This approach is also consistent with the study by Hoy et al. [40], which assessed the contribution of the waste management sector to climate mitigation challenges by allocating it 1.7% of the cumulative emissions budget in line with its historical share.

It is important to note that alternative allocation approaches (e.g., based on equity or cost-optimal considerations) could yield different conclusions regarding whether a sector is on track. This study adopts a transparent allocation to assess what projected data centre energy demand implies for emissions pathways. As the analysis focuses on a specific sub-sector (data centres), an explicit allocation of the carbon budget is required. By contrast, system-wide assessments consider all sectors simultaneously; in this context, the present analysis provides a basis for further, more comprehensive system-wide assessments of whether climate targets can be achieved collectively across sectors.

In our analysis, four carbon budget thresholds are considered: 50% and 67% probabilities of limiting warming to 1.5°C, and 50% and 67% probabilities of limiting warming to 2°C, see Table 2 [41].

GHG emissions are estimated by combining projected electricity

Table 2
Assumed carbon budgets to stay on track for 1.5°C and 2°C targets [41].

Temperature limit	Percentiles of TCRE	Global Budget (Gt CO_2)	Data Centre Budget ($GtCO_2$), assuming fixed 1% share
1.5°C	67th	400	4
1.5°C	50th	500	5
2.0°C	67th	1150	11.5
2.0°C	50th	1350	13.5

TCRE = transient climate response to cumulative carbon emissions

demand under SSP2 from Section 2.2 with assumptions about the carbon intensity of electricity also from SSP2. This analysis is performed for SSP2 only. Emissions are calculated annually and accumulated over the period 2020 to 2050, aligning with the carbon budget timelines for which the assumed remaining carbon budget begins in 2020. The central assumption for carbon intensity is taken from the SSP2 pathway (Table 3), reflecting a "middle-of-the-road" or business as usual decarbonisation trajectory. SSP2's grid carbon intensity already reflects the evolving electricity mix over time. We also include two renewable electricity sensitivity cases (refer to Table 3):

(a) 50% Renewable Electricity (50% RE): Assumes that 50% of data centre electricity demand is met by renewable energy sources, while the remaining 50% follows the SSP2 carbon intensity trajectory.
(b) 100% Renewable Electricity (100% RE): Assumes that the entire electricity demand of data centres is supplied by renewable energy sources.

These two scenarios reflect increasing commitments from industry actors toward clean energy procurement or on-site low-carbon electricity generation. Although the latter is ambitious, especially due to the intermittency of renewable sources, it may become increasingly feasible through AI-enabled strategies such as demand shifting, dynamic scheduling, and workload alignment. Additionally, the significant investment being directed toward renewable and other forms of low-carbon energy, particularly by large technology companies, may further support such transitions if well-coordinated [42]. Nuclear energy in the form of small modular reactors is not explicitly considered as one of the scenarios, given their unproven track record and high uncertainties around their deployment. The potential role of carbon dioxide removal in addressing residual emissions is also not explicitly considered in this study. 50% represents a medium-ambition case between the default (no additional procurement beyond SSP2)

Table 3
Carbon intensity assumptions for data centre electricity consumption.

Carbon Intensity Scenario for Data Centres	Data Assumption	Source
SSP2	• The global average carbon intensity is derived as a data centre-weighted mean of regional electricity intensities, with regional values changing over time under the SSP2 electricity mix. • To ensure consistency with observed data, the global average carbon intensity values are calibrated using the actual historical value for 2020 (380 gCO_2/kWh), as the original SSP2 projection for 2020 (438 gCO_2/kWh) was higher than observed. • The applied global average carbon intensity ranges from 380 gCO_2/kWh in 2020 to 338 gCO_2/kWh in 2050.	Number of data centres [37],[36]. Projected share of electricity sources under SSP2 [43]. Carbon intensity [44].
50 % RE	• 50% follows the SSP2 carbon intensity • 50% is assumed to follow the carbon intensity of solar or wind power from 2030, set at 40 gCO_2/kWh for solar (S) and 10 gCO_2/kWh for wind (W).	
100 % RE	• 100% follows carbon intensity of Solar (S) or Wind (W) from 2030	

3. Results

The historical relationships between digital transformation and electricity demand of data centre show that a 1% increase in digital transformation is associated with changes in electricity demand ranging from an average 0.5% decrease (lower bound) to a 7.5% increase (upper bound). The average 0.5% decrease in electricity demand is driven by Europe where, despite exponential growth in service demand, the change in electricity consumption from data centres from 2010-2017 given by $\Delta\ln(\text{DCEnergy})$ in Equation 1 was negative (see Supplementary Data). This period is characterised by either flat (with small fluctuations) or declining electricity consumption in data centres worldwide.

It is important to note that this relationship is used to define the lower bounds of the projections and should not be interpreted as a universal rule. Regional variations remain, and residual or constant terms specific to each region still apply (see Supplementary Data). Projected results and their implications are presented and discussed in the following sections.

4. Global and world region projections of data centre electricity demand to 2050

Projected global data centre electricity demand is illustrated in Fig. 2. As expected, SSP5driven by rapid economic growth shows the highest projected electricity demand, while SSP3 under slow and fragmented socioeconomic development shows the lowest. The shaded areas represent uncertainty ranges; the overlapping of these range indicates a high degree of uncertainty. The SSP2 projection is suggested to be around 2,500 TWh by 2050, with a range from 770 TWh to 4,300 TWh. By benchmarking the total electricity demand projected at 50,000 TWh under Stated Policies Scenario by IEA [45], it represents almost 5% of the electricity demand by 2050 (see Table S2).

For comparison, under the same SSP2 scenario, global residential building electricity demand is projected by the MESSAGEix-Buildings integrated assessment model to increase from 6,300 TWh in 2020 to 10,600 TWh (~1.7-fold) by 2050 [46], whereas data centre demand rises from 270 TWh to 2,500 TWh (~9-fold), indicating much faster relative growth for data centres. Commercial building electricity demand increases from 4,800 TWh in 2020 to 8,800 TWh in 2050 [46], corresponding to an approximately 1.8-fold. While data centres are included within this category, their electricity demand grows far more rapidly, highlighting the need to model them as a distinct component rather than relying on aggregate commercial trends. The projected value to 2035 by the IEA is shown as dot markers on Fig. 2. It has a wider range for the upper and lower cases compared to our projection but remains close and within the range. Paccou and Wijnhoven [19] estimate AI-related electricity demand reaching up to around 1,370 TWh by 2035 under high-growth scenarios, with lower-bound estimates falling below 200 TWh; this supports the plausibility of the lower range of our projections, although their estimates refer to AI only electricity use rather than total data centre demand. Similarly, Shell [47] reports that AI

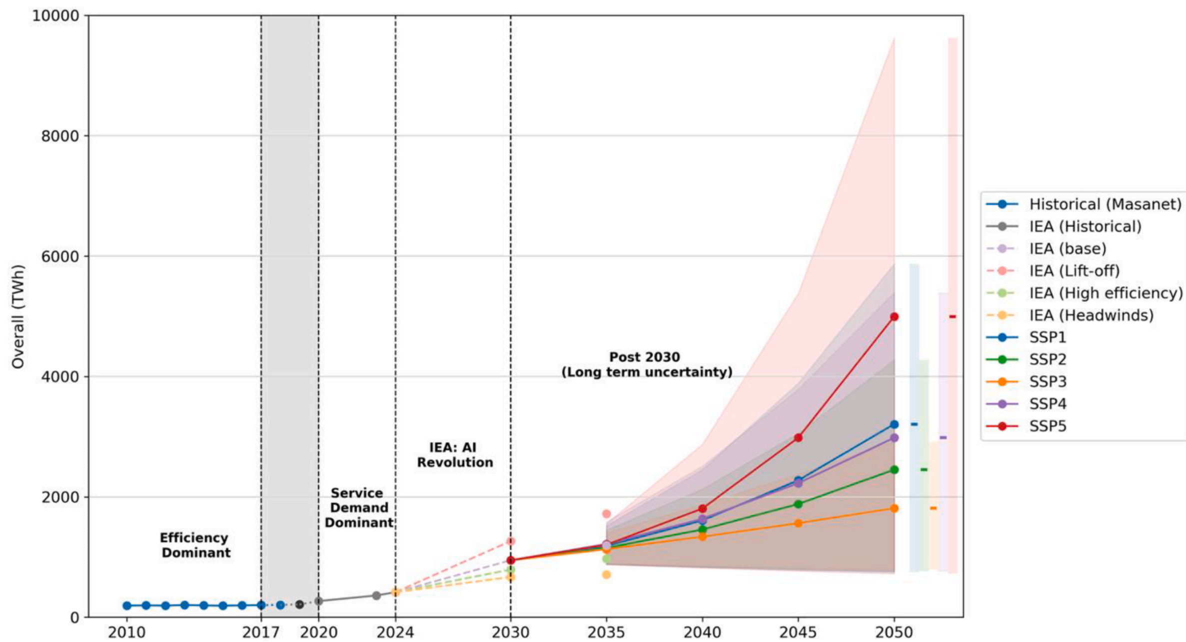

Fig. 2. Projected global electricity demand of data centres extended through 2050 consistent with the Shared Socioeconomic Pathways (SSPs). Shaded funnels = lower to upper bound ranges per SSP. Data for 2010–2024 are from Table 1. Projections to 2030 are based on IEA [24], where four scenarios represent a baseline projection grounded in industry expectations for server shipments, and three sensitivity cases capturing uncertainties in hardware and software efficiency, AI uptake, and supply bottlenecks. The IEA base scenario assumptions act as an inflection point shaping subsequent demand projections.

related energy demand for IT infrastructure could reach around 5,000 TWh by 2050 under the Surge scenario; however, this includes broader IT infrastructure.

The increase from 2024 to 2030 projected by the IEA (see Fig. 2) corresponds to a compound annual growth rate (CAGR) of 14.7% per year, ranging from 8.3% to 20.4% per year depending on the scenario, largely driven by anticipated expansion of AI deployment. When using the same baseline year (2024), the projected growth from 2024 to 2050 corresponds to an average annual increase of 7% per year, with a range of 2.4% to 9.6% per year. This represents an average annual increase of 4.9% per year over the period of 2030-2050. Details of the calculation (percentage values) are presented in the Supplementary Text and

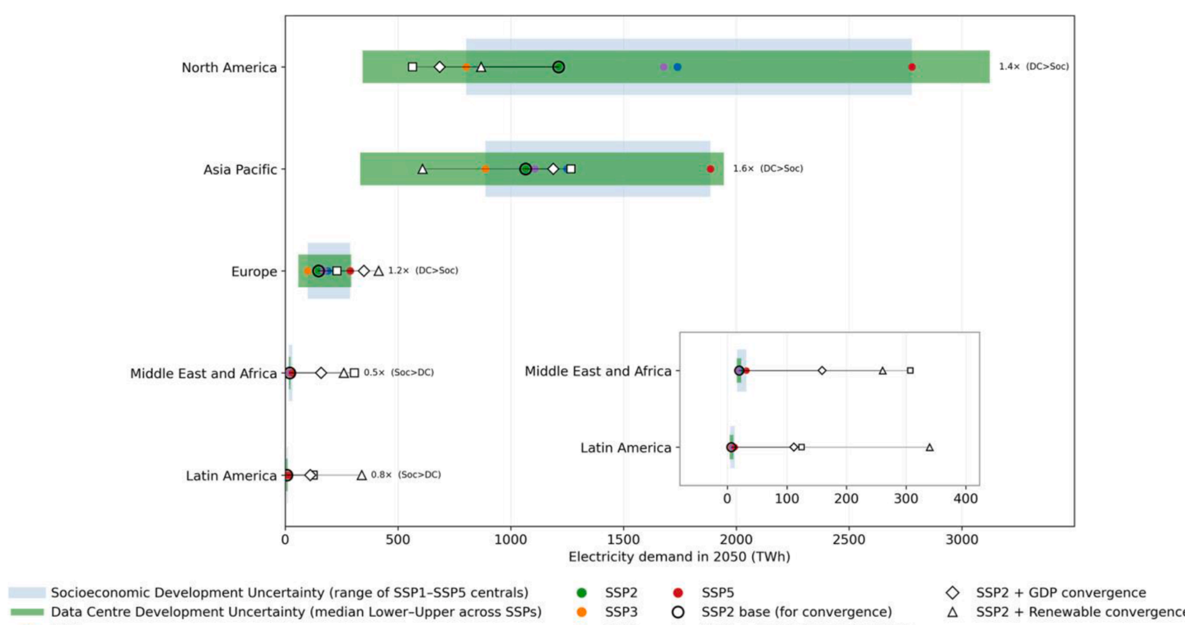

Fig. 3. Regional uncertainties in projected electricity demand of data centres by 2050 and the effects of convergence sensitivities. The blue bar represents socioeconomic development uncertainty (Soc), showing the range of central estimates across the five Shared Socioeconomic Pathways (SSP1–SSP5), from the lowest (orange marker) to the highest SSP (red marker) central value. The green bar represents data centre development uncertainty (DC), defined as the spread between "Efficiency Dominant" and "Service Demand Dominant" projections (data centre historical calibration uncertainty), bounded by the SSP with the lowest lower bound and the SSP with the highest upper bound. Ratios to the right of each bar > 1 indicate that data centre development uncertainty is higher, whereas a ratio < 1 indicates that socioeconomic uncertainty is higher. Details of the methodology underlying the sensitivity results for the three alternative regional convergence cases (square, diamond, and triangle markers) are provided in Appendix 2.

Table S2.

At the regional level, North America, Asia Pacific (including China) and Europe account for most of the global data centre electricity demand (Fig. 3). In SSP3, where regional rivalry and slower socioeconomic development prevail, projected data centre electricity demand is markedly lower.

Across regions, the dominant source of 2050 demand uncertainty is not uniform. In North America and Europe, data centre development uncertainty (green bar) exceeds the SSP envelope (blue bar) indicating that the spread driven by for example, efficiency assumptions and other within-sector trends is larger than the spread caused by divergent socioeconomic trajectories. In other words, SSP-driven variation is no longer the dominant signal, and therefore the common practice of using SSP macro-drivers as the primary source of energy demand uncertainty becomes inadequate for data centres. In contrast, in the Middle East & Africa, and in Latin America, the socioeconomic envelope remains the dominant source of uncertainty in data centre energy demand by 2050. Data centre development in the Middle East & Africa and in Latin America is still more tightly linked to broader socioeconomic conditions such as income growth, digitalisation rates, and infrastructure expansion. In these regions, data centre markets are still in earlier stages of growth, meaning that the overall pace of economic expansion and digital uptake drives demand far more strongly than sector-specific changes like efficiency gains or innovation.

Additional markers on Fig. 3 show the effect of convergence sensitivities applied to the SSP2 central case. These adjustments illustrate how regional demand would shift if disparities in demand intensity were partially reduced over time, representing a plausible future in which currently concentrated demand becomes less pronounced. In general, the convergence scenario (square and diamond markers in Fig. 3) has a stronger effect in the Middle East and Africa and in Latin America, pushing outcomes beyond the uncertainty range of the assessed SSPs representing different socio-economic development pathways. The renewable energy case (triangle markers in Fig. 3) shows a stronger sensitivity effect in Europe and Latin America. Comparisons of all regional projections over time are provided in Appendix 2 (Fig. A3).

Energy consumed in ICT infrastructure is accounted for in energy statistics under the commercial buildings sector. This includes the IEA's country energy balances which are used to calibrate the reference years or starting points of forward-looking models. For global integrated assessment models with highly reduced form representations of sectoral energy demand, commercial buildings' energy use is typically captured by historically calibrated relationships between GDP and population as floor space and demand drivers, and assumptions on building efficiency improvements over time. The very rapid growth in data centre electricity demand shown in our projections means this particular subsector within commercial buildings shows very different future dynamics from the commercial buildings sector as a whole. We illustrate this by comparing our projections against commercial buildings energy projections to 2050 in an illustrative SSP2 scenario from the MESSAGEix-Buildings integrated assessment model [46].

As an regional comparison, we find that the Asia Pacific region's data centres are projected to account for 30% of the region's 2050 commercial building electricity demand (3547 TWh [46]). This reflects the differing assumptions between continued rapid growth in data centre energy demands (our projections) and commercial building energy demands growing more slowly as a function of GDP, population, and efficiency (MESSAGEix-Buildings projections). In the North American model region, however, data centre electricity demand in 2050 of around 1,200 TWh is projected to exceed the region's total commercial building electricity consumption (987 TWh [46]). Under SSP2 assumptions in North America, commercial building energy use is projected to decline as energy efficiency improves and population falls, with GDP growth only partially offsetting these effects.

These results highlight the distinctive energy demand dynamics of data centres as an increasingly importantly subsector that needs to be represented explicitly in future scenario modelling.

4.1. Long-term data centre compatibility with climate targets

Our analysis shows that the SSP2 lower-bound scenario (Fig. 4, green line) stays below the threshold associated with a 2.0°C temperature increase. However, none of the scenarios evaluated are aligned with the more stringent 1.5°C target. Although emissions from data centres may appear relatively manageable given the potential for sourcing low-carbon electricity, especially when compared to other high energy-intensity sectors, they pose important risks for climate targets.

Considering upper-bound demand trajectories, for example driven by technological breakthroughs or rapid adoption of AI and other advancements, cumulative emissions from data centres need to be significantly reduced by around 5 Gt to 14.6 $GtCO_2$ to remain within climate-compatible limits (Fig. 4). This risk could be further amplified if electricity demand continues to rise post-2050 as new technologies gain traction across many applications and low-carbon energy infrastructure fails to keep pace with digital growth.

In the lower-bound SSP2 scenario, a reduction of around 3.4 $GtCO_2$ would still be required to meet the 1.5°C target. Including this lower bound is important because, despite investment in and construction of data centre infrastructure are currently accelerating, widespread high-value utilisation of this capacity beyond large language model development has not yet fully materialised in robust economic use cases. Some have cautioned that the rush to build AI data centres is driven top down by competitive and market concerns also shaped by investment and hype cycles that may have limited regard for actual demand [48]. Emerging reports point to underutilised capacity [48], suggesting a disconnect between infrastructure build-out and near-term demand, and indicating that growth may be less rapid than many studies have projected.

Referring to the cumulative emissions under SSP2 assumptions (dark blue in Fig. 4), the weighted average carbon intensity of electricity must be at or below around 300 gCO_2/kWh from 2030 onward to align with the 2.0°C target (67th percentile). For the 1.5°C target, this must drop to ~70 - 100 gCO_2/kWh starting in 2030 and maintained thereafter.

These results indicate that while partial data centre decarbonisation (50% renewable) can substantially reduce emissions, it may not be sufficient to achieve alignment with a 1.5°C climate pathway. In contrast, the full renewable energy scenario remains within the carbon thresholds compatible with both 1.5°C and 2.0°C limits (as illustrated by the dotted grey lines in Fig. 4), reinforcing the importance of continued and accelerated investment in clean energy infrastructure for data centres.

When compared with projected grid carbon intensities for 2050 under the IEA's Stated Policies, Announced Pledges, and Net Zero Emissions scenarios, these thresholds appear attainable, as all three scenarios project global average intensities below our suggested limits—except in emerging market and developing economies, where the average intensity is expected to remain around 145 g CO_2/kWh under the Stated Policies Scenario [45].

The analysis of long-term data centre compatibility with climate targets is centred on SSP2 as a representative baseline, illustrated with two cases (Fig. 4). This framing is intended to contextualise how projected electricity demand translates into emissions pathways under the selected budget allocation approach, rather than to provide a comprehensive assessment of climate target achievement. It reflects the study's aim to project data centre electricity demand across all SSPs, establishing a foundation for integrated assessment modelling and comprehensive climate target evaluation across scenarios.

To extend the perspective across scenarios, the implications of projected electricity demand under all five SSPs in 2050, are summarised in Fig. S2, providing a cross-scenario comparison.

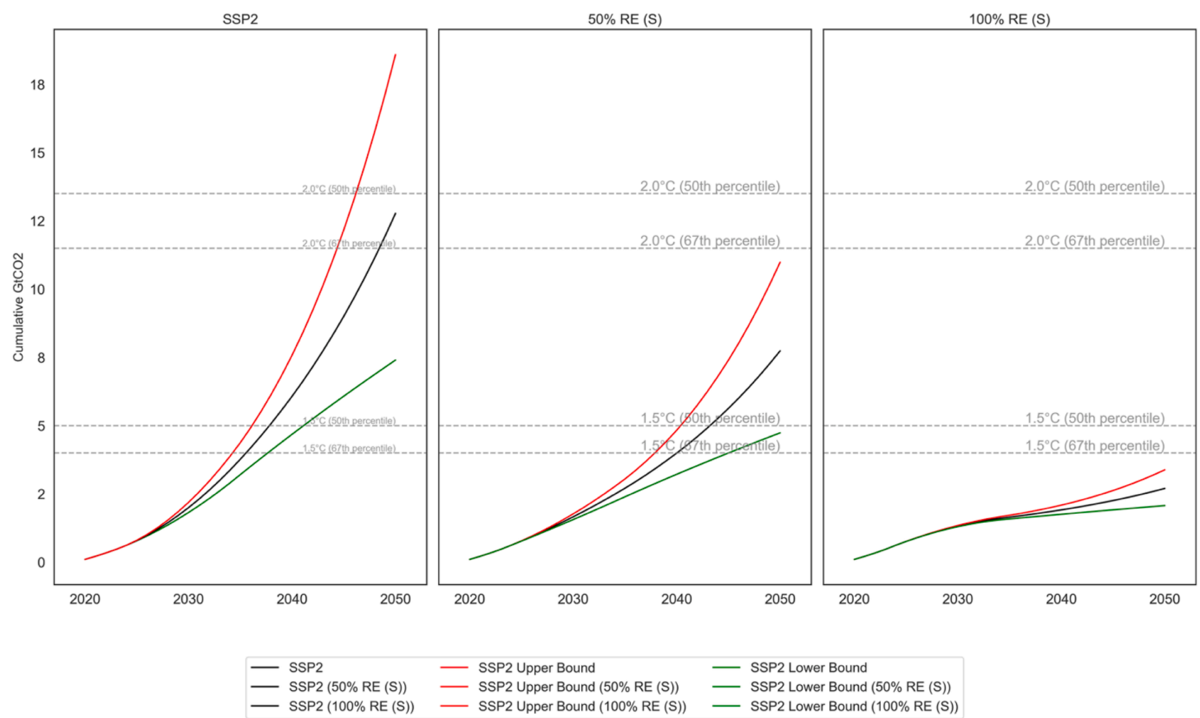

Fig. 4. Cumulative CO_2 emissions from data centre electricity demand under the SSP2 average carbon intensity of electricity and scenarios where 50% and 100% of electricity is supplied by renewable energy (solar, refer Fig. S1 for wind), with results assessed against compatibility with climate targets. Dotted horizontal lines represent threshold levels for 1.5°C and 2.0°C warming limits.

5. Discussion: use cases for long-term projections of data centre electricity demand

Our analysis provides insight on the potential role of renewable energy in decarbonising data centres over the long-term. While this study does not perform a full integrated energy systems analysis of grid mix evolution, storage needs, and renewable energy deployment, it contributes a key input by projecting global electricity demand from data centres through 2050 across all five SSPs. These projections align with the scenario architecture commonly interpreted by global integrated assessment models (IAMs) to quantify climate mitigation pathways and can serve as a consistent basis for further analysis of the additional mitigation challenge created by data centres.

Embedding these demand pathways into future pathways modelling would enable researchers to explore, for example, how increasing data centre electricity demand influences the timing and scale of renewable deployment, grid flexibility requirements, and the feasibility of meeting mid-century climate goals under varying socio-economic conditions.

There are several other use cases for our projections.

First, extending data centre analysis to include the full ICT (information and communication technology) sector including fixed and mobile data network infrastructure can support the development of more comprehensive mitigation strategies. These network components are often interlinked with data centres [39] and tend to follow trends in demand growth or saturation. Currently, ICT is not consistently treated as a standalone sector in many integrated models, with components often distributed across buildings, industry, and public services. However, given the rapid growth, distinct energy dynamics, and cross-cutting influence of digitalisation, especially with the rise of AI, there is a strong rationale for establishing ICT as a dedicated sector. Doing so would allow for more targeted mitigation strategies and more accurate assessment of its long-term climate impact, particularly when integrated into IAMs. This study's long-term projections contribute to this model development challenge by offering a structured pathway for electricity demand in one major ICT component, data centres, which could be expanded in future work to include network infrastructure and potentially end-user devices.

Second, long-term electricity demand projections can serve as a proxy to inform material consumption and e-waste assessments over time. As electricity demand scales with the deployment of servers, cooling systems, and network equipment, it can indirectly reflect the expansion of the physical ICT infrastructure. Combined with assumptions about device efficiency, lifespans, and typical material composition, this enables approximate estimation of future material requirements and electronic waste generation. Such insights are valuable for evaluating the potential of circular economy strategies, such as reuse, refurbishment, or improved end-of-life recovery, especially when considered over multi-decade timelines. Materials analysis would also be useful for identifying potential dependence on critical minerals and so exposure to supply chain risks. Over the long term, such projections are crucial for understanding how improvements in energy efficiency may interact with material flows, to mitigate the potential of footprint shifting rather than reducing environmental burdens. The importance of such assessments has been supported by Istrate et al. [49], highlighting concerns on the use of mineral and metal resources, as this impact is regarded less optimistically than other impacts of digital content consumption.

Third, long-term electricity demand projections can inform assessments of waste heat recovery potential. This option is particularly relevant for data centres, with the feasibility of waste heat integration already evaluated [50]. While the practical planning horizon for district heating integration is nearer term, longer-term projections are still useful for strategic planning and for avoiding lock-in effects. Data centres (physical building and core infrastructure) built today are likely to operate for decades [51], and if constructed without provisions for heat recovery, the opportunity to utilise their waste heat is constrained. Similarly, district heating infrastructure such as piping networks involves investments with lifespans extending well beyond mid-century and entail long lead times. By using long-term projections, decision-makers can align new-build data centre designs and retrofits with district heating opportunities, thereby maximising the feasibility of waste heat utilisation over both near and long-term horizons.

Fourth, long-term projections are valuable for assessing adaptation needs, particularly because they are developed consistent with the SSP framework. This consistency makes it possible to integrate data centre electricity demand pathways of different regions with climate hazard projections to evaluate the resilience of digital infrastructure. It could provide a baseline for assessing adaptation options. The Uptime Institute Intelligence Report [52] likewise emphasises that climate change will amplify risks of outages and operational disruptions, underscoring the need for alignment between workload or dependency growth and climate-resilient infrastructure strategies.

In sum, we extend data centre electricity demand projections over the long term to support climate mitigation and circular economy strategies, major infrastructure investment decisions, and adaptive planning. While the future is shaped by rapid technological developments and inherent uncertainty, our projections are valuable for stress testing near-term decisions, as they are developed under a range of plausible futures.

6. Conclusion

This study contributes the first structured, scenario-based projections of global and regional data centre electricity demand to 2050 consistent with the SSP scenario framework. Although the approach is based on extrapolation, it is grounded in historical trends from periods dominated by service demand growth or efficiency gains and informed by projections of regional digital transformation. The aim is not to predict the future, but to provide a transparent, evidence-informed basis for exploring plausible long-term scenarios. Such insight is essential for climate mitigation strategies, which require long-horizon perspectives to align digital growth with global climate goals. The findings highlight that direct electricity demand from data centres could vary substantially, with implications for the carbon intensity required to remain compatible with the 1.5°C target.

In addition to specific use cases for our long-term projections for informing strategy, investment and planning, it is equally important to assess the consequences of data centre growth which may be larger, more uncertain, more diffuse, and more difficult to regulate, and thus potentially more challenging for climate policy. While uncertainty is unavoidable, structured and justified long-term projections such as those presented here are critical for anticipating challenges, informing mitigation strategies, and enabling a sustainable digital transformation without the cost of delaying decarbonisation.

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CRediT authorship contribution statement

Yee Van Fan: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Charlie Wilson:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Resources, Methodology, Investigation, Funding acquisition, Conceptualization. **George Kamiya:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Conceptualization. **Alessio Mastrucci:** Writing – review & editing, Visualization, Supervision, Resources.

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.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.egycc.2026.100253.

Data availability

Data will be made available on request.

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