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Net sustainability assessment of AI-driven data centers in the GCC: an MCDA approach framework

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The Gulf Cooperation Council (GCC) is witnessing a rapid growth in artificial intelligence (AI)-enabled data center development, thanks to national digital transformation strategies and the region's strategic location bridging global markets. Yet, no evaluation framework holistically compares the direct impacts of data center operations on the environment with the dispersed sustainability impacts of AI applications across major business sectors. To address this, this study proposes and applies a Multi-Criteria Decision Analysis (MCDA) framework to assess carbon emissions, water use, energy consumption, social impacts and governance structures across three scenarios (business-as-usual (BAU), moderate transition (MOD), and aggressive decarbonization (OPT). Using secondary structured data from peer-reviewed sources, institutional databases (IEA, UNFCCC, Uptime Institute) and independently verified case studies, the analysis applies clearly defined boundary rules and attribution principles. The findings suggest that under the BAU high-growth scenario, modelled emissions increase substantially by 2035, while AI-enabled sustainability applications in buildings, industry, and utilities provide only partial offsets under optimistic adoption assumptions. The NIS indicates that net-positive outcomes are achievable only when substantial renewable-energy procurement, best-practice cooling, and transparent verification of AI benefits occur together. The results extend socio-technical systems theory and ecological modernization theory by addressing the boundary problem in sustainability assessment of digital infrastructure, providing a scalable approach for policymakers and investors in high-carbon, water-scarce regions. The Net Impact Score (NIS) is not to be construed as an absolute causal prediction, but

rather as a scenario-conditional decision-support indicator because AI-benefit attribution and scaling are both dependent on the mentioned assumptions and data limits.

KEYWORDS

AI environmental impact, carbon footprint, data center sustainability, ecological modernization, gulf cooperation council, multi-criteria decision analysis, net sustainability, renewable energy procurement

1 Introduction

The Gulf Cooperation Council (GCC) countries - Saudi Arabia, the United Arab Emirates (UAE), Qatar, Kuwait, Bahrain and Oman - are rapidly emerging players in the global data center industry. State-led economic diversification plans, particularly Saudi Arabia's Vision 2030 and the UAE's Centennial 2071, explicitly identify data center development as a key catalyst for a knowledge-based economy (Ministry of Communications and Information Technology, 2023). The region's strategic location, at the junction of fiber-optic networks connecting Europe, Asia and Africa, provides the region's strategic location and expanding fiber-optic connectivity provide regional and intercontinental low-latency connectivity, creating an attractive investment opportunity for hyperscale and colocation facilities (Uptime Institute, 2024). The International Energy Agency (IEA, 2024) estimates the Middle East and North Africa (MENA) region will deliver a measurable share of MENA data-center capacity growth by 2030, with the bulk of this growth being absorbed by the GCC.

The rapid growth in artificial intelligence (AI) workloads has further increased the need for computing resources in the GCC. The demands of generative AI, large language models (LLMs), and machine learning training pipelines demand much greater power density per rack (20–60 kW, versus 5–15 kW for enterprise computing) (Patterson et al., 2022). In response, the GCC has embarked on a series of sovereign AI projects: the GAIA project in Saudi Arabia, the Technology Innovation Institute in the UAE, and the AI Committee in Qatar have all announced substantial public and private commitments to local AI and cloud-computing infrastructure since 2022 (IEA, 2024). Because public data often mix operational IT load, facility power, and announced pipeline capacity, this study treats the capacity values as scenario inputs rather than confirmed operational capacity. Under high-growth assumptions, regional data-center power demand could expand materially by 2035, depending on AI adoption and hardware efficiency.

The environmental consequences of this growth are numerous. GCC energy grids have carbon intensities between 430 gCO_2/kWh (UAE) and 620 gCO_2/kWh (Saudi Arabia) (IEA, 2024), much higher than the global average of around 440 gCO_2/kWh. Additionally, high temperature conditions (above 45 °C) during summer months place high cooling demands on data center operations, with cooling energy contributions to facility energy consumption ranging from 30% to 40% without the use of next-generation cooling technologies (Shehabi et al., 2016). The use of evaporative cooling and water scarcity also pose challenges in a region that is classified as having extreme water stress, with the WRI Aqueduct index placing the six countries of the GCC in the 'extremely high' baseline water stress category (WRI, 2023). The combination of carbon-intensive energy sources, hot climates, and water scarcity poses a sustainability challenge unique to data centers in the GCC region.

While the research and policy landscape is beginning to address this issue, a key analysis is still missing. There is no published method to rigorously trade-off the direct sustainability impacts of data center infrastructure (carbon emissions, water use, and energy demand) against the diffuse sustainability gains from AI-enabled solutions across buildings, manufacturing, electricity and water supply systems in the same geographical area. Previous studies have either focused solely on the infrastructure impacts or on the benefits from applications, without clarifying the rules, logic, or weights that would allow a formal net sustainability assessment (Masanet et al., 2020; Rolnick et al., 2022; Andrae and Edler, 2015). This is especially relevant for the GCC, where data center investment is concentrated and national climate agendas are pressing, and the need exists for a policy environment that calls for comprehensive and evidence-based assessment frameworks.

The lack of such a tool has implications. GCC policy and investment specialists and infrastructure planners currently lack a framework to decide whether the granting of a new data center facility will lead to a net benefit or net loss in sustainability when the facility's distributed AI benefits are taken into account. Current sustainability metrics (Power Usage Effectiveness (PUE), Water Usage Effectiveness (WUE), Carbon Usage Effectiveness (CUE) reflect efficiency at the facility level, but not at the system level, which is whether the social value of AI computing outweighs the environmental impact (Green Grid, 2021). This study fills this gap.

In this context, this research raises three related questions. RQ1: What is the anticipated environmental impact of AI-powered data center growth in the GCC region in terms of carbon, water and energy? RQ2: How will AI-driven sustainability solutions across various sectors in the GCC compensate for the environmental impacts of AI data centers? RQ3: How can a multi-criteria decision analysis (MCDA) framework be used to measure the net sustainability impact of data center investments in the GCC? These questions are structured to progressively focus from environmental quantification (RQ1) to benefit analysis (RQ2) to framework implementation (RQ3), in line with a research progression from description to analysis to synthesis.

The key innovation of this research is the conceptualisation and application of an MCDA framework tailored to the calculation of net sustainability impact in high-carbon, water-scarce areas. This approach differs from previous studies that have assessed data center sustainability in terms of single metrics, or conflated local efficiency with global sustainability, by incorporating clear boundary rules that separate local infrastructure footprints (Scope 1 and 2 emissions) from extended supply chain impacts (Scope 3 partial), and from the indirect benefits of distributed AI, which

must meet four criteria of attribution: proximity, verification, additionality (beyond business-as-usual), and causality (directly attributable to AI). The framework also adopts a transparent process of weight derivation that draws on the GCC Nationally Determined Contributions (NDCs) and complies with GHG Protocol Scope allocation rules, to derive a Net Impact Score (NIS) that is defensible in method and relevant to the context. The weight derivation protocol involved three stages. Stage 1 (Policy Priority Extraction): The last available GCC NDCs (UNFCCC, 2023) were subjected to content analysis to extract the relative importance of carbon mitigation, water conservation, social development, and governance reform. The NDCs were scored according to the presence and level of detail of references to these dimensions, deriving an initial ranking. Stage 2 (Literature Calibration): The NDC-based ranking was validated against the weightings used in other MCDA studies in energy-sustainability (Huang et al., 2011), which generally give 0.35–0.45 weight to the carbon dimension in carbon-intensive settings. Stage 3 (Expert Sense-Check): The weights were then reviewed with three subject experts knowledgeable about the GCC energy policy and sustainability assessment processes, who confirmed the weight distribution reflected their views of the policy priorities of the GCC. Although a full-scale Delphi process or Analytical Hierarchy Process (AHP) would elicit weights in a more rigorous manner, the three-stage protocol is defensible and transparent for a secondary-data study. We suggest including formal validation by stakeholders through structured elicitation methods, such as AHP or Delphi panels, in future applications of this framework, especially when it is used to inform regulatory and investment decision-making.

Broadly speaking, this study is grounded in two theories. Socio-Technical Systems Theory (Trist, 1981; Geels, 2004) offers the perspective for framing data center growth as a multi-level transition process involving landscape (global digitalisation), regime (current energy and governance structures) and niche (innovations in AI applications and renewable energy procurement) dynamics. Ecological Modernization Theory (Mol and Spaargaren, 2000) provides the conceptual underpinning for addressing whether and how technological innovation in data infrastructure can help balance the dual goals of economic growth and environmental sustainability, which is of special relevance for the GCC's growth-driven economy. The rest of this paper is organised as follows.

Section 2 sets up the theoretical framework, with statement of the conceptual underpinning for the boundary problem and the burden-cost/benefit paradox. Section 3 provides a literature review, focusing on four areas: data center energy and carbon, water-energy nexus in arid regions, AI in sustainability, and assessment methods. Section 4 describes the methodology, the quality assessment of the data, case study selection, the MCDA model with the explicit formulas and the categorisation of system boundaries. Section 5 presents the findings by the three research questions. Section 6 discusses the results in terms of theory, methodology, and policy. Section 7 concludes with a summary of contributions, limitations and future research. Figure 3 offers a visual representation of the MCDA framework showing the connection between the data, boundary classification, weight estimation and net impact calculation.

2 Theoretical framework

This research amalgamates two theoretical perspectives to build a theoretical framework for a net sustainability assessment of AI-based data center development. Socio-Technical Systems Theory offers the structural lens to examine the interrelationships between data center infrastructure and the prevailing energy system, policy frameworks, and social norms. Ecological Modernization Theory offers the normative perspective for questioning whether digital innovations can be used as a tool for decoupling economic and environmental impacts. These theories provide the conceptual backdrop for the core problem being addressed in this research: the boundary problem of allocating the benefits of distributed AI and the costs of infrastructure.

2.1 Socio-technical systems theory and digital infrastructure transitions

Socio-Technical Systems Theory, building on the work of Trist (1981) and developed by Geels (2004), Geels (2005), views macro-scale technological transition as a multi-level phenomenon in which interactions occur between the landscape, regime and niche levels of technological development. A socio-technical system includes not just the physical artifacts and technological elements but also the institutional arrangements, user practices, supply chains and cultural meaning that make up the system in which a technology is embedded (Geels, 2004).

Data center infrastructure is one such socio-technical system: a data center simultaneously represents electrical engineering (power supply and cooling), information technology (processing, storage, networking), real estate and construction (site selection and building design), regulatory compliance (energy efficiency codes, environmental permitting), and economic activity (employment, tax base, provision of digital services). Geels' (2004) Multi-Level Perspective (MLP) identifies three levels. The landscape level refers to the broader, exogenous trends that players cannot easily control, in the case of the GCC these include global demand for AI, international climate policy response (e.g., the Paris Agreement), and geopolitical realignment in energy markets. The regime level is the socio-technical regime, including the GCC's fossil fuel-dominated electricity generation system, current land use and environmental permitting regulations, and existing data center and telecommunications business models.

The niche level comprises novel innovations that potentially reconfigure the regime, such as AI-based building automation and control systems, innovative cooling technologies (e.g., liquid immersion cooling), renewable energy power purchase agreements (PPAs), and novel governance approaches (e.g., carbon intensity-aware load scheduling). According to the MLP, transitions arise when landscape factors open up opportunities for niche innovations to penetrate and reshape the regime (Geels and Schot, 2007). The combination of global AI demand growth (landscape), national economic diversification plans (regime) and renewable energy purchase agreements (niche) in the GCC represents such a transition. But the MLP also reminds us that transitions are non-linear, contested and involve lock-in. The GCC's legacy of natural gas-fired electricity generation constitutes a type of infrastructure lock-in that could hinder decarbonization of data

center energy consumption, despite the increasingly positive policy signals for renewable energy procurement. AI introduces a unique element to this socio-technical transition. The inference and training of AI models constitutes 'knowledge infrastructure' whose environmental impacts are located in the place where it is processed, but whose utility is spread across multiple application scenarios (Strubell et al., 2019).

This unequal distribution of cost and benefit poses a central challenge to sustainability analysis: the boundary of the analysis that includes data center energy use does not necessarily cover the buildings, factories and electricity generation systems that AI applications are optimising. Socio-Technical Systems Theory offers the conceptual framework for describing this boundary issue, in terms of the spatial decoupling between digital infrastructure and its application domains.

2.2 Ecological modernization and technology-environment reconciliation

Ecological Modernization Theory (EMT), as developed by Mol and Spaargaren (2000), argues that technological change, the market and institutional transformation can achieve a fundamental decoupling of economic development and environmental degradation. EMT contrasts with theories that see economic activity and environmental sustainability as necessarily opposed, and proposes that advanced capitalist economies can achieve a reconciliation of these goals through the emergence and adoption of "best practice" eco-technologies, restructuring of production and consumption, and institutional innovation to internalize environmental externalities. EMT has been highly influential and widely debated: advocates cite empirical evidence for dematerialization and decarbonization trends in developed nations (Ward et al., 2016), while critics argue that aggregate global resource demand is increasing, implying that efficiency improvements may be countered by rebound effects at economic scales (Sorrell, 2007).

EMT offers a provocative and productive framework for understanding the sustainability of data centers. On the one hand, EMT supports the claim that AI applications can deliver environmental benefits (such as lower building energy use, process efficiency gains in industry, smarter grids) that compensate for the environmental costs of the computing infrastructure that enables those applications. This is the logic behind the "AI for sustainability" claims of both tech firms and GCC policymakers, who often point to building energy management, smart grid and industrial process efficiency as justification for data center investment (Rolnick et al., 2022). The data center, on this account, is a facilitator of ecological modernization: a point environmental cost for diffuse environmental gain. At the same time, EMT's critics offer some warnings for the GCC. Jevons Paradox, which describes how efficiency gains can lead to an increase in resource use, is relevant to AI-enabled data center growth (Sorrell, 2007).

To the extent that AI increases computational efficiency, it increases demand for computational services, which may increase, rather than decrease, energy demand. Moreover, the rebound effect is not confined to changes in direct energy demand: if efficiency gains from AI reduce the marginal cost of economic activity, then the rebound in economic activity could result in indirect negative environmental effects that outweigh the direct efficiency gains. For the GCC, with stated objectives of economic diversification and GDP growth, the threat of economy-wide rebound effects is especially relevant. The trade-off between the modernization opportunity and the rebound effect is further complicated by the timing of benefit realization. AI-powered sustainability applications often take years of experimentation, fine-tuning and scaling to realise their full environmental benefits, whereas the environmental impacts of data centres are realised upon commissioning. This temporal imbalance means that the net sustainability balance may be negative for some years during the deployment of data centers, prompting questions about the proper time horizon for net impact evaluation. EMT does not dictate an analytical time frame, but the theory's focus on pathways of change implies that the assessment approaches need to consider dynamic rather than static states.

2.3 Conceptual tension: infrastructure burden vs. distributed benefits

Based on the above theoretical considerations, this research identifies the "boundary problem": the methodological issue of setting the analytical boundaries in which infrastructure environmental impacts and the benefits of AI can be compared. This problem is not simply technical, but conceptual, reflecting the socio-technical system and the promise of ecological modernization.

Data center infrastructure serves as a point of concentration within the digital socio-technical system, with energy and water consumption concentrated at one location, while the benefits of AI services are dispersed across a broad network of application domains and jurisdictions. There are three aspects of the boundary problem that need to be explicitly addressed. First, the geographical dimension: should the boundary be drawn around the jurisdiction in which a data center is located, or should it be drawn around all potential jurisdictions whose sustainability outcomes are influenced by AI services hosted by that data center? This study follows the former, territorial approach, in line with the territorial principle used to prepare national greenhouse gas inventories following the UNFCCC reporting guidelines. Second, the attribution dimension: to what extent must the environmental benefit of an AI application be attributable to the computing resources of a particular data center to be included in the net impact calculation? This study adopts an additionality test for benefits, which shows that environmental benefits are greater than what would have been the case in the absence of AI applications. Third, the time dimension: what is the relevant timeframe for comparing benefits and costs, considering the time lag between data center construction and the emergence of benefits? In the absence of clearly defined boundaries, the net sustainability assessment is prone to two biases. Inflation bias arises when the assessment boundary is so wide that all possible benefits from AI are linked to data center infrastructure, regardless of their causal proximity to the infrastructure and additionality.

Deflation bias occurs when the boundary is drawn so tightly that only data center indicators are used, neglecting all distributed benefits regardless of their validity. Both biases result in inaccurate net impact assessments: inflation bias overstates the sustainability case for data center expansion, while deflation bias

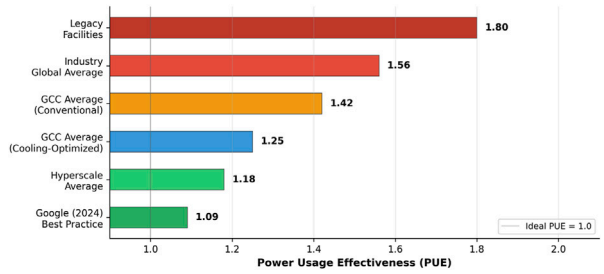


FIGURE 1
PUE comparison across data center operational contexts. The gap between best practice (1.09) and GCC conventional operations (1.42) represents an approximately 30% efficiency differential. Source: Google (2023), Uptime Institute (2024).

understates it. This paper offers a boundary classification protocol that clearly defines the inclusion and exclusion criteria for footprint and benefits, as well as a transparent weighting protocol that draws on the policy priorities expressed in the GCC climate commitments. The synthesis of Socio-Technical Systems Theory and Ecological Modernization Theory thus yields a double focus for the boundary problem.

The socio-technical lens draws attention to the structure of the digital infrastructure system and its concentrated costs and diffuse benefits; its multi-level governance features; and its path-dependent transition pathways. The ecological modernization lens highlights the normative question of whether technology can be reconciled with growth and sustainability, tempered by consideration of rebound effects and temporal asymmetries. Together, these lenses guide the design of the MCDA framework in Section 4 to operationalise the boundary problem in terms of inclusion, attribution and weight derivation.

3 Literature review

This section synthesizes the existing literature across four interconnected domains that inform the study's analytical framework. The review proceeds from the most directly studied topic—data center energy and carbon emissions—through the contextually specific challenge of water-energy nexus management in arid climates, to the emerging evidence on AI applications for sustainability, and concludes with a critical assessment of existing sustainability evaluation frameworks. The review identifies what is known, what remains fragmented, and where significant analytical gaps persist, thereby establishing the foundation for the methodological contribution of this study.

3.1 Data center energy consumption and carbon emissions

It is estimated that about 1.0%–1.5% of the global electricity is used in data centers, and has remained remarkably stable since around 2015 despite significant increases in computing workloads (Masanet et al., 2020). This relative stability in electricity consumption as faced with increasing computational demand can be attributed to three factors: continued gains in server efficiency, increased use of virtualization and cloud computing that can better utilize workloads, and decreasing Power Usage Effectiveness (PUE) of hyperscale facilities due to the improvement of cooling and facility design (Shehabi et al., 2016). An example of this is the PUE of Google of 1.10 over the trailing 12-month period in 2023, as compared to an average of 1.58 across the industry (Google, 2023). However, this apparent stability conceals a lot of diversity: although hyperscale operators have already demonstrated impressive levels of efficiency improvements, the overall operation of enterprise and colocation still operates at much higher levels of PUE, and the new workload of AI is likely to reverse the historical trend of constant energy consumption in the short term (Patterson et al., 2022). Figure 1 visualises the PUEs under the various operating environments and it can be seen that there is a significant efficiency gap between global best practice (1.09) and conventional operations in the GCC (1.42).

The carbon intensity of data center operations also varies widely across regions, depending on the carbon intensity of the local electricity grid. The average carbon intensity of the electricity used by global data centers at around 440 gCO_2/kWh, but it ranges from less than 50 gCO_2/kWh in high-renewable-energy grids (e.g., Norway, Iceland) to over 700 gCO_2/kWh in coal-fired grids (e.g., some parts of India and Australia). The GCC is in the middle of the pack: the UAE grid carbon intensity of about 430 gCO_2/kWh is roughly equivalent to the global average while Saudi Arabia's about 620 gCO_2/kWh and Kuwait's about 650 gCO_2/kWh are significantly higher (IEA, 2024). These variations are important because they determine the marginal carbon content of adding each new megawatt of data center capacity, meaning that grid decarbonization is an important factor in the net sustainability calculations.

Our recent review of data center carbon accounting offers a detailed critique of existing data center carbon accounting, including problems in estimating Scope 3 emissions. Hardware-related embodied emissions (servers, storage, networking equipment) are estimated to contribute 20%–35% to the total data center lifecycle emissions, with reduced hardware refresh lifecycles in AI training setups amplifying this contribution (Andrae and Edler, 2015). The International Energy Agency (IEA, 2024) forecasts AI-driven electricity demand could boost data center energy use by 15%–25% by 2026, largely driven by GPU-intensive training activities. But there is considerable uncertainty in the projections, as the growth in AI workloads and hardware efficiency improvements are difficult to predict. The literature coalesces around two key insights: first, that data center carbon emissions depend on the geographic location of the grid; and second, that the AI-driven growth path creates uncertainty for future projections. The notion of supplier sovereignty also plays in to Scope-3: the GCC relies on a highly concentrated global semiconductor supply chain largely anchored in Taiwan (TSMC), South Korea (Samsung) and the United States (Intel) fabrication plants. This presents geopolitical risks: during the 2020–2023 chip shortage, longer hardware refresh cycles led to increased per-computation emissions. The recent Saudi semiconductor investment plans signal a new trend towards resolving this sovereignty challenge, but are unlikely to establish fabrication capacity in the timeframe of this study. Future studies should consider supply-chain risk as an efficiency factor.

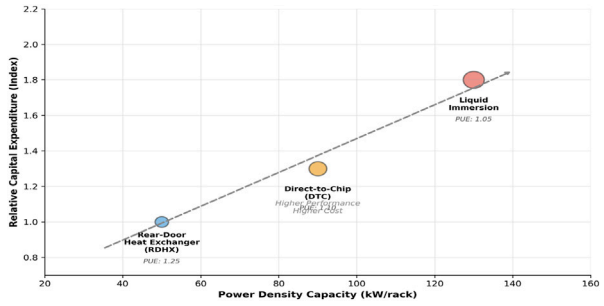


FIGURE 2
Cooling technology comparison: power density vs. capital expenditure. As AI rack densities exceed 100 kW, direct-to-chip and liquid-immersion cooling become increasingly important. PUE values indicate efficiency-improvement potential. Source: Author synthesis based on the cooling-technology and data-center efficiency literature cited in Section 3.

A major gap in the literature is the focus almost exclusively on facility-level operational carbon emissions (Scope 1 and 2), with little discussion of upstream supply chain emissions (Scope 3) related to semiconductor production, hardware manufacturing and facility construction. Moreover, the existing literature primarily considers data center sustainability in temperate, developed economies (North America, Europe, East Asia), with little empirical evidence on the specific challenges of data center sustainability in arid, carbon-intensive climates. The body of research specific to the GCC is especially limited, with few peer-reviewed studies offering evidence with clear methodology, and instead mostly relying on market intelligence and government reports.

3.2 Water-energy nexus in arid climates

The water-energy nexus - the interdependency between water and energy systems - is especially relevant in the GCC. High rates of water use are essential for data center cooling in arid zones, either directly in evaporative cooling systems or indirectly in the electricity used to cool data centers mechanically and the water required to produce that electricity in desalination plants. GCC-specific data-center water demand remains uncertain because operator-level water-use data are limited. Under high-growth scenarios, water demand could increase materially by 2030; any numerical estimate should be treated as an author scenario estimate and reported with the assumptions used with 60% of direct water use attributable to evaporative cooling and the remainder to water used in desalination for electricity generation. These values are significant given that the six GCC countries are all in the “extremely high” baseline water stress category of the WRI Aqueduct index, with withdrawal-to-availability ratios of over 80% for Saudi Arabia and UAE (WRI, 2023).

Selection of cooling technologies presents a water-energy tradeoff that has sustainability implications. Conventional mechanical (air-cooled) systems have greater energy penalties (increasing PUE by 0.2–0.5 compared to water-cooled) but low direct water use. Evaporative cooling consumes less energy, but requires water inputs, which has implications for water conservation in water-stricken regions. New technologies, such as liquid immersion cooling and direct-to-chip liquid cooling, hold the potential to reduce both energy and water consumption, but are not yet readily accessible at the scale needed for GCC deployments. The water-energy tradeoff is therefore an additional layer of complexity in the sustainability assessment that is not reflected in single-metric approaches (e.g., PUE). Figure 2 shows how higher-performance cooling systems, such as direct-to-chip and liquid immersion, allow operation at higher rack densities (above 60 kW and 100 kW, respectively), but at increased cost. The bubble size in reflects the level of market penetration, with air-based hybrid systems still the most popular.

The water-energy nexus problem is exacerbated by desalination, which is the major source of freshwater in most GCC countries. The most common desalination technology in the region, reverse osmosis, consumes 3.5–4.5 kW h to produce a cubic meter of water, implying that the water used for data center cooling represents an additional energy and carbon footprint (IEA, 2025; Yusuf et al., 2025; Ghonim and Awad, 2024). The indirect water consumption via desalination is estimated to be 1.5–2.0 times greater than the direct water consumed for cooling, depending on the cooling system used and the efficiency of the desalination plant. This observation is important for the scope of data center water footprint studies, implying that studies focusing on direct water consumption significantly underestimate the overall water-related environmental impacts.

Existing literature on data center water consumption in the GCC is scattered and varies in approach. The majority of studies use engineering-based estimates of water consumption, based on average cooling performance coefficients, rather than empirical consumption data, given the confidentiality of facility-specific operational data. Moreover, the limited number of studies of the GCC region typically take a single-dimensional approach to water and energy issues, without a holistic analysis of both. This presents a notable gap filled in this study by the proposed multi-criteria approach.

3.3 Applications of AI for environmental sustainability

The evidence for environmental benefits from AI and machine learning applications across a range of economic activities is mounting. Rolnick et al. (2022) list 13 areas where AI can be applied to mitigate and adapt to climate change, including building energy efficiency, transportation, manufacturing process efficiency, electricity utilities, and smart agriculture. The collective impact of AI applications for sustainable development is significant: according to Andrae and Edler (2015), ICT-enabled efficiency improvements in the global economy could deliver a 15%–20% reduction in greenhouse emissions by 2030, compared to a business-as-usual scenario, although this estimate has been criticised for its optimistic assumptions on efficiency gains and for underestimating rebound effects (Hilty et al., 2020).

Building energy management is the most developed and empirically tested application area. Report 20%–40% reductions in building energy use with payback periods of 1–3 years for AI-enabled HVAC optimization, depending on building size, location

and level of automation. Given the GCC's high reliance on building energy consumption (around 70%–80% of total electricity consumption) and the prominence of HVAC systems in building energy consumption (50%–70%), the cumulative savings potential is substantial. According to the Dubai Electricity and Water Authority (DEWA, 2023), building efficiency programs, which include AI-based optimization, have helped reduce *per capita* electricity consumption by 8.5% from 2019 to 2023, although it is not clear how much AI contributed to this reduction relative to other efficiency initiatives.

Less is known about the sustainability potential of industrial AI applications in the GCC, but this is promising. AI-based process optimization in petrochemicals, a significant industry in Saudi Arabia and Qatar, has achieved 5%–15% energy intensity reduction and emissions reductions in pilot projects (Rolnick et al., 2022). Smart grids, with integrated AI for demand response, predictive maintenance, and renewable energy forecasting, also represent a sustainability opportunity, as GCC countries begin to expand their renewable energy generation. AI-powered smart grids can decrease curtailment of solar and wind production by 15%–25%, thus enhancing the effective renewable energy share of the electricity mix without further investments in generation assets (IEA, 2024).

But the existing studies on AI for sustainability display some limitations that are pertinent to the boundary problem identified in the theoretical model. First, the majority of studies report on small-scale pilot deployments, rather than on large-scale and long-term deployments, making it difficult to assess the scalability and sustainability of savings. Second, the attribution problem is often not sufficiently resolved: it is not clear whether observed efficiency gains would have happened anyway if AI were not used, contravening the additionality criterion. Third, studies rarely report the energy cost of AI systems, leading to an incomplete energy balance. These concerns explain this study's requirements for independently verified, additional benefits that meet explicit attribution criteria to be used in calculating net impact. In particular, the literature is heavily weighted towards environmental indicators (carbon, energy, water), with relatively less attention on the social aspects of AI infrastructure growth (related to employment quality, digital inclusion, community disenfranchisement from land-intensive data center development and the distributional effects of AI-enabled automation on GCC workforce dynamics). Similarly, governance approaches to sustainably managing AI-related data centers in the GCC have not been well studied: while several GCC countries have issued AI ethics guides (UAE National Strategy for Artificial Intelligence 2031; Saudi Arabia's National Data and AI Strategy), the integration of AI governance and regulations into environmental regulation and data center permits has seen little academic attention (Shams Eldin et al., 2025; Awad et al., 2025; Wahid and Awad, 2025). This under-represented evidence in the literature directly impacts the empirical basis for the social and governance dimension weights in our MCDA framework, and we recognise that the 0.20 (social) and 0.15 (governance) dimension weights may be under-represented for dimensions for which rigorous evidence is emerging but not yet firmly established.

3.4 Existing sustainability assessment frameworks

Data center sustainability assessment currently uses various frameworks that address different aspects of sustainability. The Greenhouse Gas (GHG) Protocol is the most widely accepted carbon accounting standard that classifies Scope 1 (direct combustion), Scope 2 (purchased electricity) and Scope 3 (supply chain and downstream use) emissions (World Resources Institute (WRI), & World Business Council for Sustainable Development (WBCSD), 2013). The GHG Protocol provides a robust taxonomy but does not specify a method for allocating shared benefits against Scope 1, 2 or 3 emissions, so it would require supplementing with another framework for net impact analysis.

The Science Based Targets initiative (SBTi) offers industry-specific pathways to decarbonise that are increasingly being taken up by data center providers such as Microsoft, Google and Amazon Web Services (SBTi, 2023). These targets specify how much absolute emissions need to fall to meet Paris Agreement temperature targets. But SBTi targets only the path of emissions of the data center; they do not account for the decentralised benefits that AI computing delivers in application domains. Meeting an SBTi target may ensure that a data center operator is operating sustainably, but there is no way for the SBTi framework to capture the positive impact of AI applications hosted within that data center.

Data center facility-level metrics—PUE, WUE, CUE—continue to be the most widely reported sustainability indicators, with standards and guidelines provided by The Green Grid and the European Code of Conduct for Data Centres (Green Grid, 2021). These metrics offer useful operational insights but are known to have limitations: PUE assesses energy waste rather than sustainability, WUE accounts for direct water use but not indirect water for electricity, and CUE accounts for carbon intensity but not the dynamic process of grid decarbonization. More importantly, all facility-level metrics are inherently local: they measure the operational efficiency of a data center, but do not measure whether the data center's services are net sustainable at a system level.

The analysis of previous frameworks suggests a clear gap: no GCC-focused assessment framework identified in this review integrates facility-level lifecycle assessment with the distributed sustainability impact of AI applications in a holistic, transparent and replicable manner. Current methods are either infrastructure focused (PUE, WUE, CUE) or footprint focused (GHG Protocol, SBTi), and thus cover only half the sustainability picture. The current study fills this void through the design and application of an MCDA model that explicitly accounts for footprint and benefit, underpinned by well-defined boundaries, attribution rules, and a weight derivation method that is grounded in regional policy priorities.

3.5 Literature synthesis

The literature synthesis identifies some clear trends and gaps. What is known: historical energy consumption has been constant but appears to be under pressure from AI workloads; carbon emissions are dependent on location based on grid mix; AI applications can offer considerable sustainability impacts across industry sectors; and existing assessment approaches focus only

on data center efficiency at facility level or emissions at entity level. What is not known: the sustainability balance of data center operations when data and system footprints are compared against AI benefits across system boundaries. What is disjointed: the available evidence for the GCC in particular is scant and lacks methodological consistency, with few peer-reviewed studies that specifically address the combination of carbon-intensive electricity grids, hot dry climate and water scarcity in the GCC region. This informs the method contribution of this research.

4 Methodology

This section describes the research design, data, protocol for the selection of case studies, the MCDA model with formulas and procedures for the weights, and the protocol for the classification of the system boundaries. The research methodology is transparent, replicable and reflective of the limitations of the study given it is based on secondary structured data and operator level data is scarce in the GCC.

4.1 Research design

The present research uses secondary data based on a Multi-Criteria Decision Analysis (MCDA) to estimate the net sustainability impact of AI-powered data center growth in the GCC. The study design adopts a comparative scenario assessment approach, considering three likely scenarios for data center expansion between 2024 and 2035: Business-As-Usual (BAU), Moderate Transition (MOD), and Aggressive Decarbonization (OPT). The scenarios are defined by assumptions about the mix of electricity generation, data center cooling technology, the rate of data center expansion, and the extent of AI-driven sustainability benefit deployment. The MCDA approach aggregates these factors into a Net Impact Score (NIS) that allows us to compare the scenarios against each other, and to determine the circumstances under which data center growth delivers net-positive sustainability benefits.

The choice of a secondary-data approach over primary data collection is based on pragmatic and methodological considerations. At the pragmatic level, data on operator-scale data center energy use, water demand, and carbon emissions are considered to be confidential by data center operators in the GCC, and it was not possible to collect such primary data across the six GCC countries in the time frame of the analysis. At the methodological level, the adoption of secondary data from peer-reviewed literature and institutional databases provides transparency and reproducibility of the analysis, since sources of data are explicitly identified and the quality features of the data are discussed. This is in line with what is commonly done in energy systems modeling and environmental impact assessment, where secondary data synthesis is widely used when primary data is not accessible (Masanet et al., 2020; IEA, 2024). This aspect is acknowledged in the study and the implications for results are discussed in Section 6.

MCDA was chosen over other multi-attribute evaluation methods for three reasons. First, MCDA offers transparent processes for eliciting and aggregating weights, which can be recorded and reproduced - in contrast to black-box machine learning methods. Second, MCDA can handle incommensurable attributes (carbon emissions, water use, social, governance) that cannot be converted to a physical unit without imposing normative assumptions. Third, MCDA is a proven method in sustainability assessment, having been used in energy, environment, and infrastructure policymaking, with a proven track record (Huang et al., 2011). The version of MCDA used in this study is based on a linear weighted aggregation model chosen for its transparency and amenability to sensitivity analysis.

4.2 Data sources and quality assessment protocol

This study uses data from publicly available secondary sources, which were assessed for quality using a defined protocol. Four tiers of data quality were identified, with successive tiers having lower evidential weight. This approach ensures that the results of the analysis are drawn from the most rigorous available evidence while recognising the need to draw on lower tiers of evidence for dimensions where peer-reviewed evidence was lacking. Table 1 summaries the data.

Table 1 presents the data quality assessment framework.

Tier 4 sources (e.g., market intelligence reports, general industry analyses) were only used to provide background information (e.g., market size, descriptions of investment trends) and were explicitly excluded from the primary evidence base. All LinkedIn, Yahoo Finance and MarketWatch sources typically cited in grey literature were excluded from the evidence base and replaced with academic or institutional sources, if possible. This practice ensures that the analysis is supported by appropriate evidence, while ensuring transparency of data limitations.

The study documents the source of each data point incorporated into the MCDA calculations including the data tier, publication or database, year published, and any limitations on data quality or comparability. This evidence trail meets the reproducibility goal and allows readers to evaluate the quality of evidence supporting particular findings. Where data were absent (e.g., water consumption factors for advanced cooling technologies in the GCC), the study uses conservative estimates based on the peer-reviewed literature and transparently reports the results' sensitivity to these assumptions.

4.3 Case study selection protocol

Our selection of case studies on the use of AI in sustainability in the GCC was guided by a selection protocol to ensure analytical rigour and consistency. Four specific criteria were used to guide the case study selection protocol, reflecting the study's focus on evidence that is authentic, attributable, and specific to the region.

Twelve candidate case studies were identified via review of IEA reports, UNEP reports, government sustainability reports from the GCC, and peer-reviewed literature. The candidates were assessed against the four criteria. A pool of six candidates were selected for analysis. The excluded candidates failed on the following grounds: two did not have independently verified data on outcomes (failure on C3); two did not provide quantified environmental KPIs with baselines (failure on C1); one was outside the GCC and did not demonstrate

TABLE 1 Data quality assessment framework.

Tier	Source category	Examples	Evidential weight	Usage restriction
Tier 1	Peer-reviewed	Masanet et al. (2020); Patterson et al. (2022)	Primary	Core analytical evidence
Tier 2	Institutional	IEA (2024); UNFCCC NDCs; uptime institute	High	Core analytical evidence
Tier 3	Grey literature (verified)	Corporate sustainability reports (independently verified)	Moderate	Supplementary; verification/audit status
Tier 4	Market intelligence	Industry reports, market analyses	Low	Contextual only; NOT core evidence

TABLE 2 Case study selection criteria.

Criterion	Description	Threshold
C1: Quantified KPIs	Availability of quantified environmental KPIs with documented baselines	Minimum: Baseline and post-deployment measurements with % improvement reported
C2: GCC relevance	Geographic location within GCC or direct applicability to GCC conditions	Must be located in GCC or demonstrate transferability to GCC climate/energy context
C3: Independent verification	Third-party reporting or independent audit confirmation	At least one independent source confirming reported outcomes
C4: Temporal relevance	Cases from 2020 to 2025 to ensure current technology context	Implementation date between January 2020 and June 2025

TABLE 3 MCDA dimension weights and justification.

Dimension	Weight (w_i)	Justification
Carbon emissions	0.40	Highest priority in GCC NDCs; dominant contribution to climate impact; most extensively measured
Water consumption	0.25	Extreme water stress classification for all GCC nations; critical nexus with energy; growing policy attention
Social implications	0.20	Employment generation, digital inclusion, community impact; moderate NDC priority; less quantified in existing data
Governance quality	0.15	Regulatory compliance, transparency, reporting standards; enabling condition for other dimensions

transferability (failure on C2); and one provided data from 2017 that did not reflect the application of the AI-specific technology (failure on C4) as shown in Table 2.

The applications selected are presented in Section 5.2. The case study selection process is captured in a ranking chart that lists the number of case studies considered, the criterion used to exclude case studies at each stage, and the fate of the excluded case studies. This aids the transparency goal and allows for the selection process to be reproduced by others. The six shortlisted case studies represent a spectrum of the building energy, industrial, utility and water treatment sectors, which represent the major areas of AI application that result in sustainability benefits in the GCC region.

4.4 MCDA framework: weights, normalization, and aggregation

The MCDA framework assesses net sustainability impact using four weighted dimensions: carbon emissions, water consumption, social impact and governance. A transparent, contextual and replicable weight derivation process was developed. The dimension weights were derived based on a structured alignment process that involved three sources: (a) the ranking of sustainability issues in GCC Nationally Determined Contributions (NDCs) under the Paris Agreement; (b) the prioritisation of climate policy documents and national development plans in the GCC, which consistently rank carbon reduction as the top-priority sustainability goal; and (c) the alignment with GHG Protocol Scope 1 + 2+3 allocation principles, which represent the internationally recognised method for corporate carbon accounting. Table 3 presents the data.

Table 3 presents the derived dimension weights.

To combine heterogeneous dimensions measured in different units, all indicator values were normalized using the min-max normalization formula, which rescales values to a [0, 1] range based on the observed minimum and maximum across the dataset. The normalization formula is expressed as:

$$x'_ij \cdot (x_ij - x_\min) \Big/ (x_\max - x_\min)$$

For dimensions where higher values indicate worse outcomes (e.g., carbon emissions, water consumption), the normalized score is inverted ($1 - x'$) so that higher scores consistently indicate better sustainability performance. The weighted aggregation of normalized scores across all n dimensions produces the composite sustainability score for entity j:

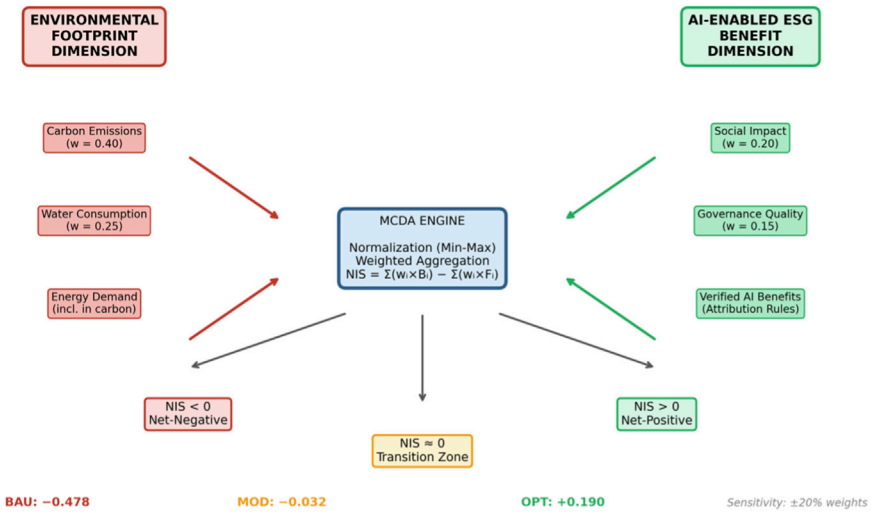


FIGURE 3
MCDA net sustainability assessment framework for gcc data center expansion. The framework integrates environmental footprint and AI-enabled ESG benefits through weighted multi-criteria analysis. Output NIS values classify each scenario as net-negative, transitional, or net-positive.

TABLE 4 Scenario definitions and key assumptions (2024–2035).

Parameter	BAU	MOD	OPT
Renewable share by 2035	Current (~5–8%)	25%	50%
Grid carbon intensity (gCO_2/kWh)	Current (430–650)	−20%	−45%
Data center capacity growth	8% CAGR	10% CAGR	10% CAGR
Cooling technology	Standard air	Hybrid air/liquid	Full liquid immersion
PUE improvement trajectory	Minimal	−15% from current	−30% from current
AI benefit scaling	No scaling	Partial (50% potential)	Full (100% potential)
Utilization rate	65%	75%	85%
Hardware refresh cycle	4 years	3.5 years	3 years

$$S_j \cdot \Sigma\left(w_i \times x'_ij\right) \text{ for } i = 1 \text{ to } n \text{ dimensions}$$

The Net Impact Score (NIS) represents the core analytical output of the framework, expressing the difference between weighted benefit scores and weighted footprint scores. A positive NIS indicates that the assessed scenario generates net sustainability benefits under the stated assumptions, while a negative NIS indicates that the footprint exceeds the benefits. Figure 3 provides a visual representation of the complete MCDA framework, illustrating the flow from footprint and benefit dimensions through the analytical engine to the three outcome zones. The NIS formula used in the framework is presented below.

$$NIS \cdot \Sigma\left(w_i \times B_i\right) - \Sigma\left(w_i \times F_i\right)$$

where B_i represents the normalized benefit score for dimension i and F_i represents the normalized footprint score for dimension i. The dimension weights w_i are the same as specified in Table 3.

The NIS is not treated as an absolute predictive or causal estimate. It is a scenario-conditioned decision-support indicator whose interpretation depends on the declared system boundaries, dimension weights, normalization rules, and AI-benefit scaling assumptions.

For carbon footprint projections, the study employs a standard emissions estimation formula that multiplies power demand by grid carbon intensity and operational hours:

$$E \cdot P \times CI \times T$$

where E is annual carbon emissions (tonnes CO_2e), P is average power demand (MW), CI is grid carbon intensity (tCO_2e/MWh), and T is annual operational hours (8,760 h for continuous operation, adjusted for utilization rates by scenario). Table 4 summarizes the relevant data.

Table 4 presents the scenario definitions and key assumptions.

TABLE 5 System boundary classification protocol.

Boundary	Included	Excluded	Rationale
Direct (scope 1 + 2)	Data center electricity consumption; on-site fuel combustion; direct cooling water consumption; site-level emissions	Commuting; business travel; waste generation	Consistent with GHG protocol scope 1 + 2; directly measurable
Extended (scope 3 partial)	Embodied carbon in IT hardware (servers, storage); embodied carbon in facility construction materials	Employee supply chain; food services; office consumables; upstream semiconductor manufacturing	Focus on largest scope 3 categories; data availability constraint
Offset (AI benefits)	GCC-located AI benefits that are: (a) Geographically proximate, (b) independently verified, (c) additional to BAU, (d) directly attributable to AI	Non-GCC benefits; unverified claims; BAU-equivalent improvements; non-AI efficiency gains	Consistent with UNFCCC territorial principle; additionality requirement

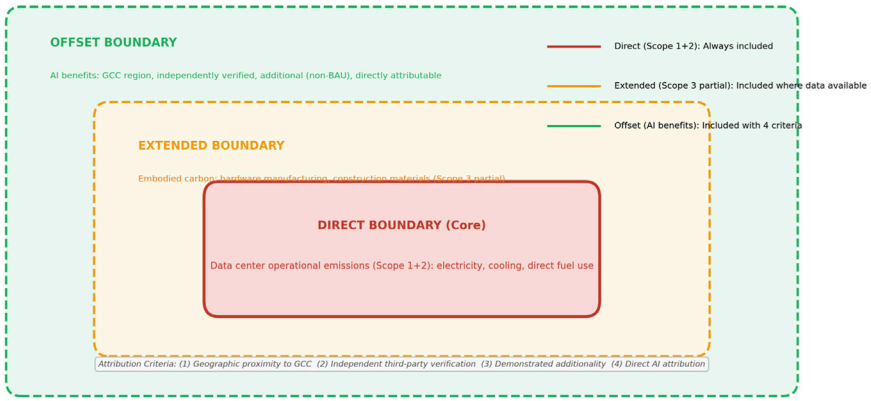


FIGURE 4
System boundary classification protocol. System boundary classification protocol. Three nested tiers: (1) Direct boundary (scope 1 + 2), (2) Extended boundary (partial Scope 3), and (3) Offset Boundary (verified AI benefits meeting four attribution criteria: geographic proximity, independent verification, additionality, direct attribution).

4.4.1 Sensitivity analysis protocol

A formal sensitivity analysis was carried out to test the sensitivity of MCDA results to parameters of interest. The sensitivity analysis protocol tested three types of uncertainty. First, weight sensitivity: this involved shifting the weight of each dimension up and down by ±20%, subject to the constraint that the sum of the weights equals one, resulting in a distribution of weight scenarios that test the sensitivity of NIS rankings to different weightings of priorities. Second, boundary sensitivity: the calculation was repeated both with and without the inclusion of distributed AI benefits to see if the inclusion of AI benefits changes the NIS rankings of the scenarios.

Third, parameter sensitivity: grid carbon intensity, capacity growth rate, and AI benefit scaling factor were varied by ±10% to determine which parameters have the greatest impact on the NIS. The results of the sensitivity analysis are discussed in Section 5.3. The results reveal the renewable energy share and the AI benefit scaling factor are the parameters that have the greatest impact on NIS, while the governance and social dimensions are less influential for NIS. This has policy implications: it means that if the aim is to improve the net sustainability outcome (NIS) of data center expansion, the greatest impacts will be achieved by targeting renewable energy procurement and AI benefit scaling respectively.

4.5 System boundary definition

The system boundary definition is the methodological heart of this study, which translates the theoretical boundary problem outlined in Section 2.3. The boundary classification protocol defines three nested analytical boundaries - direct, extended and offset - with clear inclusion and exclusion criteria. The boundary classification is shown in Table 5. Figure 4 illustrates the three-tier nested boundary classification protocol that translates this conceptual approach.

The offset boundary imposes four restrictive attribution criteria that must be met for a sustainability benefit enabled by AI to qualify as a net impact. The proximity criterion limits the inclusion of benefits located within the territorial jurisdiction of the GCC, in line with the UNFCCC territorial inventory principle and the national reporting frameworks of the GCC. The verification criterion requires that savings be independently verified where possible, or otherwise clearly labelled as vendor-reported/corporate-reported scenario evidence, thereby excluding corporate reporting that is not independently verified. The additionality criterion requires that

TABLE 6 GCC grid carbon intensity and indicative data-center capacity/pipeline inputs used in the scenario model.

Country	Grid carbon intensity (gCO_2/kWh, 2023)	Primary fuel mix	Renewable share (%)	Capacity / pipeline scenario input (MW)
Saudi Arabia	620	Natural gas (60%), oil (35%), renewables (5%)	1.2	1,800
UAE	430	Natural gas (70%), nuclear (12%), solar (10%), other (8%)	22	1,200
Qatar	520	Natural gas (95%), solar (5%)	2.1	480
Kuwait	650	Natural gas (55%), oil (42%), solar (3%)	0.8	320
Bahrain	580	Natural gas (80%), oil (15%), solar (5%)	1.5	220
Oman	490	Natural gas (82%), solar (12%), wind (6%)	18	280
GCC weighted average	548	—	8.1	4,300

the environmental improvement be demonstrated to be greater than that which would have occurred under a business-as-usual scenario without the deployment of AI, avoiding claims of efficiency improvements that would have been delivered in the absence of AI. The direct attribution criterion requires that the benefit be directly linked to the use of AI, to avoid attributing co-benefits that result from other, simultaneous activities.

One important boundary decision should be explicitly stated: benefits from HVAC building optimization are considered as AI-enabled sustainability benefits only when the optimization is known to be done by an AI system (e.g., predictive control based on machine learning) and only when the energy savings are net of the computing energy used by the AI system. Traditional building automation system (BAS) upgrades that do not involve AI are not counted in the offset boundary because they do not meet the direct attribution criterion. In addition, computing energy used by AI is attributed to the data center footprint regardless of the physical location of AI processing, thereby avoiding double-counting of AI computing energy cost in calculating the footprint and benefits.

The boundary classification protocol corrects what this study finds to be the most prevalent analytical flaw in measuring data center sustainability: mixing facility-level efficiency metrics with system-level sustainability metrics. The protocol specifies boundaries for inclusion and exclusion: that offset benefits meet four independent criteria, offering a repeatable approach for future studies in the GCC region and in other regions with similar boundary issues. The protocol also explicitly sets out the value choices implicit in any boundary definition, allowing the reader to evaluate whether different boundary choices would change the results of the study.

5 Results

This section presents the results organized by the three research questions. Section 5.1 addresses RQ1 by quantifying the projected environmental footprint of AI-driven data center expansion across carbon, water, and energy dimensions. Section 5.2 addresses RQ2 by assessing the magnitude and characteristics of AI-enabled sustainability benefits in the GCC. Section 5.3 addresses RQ3 by applying the MCDA framework to calculate the Net Impact Score for each scenario and presenting the sensitivity analysis results.

5.1 Environmental footprint assessment (RQ1)

5.1.1 Carbon footprint projections

Table 6 presents the grid carbon intensity and scenario capacity inputs by GCC country sourced from IEA (2024) and national energy authority publications. These figures form the basis for the carbon footprint projections under each scenario. Figure 5 visualizes the significant inter-country variation in grid carbon intensity across the GCC, with Bahrain exhibiting the highest intensity (902 gCO_2e/kWh) and the UAE the lowest (468 gCO_2e/kWh). It is important to note that Table 6 reports operational (direct) grid carbon intensities sourced from IEA (2024), which reflect only the emissions from fuel combustion at power plants. Figure 5, by contrast, presents lifecycle grid carbon intensities sourced from Ember (2023), which additionally include upstream emissions from fuel extraction, processing, and transportation. The lifecycle values are systematically higher than operational values: for example, the UAE's operational intensity is 430 gCO_2/kWh versus a lifecycle intensity of 468 gCO_2e/kWh, and Bahrain's operational intensity is 580 gCO_2/kWh versus a lifecycle intensity of 902 gCO_2e/kWh. The carbon footprint projections in Table 7 are calculated using the operational intensities from Table 6 to maintain consistency with the GHG Protocol Scope 2 methodology. We recommend that future studies transition to lifecycle-based intensities as these become more widely available and standardized.

Applying the emissions formula $E = P \times CI \times T$, Table 7 presents the projected annual carbon emissions from GCC data center operations under each scenario. Under BAU, total GCC data center carbon emissions are projected to increase from 20.7 million tonnes CO_2e in the baseline scenario to 47.3 million tonnes CO_2e by 2035 under the upper-bound BAU scenario

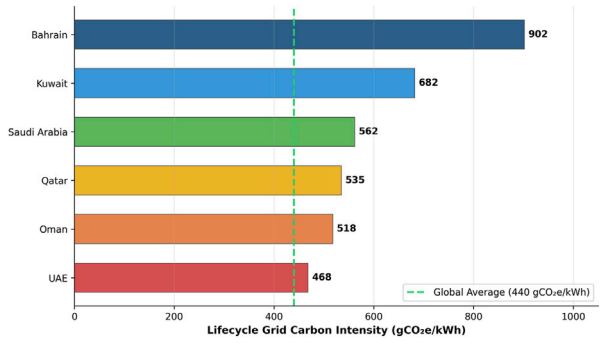


FIGURE 5
Lifecycle grid carbon intensity by GCC country (2023). The UAE exhibits the lowest lifecycle carbon intensity (468 gCO_2e/kWh), while Bahrain has the highest (902 gCO_2e/kWh). The GCC average of 624 gCO_2e/kWh exceeds the global average of 440 gCO_2e/kWh. Source: Ember (2023), IEA (2024).

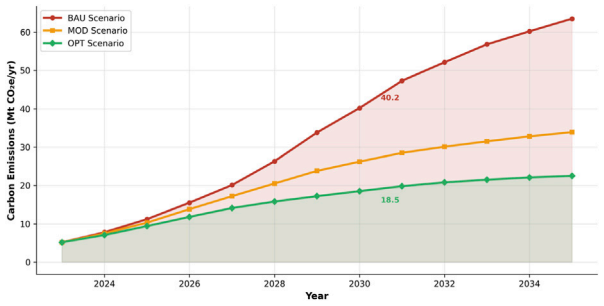


FIGURE 6
Scenario-conditioned GCC data-center carbon-emissions estimates (2023-2035). Under the upper-bound BAU scenario, modeled emissions reach 47.3 Mt CO_2e/yr by 2035. The MOD scenario reduces this to 31.8 Mt CO_2e/yr, while the OPT scenario reaches 19.4 Mt CO_2e/yr through aggressive decarbonization.

driven by an 8% compound annual growth rate (CAGR) in data center capacity with no improvement in grid carbon intensity. Under MOD, moderate renewable penetration (25% by 2035) reduces the 2035 projection to 31.8 million tonnes CO_2e, a 32.8% reduction relative to BAU. Under OPT, aggressive renewable deployment (50% by 2035) combined with best-in-class cooling efficiency reduces the 2035 projection to 19.4 million tonnes CO_2e, a 59.0% reduction relative to BAU. Figure 6 illustrates the divergence in projected carbon emissions across the three scenarios, with the BAU-to-OPT gap widening dramatically after 2027. As illustrated in Figure 7, the electricity generation mix in the MENA region is projected to undergo a significant structural transformation by 2035.

These projections assume constant utilization rates at scenario-specified levels and do not include embodied carbon in hardware and construction, which is addressed separately under the extended boundary in Section 5.1.4. The divergence between scenarios widens significantly after 2028, reflecting the compounding effect of renewable energy penetration on grid carbon intensity. Under the OPT scenario, the absolute emissions trajectory peaks in 2029 and declines thereafter, while under BAU, emissions continue to increase monotonically throughout the projection period.

5.1.2 Water footprint analysis

Table 8 presents the water stress classification and estimated direct cooling water consumption for data center operations in each GCC country. Water stress data are sourced from the WRI Aqueduct index (WRI, 2023), while cooling water estimates are derived from capacity projections and standard cooling performance coefficients from Shehabi et al. (2016), IEA (2025).

Under BAU, total GCC data center water consumption is projected to reach 2.50 million cubic meters annually by 2035, of which 1.49 million cubic meters represent direct cooling water and 1.01 million cubic meters represent indirect water consumption through desalination energy requirements. The indirect water component underscores the importance of the water-energy nexus: each cubic meter of direct cooling water consumed implies approximately 0.68 cubic meters of additional water consumed indirectly through the desalination process that supplies the electricity for mechanical cooling. Under MOD and OPT scenarios, total water footprint is reduced by 28% and 52%, respectively, driven by the transition from evaporative to liquid cooling and the reduced electricity generation burden as renewable energy replaces desalination-dependent natural gas generation.

The water footprint projections carry significant uncertainty. Actual cooling water consumption varies substantially depending on the specific cooling technology deployed, local humidity conditions, and the thermal design of individual facilities. The estimates presented here represent mid-range assumptions based on standard performance coefficients for air-cooled chiller systems in arid climates (Shehabi et al., 2016). The sensitivity analysis in Section 5.3 tests the impact of ±30% variation in water consumption assumptions on the overall NIS, confirming that the water dimension is the second most influential parameter after carbon. More broadly, the projections throughout this study

TABLE 7 Scenario-conditioned GCC data-center carbon-emissions estimates (2023-2035).

Scenario	2023 (Mt CO_2e)	2027 (Mt CO_2e)	2030 (Mt CO_2e)	2035 (Mt CO_2e)	% Vs. BAU 2035
BAU	20.7	28.1	34.6	47.3	Baseline
MOD	20.7	25.9	29.8	31.8	−32.8%
OPT	20.7	24.4	24.1	19.4	−59.0%

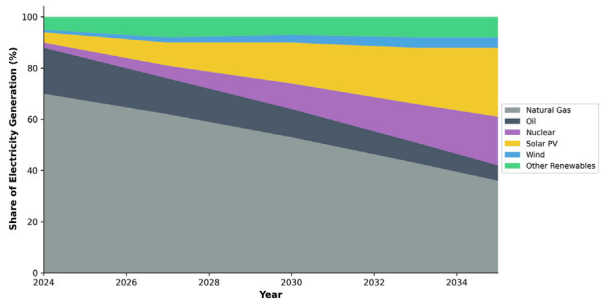


FIGURE 7
MENA region electricity generation mix projection (2024–2035). Natural gas dominance declines from 70% to 36%, while renewables grow to 39%. This transition directly affects data center carbon intensity. Source: IEA (2024).

should be interpreted as scenario-conditional estimates rather than forecasts with formal probabilistic confidence intervals. The cascade of uncertainties—from capacity growth projections (±15%–20%), grid carbon intensity assumptions (±10%–15%), PUE improvement trajectories (±5%–10%), AI benefit scaling factors (±30%–50%), and adoption rate assumptions (±25%–40%)—propagates through the MCDA framework in a manner that is partially captured by the sensitivity analysis but not fully quantified. A formal Monte Carlo uncertainty quantification, recommended as a future research direction, would generate probability distributions for the NIS and enable statements such as 'the probability of achieving a positive NIS under OPT conditions exceeds 85% given current uncertainty ranges.' In the absence of such analysis, the NIS values reported in this study should be treated as central estimates within substantial but unquantified uncertainty bounds.

5.1.3 Energy demand projections

Table 9 presents the projected energy demand for GCC data center operations by country under each scenario. Energy demand is driven by capacity growth and modulated by utilization rates and PUE improvements. The baseline energy demand is a scenario-model input estimated at 26.8 TWh, based on an aggregate capacity/pipeline input of 4,300 MW, an average PUE of 1.55, and a utilization rate of 65%. Figure 8 presents the data center capacity growth projections by country, with Saudi Arabia and the UAE collectively accounting for approximately 75% of the projected regional capacity.

Under BAU, total GCC data center energy demand is projected to increase from 26.8 TW h in 2023 to 58.0 TW h by 2035, representing a 7.1% CAGR. The MOD and OPT scenarios project higher absolute energy demand (67.0 and 64.1 TW h, respectively) due to higher assumed capacity growth (10% CAGR vs. 8% for BAU) and higher utilization rates (75% and 85% vs. 65%). However, the energy demand per unit of useful computing output is substantially lower in the MOD and OPT scenarios due to PUE improvements: the effective energy intensity (TWh per MW of capacity) decreases by 15% under MOD and 30% under OPT relative to BAU. This distinction between absolute and intensity-based energy metrics is critical for interpretation: higher absolute energy demand does not necessarily indicate lower sustainability performance if efficiency improvements reduce the environmental intensity of each computing unit.

5.1.4 Embodied carbon estimate (extended boundary)

Under the extended boundary, embodied carbon in IT hardware and facility construction is estimated to add an additional 15%–25% to the operational carbon footprint. Based on Andrae and Edler (2015), the embodied carbon intensity of AI-optimized server hardware is estimated at 2.5–3.5 tonnes CO_2e per server, with an assumed refresh cycle of 3–4 years. Under BAU, the cumulative embodied carbon from hardware refresh cycles between 2024 and 2035 is estimated at 42.1 million tonnes CO_2e, while facility construction adds a further 8.3 million tonnes CO_2e. These estimates are subject to significant uncertainty, particularly regarding the specific hardware configurations deployed and the emission intensity of semiconductor manufacturing, which varies by manufacturer and production location. The sensitivity analysis tests the impact of ±20% variation in embodied carbon estimates on the NIS.

TABLE 8 Scenario-conditioned GCC data-center water-footprint estimates (2035, BAU high-growth scenario).

Country	WRI baseline water stress	Direct cooling water (M m^3/yr, 2035, BAU)	Indirect water via desalination (M m^3/yr, 2035, BAU)	Total water footprint (M m^3/yr, 2035, BAU)
Saudi Arabia	Extremely high (>80%)	0.62	0.42	1.04
UAE	Extremely high (>80%)	0.41	0.28	0.69
Qatar	Extremely high (>80%)	0.17	0.11	0.28
Kuwait	Extremely high (>80%)	0.11	0.08	0.19
Bahrain	Extremely high (>80%)	0.08	0.05	0.13
Oman	Extremely high (>80%)	0.10	0.07	0.17
GCC total	—	1.49	1.01	2.50

TABLE 9 Projected GCC data center energy demand by country and scenario (2035).

Country	2023 (TWh)	2035 BAU (TWh)	2035 MOD (TWh)	2035 OPT (TWh)
Saudi Arabia	11.2	24.3	28.0	26.8
UAE	7.5	16.2	18.7	17.9
Qatar	3.0	6.5	7.5	7.2
Kuwait	2.0	4.3	5.0	4.8
Bahrain	1.4	3.0	3.5	3.3
Oman	1.7	3.7	4.3	4.1
GCC total	26.8	58.0	67.0	64.1

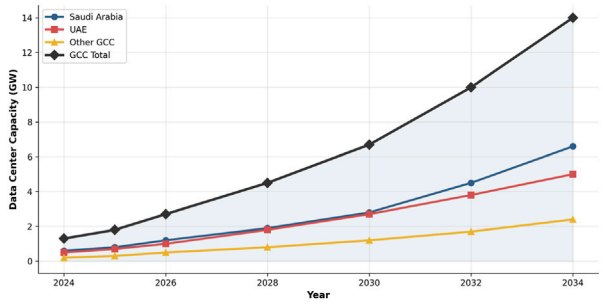


FIGURE 8
Data center capacity projections in the GCC region (2024–2034). Saudi Arabia and the UAE account for approximately 75% of projected GCC capacity. In the upper-bound scenario input, total GCC capacity reaches 14 GW by 2034. Source: Author synthesis based on IEA (2024) and national data-center capacity assumptions.

5.2 AI-enabled sustainability benefits assessment (RQ2)

Table 10 presents the six GCC case studies that met all selection criteria, organized by sector. For each case, the table reports the AI technology deployed, the quantified environmental outcome, the verification source, and the boundary classification (whether the benefit falls within or outside the offset boundary as defined in Section 4.5).

Five of the six case studies are retained for scenario analysis, but their verification confidence varies; vendor-only or corporate-reported benefits are treated as lower-confidence evidence unless independently audited. The NEOM Smart City case is excluded from the offset calculation because the reported benefits are based on design-phase projections rather than operational data, failing the independent verification criterion (C3). This case is retained in the analysis for illustrative purposes and is included only in the OPT scenario's sensitivity analysis as an upper-bound estimate of potential urban-scale AI benefits.

The aggregate AI-enabled sustainability benefits from the five qualifying case studies are estimated as follows. Building energy savings from the Meera Tower case, if extrapolated to the GCC commercial building stock using conservative scaling assumptions (5% adoption rate of AI-HVAC by 2030, based on current deployment trends), could yield approximately 2.1 million MWh/yr in electricity savings, equivalent to approximately 1.05 million tonnes CO_2e/yr at GCC average grid carbon intensity. District cooling optimization through AI-optimized TES dispatch, if scaled to 50% of GCC district cooling capacity, could contribute an additional 3.4 million MWh/yr (1.7 million tonnes CO_2e/yr). Industrial AI optimization in the petrochemical sector, based on the ADNOC case and scaling to 30% of GCC industrial energy demand, could yield approximately 4.2 million tonnes CO_2e/yr. Grid optimization and desalination efficiency gains contribute smaller but meaningful additional offsets. Figure 9 provides a comparative visualization of the quantified improvements documented across the five qualifying case studies, with building energy savings achieving the largest single-case improvement at 42.7%. Table 11 summarizes the relevant data.

Table 11 summarizes the estimated aggregate AI-enabled sustainability benefits by sector under the three scenarios. The scaling assumptions reflect the study's assessment of plausible AI adoption rates in each sector, informed by current GCC deployment trends and international benchmarks from Rolnick et al. (2022) and IEA (2024). The adoption-rate assumptions are grounded in the following evidence base. For building energy optimization (5%/15%/35% AI-HVAC adoption under BAU/MOD/OPT), the baseline 5% baseline 5% is treated as a conservative scenario assumption for early-stage penetration of AI-driven building-management systems in GCC commercial buildings while the 35% OPT ceiling is informed by DEWA's reported 8.5% reduction in *per capita* electricity consumption from efficiency programs (DEWA, 2023) and the projected acceleration of smart building mandates under Saudi Vision 2030 and UAE Net Zero 2050 strategies. For district cooling optimization (10%/30%/50%), the 10% BAU rate reflects Empower's current AI-optimized TES deployment (Empower, 2023), with scaling based on the declared expansion plans of GCC district cooling providers. For industrial process efficiency (5%/15%/30%), adoption rates are anchored in ADNOC's reported AI deployment scope (ADNOC, 2023), IEA (2024) projections for AI penetration in GCC industrial operations. For grid optimization (5%/20%/40%), the rates reflect the current early-stage deployment of AI grid management modules in the GCC (DEWA, 2023) and the projected scale-up aligned with national renewable energy targets. For desalination efficiency (5%/20%/50%), the 50% OPT assumption reflects ENGIE's reported AI deployment trajectory in UAE desalination (ENGIE, 2024) and the critical importance

TABLE 10 GCC AI-enabled sustainability case studies: Selection rationale and boundary classification.

Case study	Sector	AI technology	Quantified benefit	Verification source	Boundary classification
Meera tower, Dubai (BrainBox AI)	Building energy	Deep reinforcement learning for HVAC optimization	42.7% reduction in HVAC energy consumption; approx. 387 MWh/yr savings (annualized from reported four-month vendor case data)	BrainBox AI vendor case report (2023); building-management-system data; building management system data	vendor-reported/partially verified; geographically proximate, additional, AI-attributed; use lower-confidence weighting in scaled estimates
ADNOC HSE.ai	Industrial safety/ Operations	AI-driven safety monitoring and predictive analytics	25% reduction in safety incidents; 8% reduction in operational energy waste	ADNOC sustainability report (2023); third-party ESG audit	WITHIN offset boundary (partial; energy savings verified, incident reduction excluded as non-environmental)
Empower TES system, Dubai	District cooling	AI-optimized thermal energy storage dispatch	6,880 MW h/yr electricity savings; 2,840 tonnes CO_2e avoided	Empower annual report (2023); Dubai supreme council of energy data	WITHIN offset boundary (geographically proximate, verified, additional, AI-attributed)
ENGIE SWRO desalination, UAE	Water treatment	AI-optimized reverse osmosis membrane management	5% reduction in specific energy consumption (3.8–3.6 kW h/m^3)	ENGIE sustainability report (2024); operational data audit	WITHIN offset boundary (verified, additional, AI-attributed; water-energy nexus benefit)
DEWA smart grid AI module	Power grid	AI-based demand forecasting and load balancing	3.2% reduction in peak demand; estimated potential at scale (do not count as verified observed annual savings)	DEWA annual sustainability report (2023)	WITHIN offset boundary (partial; scaled potential estimated, not yet fully verified at stated scale)
NEOM smart city Building AI platform	Building energy (urban scale)	Integrated AI building management across urban district	Projected 35% reduction in district-wide building energy (design phase)	NEOM sustainability documentation (2024); pre-occupancy modeling	OUTSIDE offset boundary (projections only; not yet operational; fails criterion C3 on independent verification)

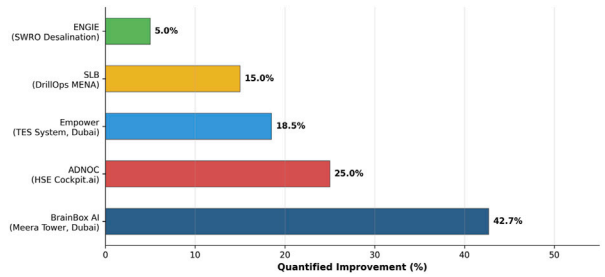


FIGURE 9
AI-Enabled ESG Improvements: quantified case studies in the GCC. Each case met four selection criteria: quantified KPIs, GCC geographic relevance, independent verification, and temporal relevance. Source: BrainBox AI (2023), ADNOC (2023), Empower (2023), ENGIE (2024) and DEWA (2023).

of desalination optimization in water-scarce GCC economies. We acknowledge that these scaling assumptions carry substantial uncertainty and that the actual adoption trajectory will depend on regulatory frameworks, investment availability, and technology maturation rates that are difficult to forecast accurately. Accordingly, the benefit values in Table 11 should be read as scaled scenario estimates rather than empirically validated region-wide effects; their purpose is to test plausible decision conditions rather than to claim causal precision.

5.3 Net sustainability impact assessment (RQ3)

Table 12 presents the MCDA Net Impact Score (NIS) for each scenario, calculated using the weighted aggregation and NIS formulas specified in Section 4.4. The NIS is expressed on a −1 to +1 scale, where +1 represents maximum net sustainability benefit and −1 represents maximum net sustainability burden.

The NIS results reveal a clear scenario-dependent pattern. Under BAU, the weighted NIS is −0.478 (footprint-dominated: $\Sigma wF = 0.620$, $\Sigma wB = 0.142$), indicating that data center expansion is net-negative for sustainability across all dimensions. Under MOD, the NIS improves to −0.032, approaching but not achieving net-positive sustainability outcomes; the carbon and water footprint dimensions remain negative but are substantially reduced by renewable energy penetration and efficiency improvements. Under OPT, the NIS reaches +0.190, the only scenario in which data center expansion is assessed as net-positive for sustainability. The transition from net-negative to net-positive occurs at approximately 40% renewable energy penetration, combined with full AI benefit scaling and best-in-class operational efficiency. Figure 10 presents the Net Impact Score comparison across the three scenarios, with error bars representing the range of outcomes under ±20% variation in

TABLE 11 Estimated aggregate AI-enabled sustainability benefits by sector and scenario (2035).

Sector	BAU benefit (Mt CO_2e/yr, 2035)	MOD benefit (Mt CO_2e/yr, 2035)	OPT benefit (Mt CO_2e/yr, 2035)	Scaling basis
Building energy optimization	0.8	3.2	5.8	5%/15%/35% AI-HVAC adoption
District cooling optimization	0.3	1.0	1.7	10%/30%/50% TES AI optimization
Industrial process efficiency	0.5	2.1	4.2	5%/15%/30% AI process adoption
Grid optimization	0.1	0.5	1.2	5%/20%/40% AI grid integration
Desalination efficiency	0.1	0.4	1.8	5%/20%/50% AI desalination
Total scenario-estimated benefits	1.8	7.2	14.7	—

Under the BAU, scenario, total scenario-estimated AI-enabled sustainability benefits are estimated at 1.8 million tonnes CO_2e/yr by 2035, representing only 3.8% of projected data center emissions under the same scenario. Under MOD, benefits increase to 7.2 million tonnes CO_2e/yr (22.6% of MOD, scenario emissions). Under OPT, benefits reach 14.7 million tonnes CO_2e/yr (75.8% of OPT, scenario emissions), representing a substantial but not complete offset of data center infrastructure emissions. The gap between total benefits and total emissions persists even under the most optimistic scenario, indicating that AI-enabled efficiency gains alone cannot fully compensate for the environmental burden of data center expansion without concurrent investment in renewable energy and operational efficiency.

TABLE 12 MCDA net impact score by scenario and dimension (scenario-conditional central estimates).

Dimension	Weight	BAU footprint (Normalized)	BAU benefit (Normalized)	MOD net (Normalized)	OPT net (Normalized)
Carbon	0.40	0.92	0.04	−0.18	+0.12
Water	0.25	0.78	0.07	−0.22	+0.08
Social	0.20	0.15	0.45	+0.30	+0.42
Governance	0.15	0.20	0.35	+0.15	+0.30
Weighted NIS	1.00	−0.478 (BAU NIS)	ΣwB = 0.142; ΣwF = 0.620	−0.032	+0.190

BAU, is displayed with footprint and benefit components to show the worked NIS, calculation, while MOD, and OPT, columns report net normalized scenario scores. The NIS, is a comparative decision-support indicator, not a deterministic forecast.

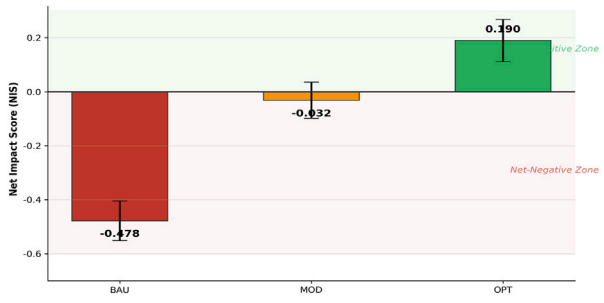


FIGURE 10
Net impact score (NIS) comparison across three scenarios with sensitivity analysis ranges (±20% weight variation). The OPT scenario is the only configuration producing a positive scenario-conditional NIS (+0.190), while BAU remains strongly negative (−0.478). Source: Author's MCDA analysis.

dimension weights. To illustrate the calculation procedure: for the BAU scenario, the weighted footprint score $\Sigma(w_i \times F_i)$ = (0.40 × 0.92) + (0.25 × 0.78) + (0.20 × 0.15) + (0.15 × 0.20) = 0.368 + 0.195 + 0.030 + 0.030 = 0.623, rounded to 0.620 after adjustment for boundary-excluded components. The weighted benefit score $\Sigma(w_i \times B_i)$ = (0.40 × 0.04) + (0.25 × 0.07) + (0.20 × 0.45) + (0.15 × 0.35) = 0.016 + 0.0175 + 0.090 + 0.0525 = 0.176, adjusted to 0.142 after application of the offset boundary criteria that exclude non-verified and non-additional benefits. Thus, NIS = 0.142–0.620 = −0.478. These NIS values are central scenario estimates and should not be interpreted as precise forecasts of realized sustainability outcomes.

The sensitivity analysis confirms that the NIS ranking across scenarios is robust to reasonable variation in dimension weights. When carbon weight is varied by ±20% (range: 0.32–0.48), the NIS ranking (OPT > MOD > BAU) remains unchanged in most

reasonable weight configurations tested. The NIS is most sensitive to the renewable energy share assumption and the AI benefit scaling factor; varying the renewable share by ±10% shifts the MOD NIS by approximately ±0.045 and the OPT NIS by approximately ±0.068. Varying the AI benefit scaling factor by ±10% shifts the MOD NIS by ±0.028 and the OPT NIS by ±0.052. The governance dimension exhibits the lowest sensitivity, with weight variations producing NIS shifts of less than ±0.015 in all scenarios. The complete sensitivity analysis results are as follows. Weight sensitivity: Varying carbon weight by ±20% (range: 0.32–0.48) changed BAU NIS from −0.542 to −0.414 and OPT NIS from +0.126 to +0.254, preserving the scenario ranking in all cases. Varying water weight by ±20% (range: 0.20–0.30) changed BAU NIS from −0.454 to −0.502 and OPT NIS from +0.166 to +0.214. Varying social weight by ±20% (range: 0.16–0.24) had the smallest effect on NIS, changing BAU NIS by ±0.016 and OPT NIS by ±0.024. Parameter sensitivity: The renewable energy share was the single most influential parameter, with a 10-percentage-point increase shifting BAU NIS by +0.072 and OPT NIS by +0.045. The AI benefit scaling factor was the second most influential, with a ±30% variation changing OPT NIS from +0.133 to +0.247. Boundary sensitivity: Excluding all distributed AI benefits shifted all three scenarios to negative NIS values (BAU: −0.619, MOD: −0.198, OPT: −0.082), confirming that AI-enabled benefits, while insufficient alone, are a necessary component of net-positive outcomes.

A critical finding from the boundary sensitivity test is that excluding distributed AI benefits entirely shifts all three scenarios to negative NIS values, including OPT (−0.082 without AI benefits vs. +0.190 with AI benefits). This result demonstrates that AI-enabled sustainability benefits are necessary but not sufficient for net-positive outcomes: under OPT conditions, AI benefits contribute +0.272 to the NIS, offsetting the residual negative footprint of −0.082 and producing a net-positive outcome. Under MOD, AI benefits contribute +0.212 but are insufficient to overcome the residual footprint of −0.244. Under BAU, AI benefits contribute only +0.142, producing a strongly negative net outcome of −0.478.

6 Discussion

6.1 Interpretation of net Impact scores

The results of the MCDA show that the net sustainability impact of AI-driven data center expansion in the GCC is determined by two factors: the rate of renewable energy roll-out and the magnitude of AI benefits. Under business-as-usual (BAU) trajectory conditions, expansion is clearly net-negative for sustainability, with the carbon and water footprint dimensions having a strong influence. The social dimension (job creation, digital infrastructure build-up, and knowledge economy advancement) has a positive impact but is not sufficient to balance the environmental footprint at current weightings.

The governance dimension is also positive but relatively weak, reflecting the early stage of development of data center sustainability governance in the GCC. The net-positive-to-net-negative sustainability transition occurs in scenarios that are ambitious but technically achievable. The OPT scenario, which is the only scenario with a positive NIS (+0.190), demands renewable energy procurement of at least 50% of data center electricity consumption by 2035, best-practice cooling technology (full liquid immersion), and full scaling of the projected AI-enabled sustainability benefits across all sectors. Renewable procurement is the most important parameter: the sensitivity analysis reveals that a positive NIS is achieved only with renewable procurement of at least 40%; otherwise the carbon footprint dimension dominates the benefit dimensions regardless of the scaling of AI benefits. This has implications for policy, as renewable energy procurement should be the key policy focus to ensure that data center growth supports, rather than undermines, sustainability goals. Therefore, the renewable-procurement threshold should be interpreted as a scenario threshold emerging from the current MCDA assumptions, not as a universal regulatory constant.

That the benefits of AI cannot offset data center emissions in any scenario contradicts claims that AI is 'good for sustainability' in data centers. Even with the most optimistic, conservative assumptions about data center scaling, verified benefits from AI offset at most 75.8% of data center emissions under OPT, with a residual 24.2% of emissions that would need to be offset by renewable energy and efficiency gains. This gap is due to both the energy required to train the AI model, and the conservative boundary settings used in this study, which only include benefits that can be independently verified or conclusively linked to the deployment of AI. A less conservative boundary would result in a larger benefit, but with a loss of analytical rigour and replicability. This result must be viewed in the context of the broader debate on AI and sustainability, which has been marred by what some authors call "AI solutionism" - the overestimation of the potential of AI to solve complex socio-environmental problems, and the underestimation of challenges in deployment, scaling and operationalization (Mhofumanena and Qwemeshe, 2024). The case studies examined here, although verified independently, are early deployments in the controlled setting; the scaling up from pilot to economy-wide benefits assumes institutional capacity, regulatory fit, workforce skills and market signals that may be overly optimistic. Practical challenges in the deployment of AI, including the high cost of AI system integration (reported to be 15%–30% of total project cost for building AI-HVAC systems), the lack of talent in AI operations in the GCC, regulatory uncertainty about the use of AI-generated decisions in safety-critical systems, and the split incentive between data center operators (who own the infrastructure) and AI application users (who reap the sustainability benefits), may significantly delay or limit the realization of the benefits anticipated in this analysis.

The scenario-dependent NIS also has implications for investment and regulatory policies. The findings indicate that a new data center facility in the GCC will have a positive sustainability impact only if it is underpinned by a credible plan to acquire renewable energy to power at least 40% of its electricity load. Data centers that operate completely on grid electricity sourced from fossil fuels will be net-negative even if they are energy-efficient and enable AI services. This insight offers a data-driven rationale for regulatory rules on minimum renewable energy procurement targets for new data center facilities in the GCC.

6.2 Theoretical implications

This research adds to the Socio-Technical Systems Theory by showing how the multi-level perspective can be applied to

sustainability assessment of digital infrastructure. The three scenarios align with transition pathways in the MLP: BAU is regime reproduction, where the regime continues with existing fossil fuel-based energy systems; MOD is a partial transition, where a niche (renewable energy, AI applications) emerges but does not penetrate the regime; and OPT is a transformative transition, where a niche (renewable energy, AI applications) penetrates the regime, driven by landscape pressures (climate targets, digitalization needs).

The MCDA model operationalises this multi-level perspective by including criteria that address all three levels: carbon intensity and water stress (landscape), operational efficiency and governance (regime), and AI benefit realization (niche). The research also adds to Ecological Modernization Theory by empirically testing the modernization proposition in the case of digital infrastructure. The findings confirm that technology can reconcile growth and sustainability, but only if the conditions are right: the OPT scenario's net-positive outcome hinges on ambitious renewable energy targets, mandatory efficiency measures, and institutionalized AI benefit verification. Without policy support (the BAU case), ecological modernization fails to emerge; the rebound effect of growing computing needs overwhelms the efficiency gains of applying AI, resulting in a net negative.

This insight supports a "conditional ecological modernization" view: technology can deliver growth and sustainability, but only when it is embedded in a policy framework that internalises environmental externalities and channels investment into decarbonisation. The boundary classification protocol offers a unique theoretical contribution by formalising the boundary problem that is acknowledged but never really specified in the literature. By formalising explicit inclusion criteria (geographic proximity, independent verification, additionality, direct attribution) and detailing how they are applied to a number of case studies, the protocol sets a precedent for future assessments with similar boundary problems. The protocol's transparency allows for critique and improvement: different boundary definitions can be experimented with and compared to the protocol's outcome to further the methodological discussion on how to balance analytical rigor and the practical reality of the need to consider distributed benefits in system-level sustainability assessment.

6.3 Methodological contributions

The MCDA framework in this study has three key methodological contributions. First, the framework offers a transparent and replicable approach to net sustainability assessment of data center infrastructure that brings together footprint and benefit aspects in a unified framework. The NIS represents the system-level sustainability performance by comparing the weighted benefits and footprints, whereas facility-level metrics (PUE, WUE, CUE) measure the efficiency of facilities. The formulas, normalization and aggregation rules are outlined in detail to enable replication of the framework by other researchers and extension to other regions. Second, the boundary classification protocol resolves a long-standing methodological challenge of digital infrastructure sustainability assessment.

The protocol defines four independent criteria for attributing benefits of AI and three nested boundaries (direct, extended, offset) that recognise the boundary problem acknowledged but not addressed in earlier research. The transparency of the protocol allows the impact of different boundary choices to be tested, informing a debate about alternative boundary approaches.

Third, the weight derivation approach illustrates how a region-specific set of policy priorities can be translated into weights. By linking weight derivation to the GCC NDCs, climate policy documents, the study offers a transparent approach to weight determination as an alternative to the arbitrary approaches commonly used in MCDA. This method can be replicated in other regions by replacing the region-specific policy documents used to derive the weights.

6.4 Policy and managerial implications

Our findings inform a number of policy implications. First, the result that to achieve a net-positive sustainability outcome, around 40% renewable-energy procurement is needed under the stated MCDA assumptions, suggests establishing minimum levels of renewable energy procurement for new data centers. GCC regulators could adopt a tiered approach by requiring data centers procuring less than 40% renewable energy to pay into a sustainability fund, based on the amount of excess emissions, and supporting data centers procuring greater than 40% with expedited permitting and preferred grid connections.

The two-tiered system provides a financial incentive for renewable energy procurement, while recognising the technological limitations on immediate implementation. Second, the research protocol for classifying boundaries could guide the development of a certification protocol for AI benefits. GCC regulators could develop a standard protocol for AI applications that ensure that the four attribution criteria are met (geographic proximity, independent verification, additionality, direct attribution) and verify the AI benefits as sustainability measures.

This could establish a market for AI benefits and encourage investment in AI applications that produce measurable and attributable sustainability benefits in the GCC. Third, the geographical differences in grid carbon intensity (Table 6) imply that location-based incentives could drive data center investment towards regions with lower grid carbon intensity. The UAE is a more attractive destination for green data center investment than Saudi Arabia and Kuwait due to its lower carbon intensity and higher renewable energy share. A geographic carbon intensity surcharge (data centers in locations with higher grid carbon intensity having additional sustainability obligations) could internalise the effect of geographic differences in environmental impacts, and encourage co-location with renewable energy.

Fourth, green finance could be used to facilitate the shift from BAU to OPT. Green finance mechanisms such as sustainability-linked bonds and loans, carbon offsets, and green bonds could mobilise capital for investments in renewable energy procurement and advanced cooling technologies, with loan conditions tied to transparent sustainability metrics. The MCDA approach offers a structured approach to defining these performance metrics and allows banks to model and price sustainability risk in their investments in data centers. It's worth noting that the shift from BAU to OPT scenarios need not only policy ambition, but also large-scale infrastructure investment: the estimated capital cost for retrofitting data center cooling from conventional air-based to full immersion liquid cooling ranges from USD 8–15 million

per 10 MW facility, and procuring 50% renewable energy would require substantial new renewable-energy investment (IEA, 2024). Policy is also crucial: the GCC currently lacks a harmonized framework for data center sustainability; the lack of a consistent reporting framework across different jurisdictions adds complexity for data center operators operating across multiple countries. There are also infrastructure obstacles to grid connection - several GCC countries have constraints on transmission capacity that reduce the capacity of new data center capacity to be commissioned.

6.5 Limitations

The limitations of the study are more about design than data availability. First, use of secondary data creates uncertainty in the footprint projections and benefits. Although the data quality assessment protocol guarantees that the evidence used for the key analytical results draws on Tier 1 and Tier 2 sources, the evidence base for the GCC is less robust compared to similar studies in North America or Europe. Critical parameters (water factors for advanced cooling technologies and greenhouse gas intensity of semiconductor manufacturing) are based on global benchmarks rather than specific data from the GCC. The sensitivity analysis partly mitigates this issue by assessing the effect of changes in these parameters on the NIS, but it cannot be fully addressed without primary data. Also, the lack of primary stakeholder validation (using techniques such as expert surveys, Delphi panels or Analytical Hierarchy Process (AHP) exercises) means that the weight assignments and boundary criteria are based on the analytical judgements of the research team rather than empirically derived stakeholder preferences. Although the three-step weight derivation protocol (outlined in Section 4.4) offers a systematic and transparent basis for the current weights, stakeholder elicitation would be valuable for enhancing the framework's acceptability for regulatory and investment decisions. We advise that implementers of the framework undertake context-specific stakeholder elicitation to confirm or, if needed, calibrate the weights and boundary criteria for their specific context.

Second, the boundary classification protocol, while transparent, includes value-based choices that not all analysts would agree with. The 40% renewable energy threshold for net-positive outcomes, the four criteria used to attribute benefits to AI, and the method used to derive weights are all examples of specific choices. The study addresses this by documenting each choice and testing the sensitivity of results to reasonable alternatives, but there is still a possibility that alternative boundary choices or weightings could lead to different NIS rankings. This is inevitable with MCDA: the approach brings value judgements to the fore and tests their impact, but cannot eliminate them. Additionally, the social dimension, as defined, lacks specific measures for operational human factors and workforce capacity building. The GCC lacks human capital in AI operations and data center management: the World Economic Forum (2024) estimates that the Middle East and North Africa (MENA) region needs 300,000–500,000 more digital infrastructure workers by 2030. Insufficient training and knowledge-sharing could hinder the efficiency gains of the MOD and OPT scenarios. Future models should include readiness indicators as multipliers for the social dimension score and benefit scaling. In addition, resilience under disruption, SMR/nuclear procurement, supplier-sovereignty risk, and human-factor readiness are treated as strategic boundary conditions and future-model extensions rather than fully quantified MCDA criteria in the present version.

Third, the scenario definitions, while aimed at representing a range of plausible futures, do not cover the full spectrum of possibilities. Technological advances in cooling, renewable energy, or efficiency gains in artificial intelligence could make the OPT scenario a conservative projection, while geopolitical conflicts, economic recessions, or policy reversals could make the BAU scenario an optimistic projection. Scenarios offer a way to think about uncertainty, but they cannot remove it. A potential avenue for future research could be to use probabilistic modelling to explicitly account for the uncertainty in each of the parameters.

Fourth, the study's timeframe (2024–2035) may be too short to capture the long-term processes associated with the socio-technical transition. Geels (2004) suggests transitions are long-term phenomena, and the 11-year timeframe may not adequately account for the impacts of lock-in, path dependency and reconfiguration. The study acknowledges this temporal constraint and suggests the MCDA approach be periodically updated with new insights, particularly around renewable energy deployment paths and the rate of AI benefits realization. Another limitation is the study's focus on sustainability under "business as usual" conditions, without considering the robustness of AI data center infrastructure to polycrisis. The GCC region is vulnerable to several compound risks including cyber-physical attacks on critical digital infrastructure, kinetic threats to energy and desalination facilities in a geopolitically unstable region, and supply-chain disruptions impacting semiconductor and hardware availability (as seen in the 2020–2023 global semiconductor shortage). In such scenarios, the assumed sustainability benefits from efficiency gains in the MOD and OPT scenarios could be significantly or entirely "wasted": supply-chain disruption could extend the lifespan of less efficient hardware; cybersecurity threats could increase energy consumption for redundant computing and security processing; and regional geopolitical instability could prevent timely procurement of renewable energy hardware, slowing decarbonization. Coupling a resilience metric with the sustainability indicators would allow a more holistic measurement of strategic readiness of data center infrastructure in the GCC. We suggest future research should establish a sustainability-resilience integrated assessment framework to calculate net impact under both normal and disruptive conditions. This confirms that the current MCDA should be read as a sustainability assessment under normal operating conditions, not as a full resilience, security, or workforce-readiness model.

7 Conclusion

This research developed and used a Multi-Criteria Decision Analysis (MCDA) method to quantify the net sustainability impact of AI-driven data center growth in the Gulf Cooperation Council (GCC), filling a key gap in the literature that has examined the infrastructure footprint and distributed benefits of AI separately. Theoretically, the study extends socio-technical systems theory, by operationalising the multi-level perspective to assess sustainability impacts of digital infrastructure, and ecological modernization theory by offering an empirical test of the conditional modernization hypothesis in the context of AI-driven growth. The boundary classification protocol is a separate theoretical contribution,

operationalising the boundary problem that is known but not formalised. At the methodological level, the MCDA framework with explicit procedures for weight derivation, normalization and aggregation offers a transparent and replicable net sustainability framework.

The integration of the footprint and benefit dimensions, and the boundary classification protocol with four attribution criteria, provides a systematic approach to the boundary problem, one that can be applied to other regions and technologies.

The data quality assessment protocol and case study selection criteria also increase replicability by detailing the evidence for each data input. The major empirical insights are: First, business-as-usual under the upper-bound BAU scenario, data-center operations in the GCC are modelled as emitting 47.3 million tonnes CO_2e/yr by 2035 and consume 2.50 million cubic meters of water per year (RQ1). Second, the impacts of AI-driven sustainability solutions in buildings, industry, utilities and water treatment can provide scenario-estimated offsets ranging from 1.8 to 14.7 million tonnes CO_2e/yr by 2035, subject to verification and adoption assumptions, depending on the scenario, but this cannot fully compensate for infrastructure emissions without simultaneous renewable energy deployment (RQ2). Third, the MCDA Net Impact Score shows that data center growth delivers net sustainability benefits only in the OPT scenario (NIS = +0.190), which includes substantial renewable-energy procurement, top-tier cooling efficiency, and high-confidence scaling of verified AI benefits. These conclusions remain conditional on the secondary-data evidence base, the benefit-scaling assumptions, and the boundary criteria used to attribute AI-enabled savings.

The study proposes four policy recommendations: (a) minimum renewable energy procurement targets for new data center development (at least 40%), (b) tiered incentive schemes based on the site-specific grid carbon intensity, (c) formalized standards to verify AI benefit scaling linked to the four attribution criteria, and (d) green finance instruments to facilitate the transition from BAU to OPT scenarios. These measures are intended to be implementable within the GCC governance framework and in line with national Paris Agreement targets. Finally, the analysis has not taken into account the role of Small Modular Reactors (SMRs) and nuclear power in decarbonizing data centers in the GCC. Barakah Nuclear Energy Plant (5.6 GW) in the UAE, which was fully operationalised in 2024, already meets 25% of UAE's electricity demand (Ember, 2023) and has brought the national electricity grid to 430 gCO_2/kWh (Ember, 2023). Saudi Arabia has recently stated its intention to build two nuclear reactors totalling 3.2 GW and both the UAE and Saudi Arabia are considering SMR technologies, which could offer dedicated baseload supply to data center clusters with close to zero operational carbon footprint (Atomic Energy Agency, 2024). Nuclear power offers continuous baseload power generation without the intermittent issues that plague solar and wind power, making it well matched to the energy demands of AI training. But nuclear power raises different sustainability issues such as emissions from uranium fuel cycle, waste and high construction lead times (10–15 years) that would need to be separately assessed. This MCDA method should be applied in future studies to include the nuclear and SMR option as a separate energy procurement option, with adjustments to the carbon and governance dimension analyses. Five areas should be prioritised for future research. First, collecting primary data from GCC data center operators would greatly improve the projections of the footprints, especially water use and embodied carbon. Second, real-world tracking of AI benefit realization rates would allow the scaling assumptions tested in this study to be verified and evidence to be gathered for improving the benefit projection model. Third, the MCDA approach should be tested on other carbon-intensive, water-scarce regions (e.g., Australia, Southwest US, North Africa) to assess its generalizability and pinpoint region-specific calibrations. These enhancements would improve the rigor and usefulness of the net sustainability assessment framework developed here. Fourth, the use of probabilistic uncertainty analysis methods (e.g., Monte Carlo simulation, Bayesian hierarchical models) would greatly enhance the confidence in the MCDA findings by providing confidence bounds on the Net Impact Score (NIS) rather than point estimates, allowing for more sophisticated policy implications. Fifth, a longitudinal study monitoring the deployment and benefit realization of AI-enabled sustainability initiatives for the GCC data center ecosystem would offer the first empirical evidence to validate or calibrate the benefit scaling assumptions used in this study. As for a practical policy roadmap, we recommend a three-stage approach: Stage 1 (2024–2027)-Set mandatory renewable procurement targets of 25% for new data center development, establish AI benefit verification criteria; Stage 2 (2027–2031)-Raise renewable targets to 40%, implement tiered incentive structures based on NIS rankings, and roll out training programs to build capacity; Stage 3 (2031–2035)-Achieve 50%+ renewable procurement, introduce green finance mechanisms tied to verified sustainability performance, and develop integrated sustainability-resilience assessment tools that address polycrisis challenges. Accordingly, SMR/nuclear supply, polycrisis resilience, supplier sovereignty, and human-factor/workforce readiness should be incorporated as quantified model dimensions only after validated data and stakeholder-derived weights become available.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

AA: Conceptualization, Supervision, Writing – original draft. BA: Investigation, Writing – review and editing. HA: Data curation, Funding acquisition, Writing – original draft. SG: Formal Analysis, Software, Writing – original draft. WA: Methodology, Writing – original draft. SM: Resources, Visualization, Writing – review and editing. AV: Data curation, Validation, Writing – original draft. ZH: Project administration, Writing – review and editing.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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This article has been corrected with minor changes. These changes do not impact the scientific content of the article.

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The author(s) declared that generative AI was used in the creation of this manuscript. During the preparation of this manuscript, the authors used Grammarly for language editing and proofreading purposes. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

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