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Research Article

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Green Computing and Artificial Intelligence Infrastructure: Design, Mathematical Modeling, and Experimental Evaluation of the AI Environmental Impact Framework (AI-EIF)

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Abstract
The rapid expansion of artificial intelligence (AI) systems has introduced substantial yet largely unquantifiable environmental costs. Existing green computing standards such as Power Usage Effectiveness (PUE), Carbon Usage Effectiveness (CUE), and Software Carbon Intensity (SCI) were developed for legacy data centers and fail to capture the multi-faceted ecological footprint of modern AI workloads. To address this limitation, this paper introduces the AI Environmental Impact Framework (AI-EIF), a novel four-pillar framework combining energy consumption, carbon emissions, resource depletion, and standardized measurement metrics. Mathematically formalized through 10 core equations, AI-EIF is operationalized via the AI-EIF-Eval algorithm with an efficient computational complexity of O (k * p). Experimental validation conducted on the Google Cluster Trace v3 dataset spanning 3,847 AI-class workloads across eight cluster configurations demonstrates that AI-EIF-Eval achieves 94.3% measurement accuracy, surpassing SCI, CarbonTracker, and MLPerf-Energy by 15.7, 13.1, and 10.6 percentage points, respectively. Application of the framework yielded mean reductions of 38.4% in energy consumption, 41.2% in carbon emissions, and 22.7% in water usage, while driving a 47.3% increase in the composite GreenFLOPS Index. AI-EIF is unique in introducing cross-dimensional linkage (CDL) modelling, part of the 9-metric Green AI Metrics Suite (GAMS), and introducing a composite GreenFLOPS scoring index as the first unified environmental benchmarking tool for AI infrastructure. Comparative analysis to ten frameworks existing in the literature shows that AI-EIF has a dimensional coverage of 5.0/5.0, while all the rest have a maximum of 3.0/5.0. These contributions provide a robust basis for sustainable AI policy, benchmarking and regulation.

Keywords: Green computing; AI infrastructure; Environmental impact framework; Energy efficiency; Sustainable AI; AI-EIF.

1. Introduction

One of the most significant 21st century technological advances is the rise of large-scale systems of artificial intelligence. AI can provide unprecedented productivity, scientific advances, and economic value, ranging from generative language models to real-time computer vision solutions. But this computational revolution comes at a heavy and poorly characterized ecological price tag that is the subject of serious academic inquiry. The CO2 equivalent of training a single large language model is greater than 280 tonnes, which is equivalent to five typical cars being driven for their lifetime. [1] In 2023, global use of electricity in data centres was 200-250 TWh, and is expected to double by 2026.[2] In addition to energy, AI facilities use billions of litres of fresh water each year, rare earth minerals in creating hardware, and produce increasing amounts of electronic waste that account for over 57 million metric tonnes of waste each year globally.[3] However, despite this magnitude of environmental impact, there is no single agreement on the metrics to measure AI's environmental footprint.[4]

This gap is not just learning related. If there are no consistent, complete metrics, then AI developers cannot measure the environmental performance, operators cannot prioritize what they need to optimize, and policymakers cannot know what and how to regulate. The current green computing definitions and concepts are structurally inadequate to address this challenge.[5] PUE and WUE are used to measure efficiency at the facility level, but are unable to allocate costs to individual AI workloads.[6,7] The SCI specification takes into account operational carbon but does not consider energy efficiency, water usage or hardware life cycle impacts.[8] There are tools like CarbonTracker which focus on training-phase Scope 2 emissions, but have no theoretical basis and are not cross-phase.[9] What is missing is an approach that explicitly models cross-dimensional interactions, such as the impact of the adoption of renewable energy on water usage, or the embodied carbon of hardware longevity decisions and their operational benefits.

This paper aims to tackle these limitations by introducing the AI Environmental Impact Framework (AI-EIF). This second version of the manuscript provides the following five enhancements over the previous version, as requested by the reviewers: (1) Ten mathematical formulations for the six GAMS metrics and the GreenFLOPS Index; (2) the AI-EIF-Eval algorithm with pseudocode and complexity analysis; (3) experimental validation on Google Cluster Trace v3 with quantitative results across the six performance dimensions; (4) comparative study with the existing ten frameworks; and (5) a dedicated part on novelty and contributions, clearly distinguishing from the previous work. The paper is organized as follows: Section 2 presents a literature review that covers the related work. Section 3 contains theory background.[10] In Section 4, the AI – EIF framework and mathematical model are defined. In section 5, you will express novelty and contributions. The AI-EIF-Eval algorithm is discussed in Section 6. The experimental setup is described in section 7. Results and discussion are given in section 8. Comparative analysis is given in Section 9. Section 10 is on the policy implications. Future work is included as the conclusion of Section 11.

2. Literature review

2.1 Green computing and data centre efficiency

The US EPA Energy Star program in 1992 was the origin of green computing, which is the environmentally responsible design, production, utilization, and disposal of computing resources.[11,12] In 2007 the Green Grid presented a new metric for data centres, known as the PUE, a ratio of the total energy used by a facility and IT equipment became the de facto standard for data centre efficiency. [6] Later measures included carbon (CUE) and water (WUE).[7] Dayarathna *et al*. surveyed more than 200 of these data centre energy models, and none were specific to AI workloads, which is further evidence of a structural measurement gap.[13] Masanet *et al*. showed that for many years the efficiency improvements have more than compensated for the growth of demand while cautioning that AI's computational demands are threatening this.[14]

2.2 Environmental impact of AI systems

Strubell *et al*. sparked interest in academia by calculating 284 tCO2e for training a single large NLP model.[1] There was significant variation found by Patterson *et al*. between hardware and location. Schwartz *et al*. presented the Red AI vs Green AI paradigm.[15,16] Henderson *et al.* called for "systematic" reporting standards.[17] Gupta *et al*. demonstrated that in the case of inference-dominated deployments, the amount of carbon embedded in the hardware accounts for 50–80% of the total LC emissions. Luccioni *et al*. did an empirical lifecycle analysis of a 176B-parameter model. [18,19] According to Li *et al*. the training process for GPT-3 requires ~700,000 liters of fresh water. [20] Dhar put AI emissions into the broader picture of ICT. Carbon accounting wasn't the only hidden impact that was identified by Ligozat *et al*.; they also found impacts of land use and hardware toxicity. [21,22]

2.3 Existing measurement tools and their limitations

There are tools that can estimate Scope 2 carbon during training, such as CarbonTracker and the ML Emissions Calculator which do not have theoretical foundations, nor do they span across different phases.[9,23] Bannour *et al*. identified some significant methodological inconsistencies between and within the NLP carbon tools.[24] Dodge *et al*. showed that the carbon intensity of clouds is three orders of magnitude different from place to place.[25] For example, the systematic review by Verdecchia *et al*. which aggregated 98 green AI studies found that there is no unified framework and methodology in the field.[26] Kaack *et al*. showed that AI is a key emitter and potential enabler of climate mitigation.[27] AI-EIF brings four-pillar coverage for a single framework, cross-dimensional linkage modelling and composite scoring which no reviewed framework offers.

3. Theoretical foundations

3.1 Lifecycle Assessment (LCA) theory

LCA, as standardized in ISO 14040 and 14044 assesses environmental impacts throughout the entire life cycle of a product, from raw material extraction through manufacturing, use and end-of-life disposal.[28] AI-EIF implements a cradle-to-grave boundary by covering hardware production (including semiconductor fabrication and extraction of rare earth minerals), training, inference, storage and end-of-life management. AI-EIF's LCA functional unit is a “normalized” AI computational throughput: one TeraFLOP-second (TFLOPS), allowing systems to be compared on a consistent performance level.

3.2 Industrial ecology

Industrial Ecology examines material and energy flows through industrial systems to minimize environmental externalities.[29] AI-EIF applies this systemic perspective to conceptualize AI infrastructure as an interconnected socio-technical system where interventions in one environmental dimension produce cascading effects in others. This motivates the Cross-Dimensional Linkage (CDL) layer in AI-EIF, which models such trade-offs explicitly.

3.3 Ecological Modernization Theory (EMT)

EMT posits that technological innovation and institutional reform can achieve environmental sustainability within existing economic structures.[30] AI-EIF is informed by EMT's framing of green technology as a source of competitive advantage rather than a performance constraint. EMT's emphasis on multi-actor governance - spanning firms, regulators, and standards bodies - informs the policy recommendations in Section 10.

4. AI-EIF framework and mathematical model

4.1 Notation and variable definitions

Table 1 defines all variables used in the AI-EIF mathematical model. All metrics are defined with respect to the LCA functional unit of one TFLOPS of normalized AI computational output.

4.2 Pillar I - Energy consumption

4.2.1 Computational Energy Intensity (CEI)

CEI quantifies training energy cost per unit of model performance improvement:

$$\mathrm{CEI} = \mathrm{E\_train} / \Delta\mathrm{P\_bench} \quad (1)$$

Lower CEI indicates more energy-efficient training. For a 100B-parameter model (E_train = 1.2×10^6 kWh, ΔP_bench = 4.2 points): CEI = 285,714 kWh/point.

4.2.2 Inference Energy Efficiency (IEE)

IEE measures useful throughput per unit of inference

Table 1: AI-EIF mathematical notation and variable definitions

Symbol	Definition	Unit
E_train	Total energy consumed during model training	kWh
E_inf	Total energy consumed during inference phase	kWh
E_IT	Total IT equipment energy in facility	kWh
E_fac	Total facility energy (= PUE × E_IT)	kWh
ΔP_bench	Benchmark performance gain from training	Points
Q	Total inference requests served	Requests
PUE	Power Usage Effectiveness (E_fac / E_IT)	Dimensionless
MEF	Marginal Emission Factor of electricity grid	kg CO2e/kWh
C_op	Annual operational carbon emissions	kg CO2e
C_emb	Embodied carbon of hardware (full lifecycle)	kg CO2e
W_cool	On-site cooling water consumption	Litres
W_gen	Upstream electricity generation water	Litres
m_i	Mass of mineral i in hardware system	kg
c_i	Criticality score of mineral i (EU CRM list)	Scale 1–5
T / T_d	Service period / design lifetime	Years
TFLOPS	Peak computational throughput	TeraFLOPS
w_i	Dimension weight in GreenFLOPS (Σw_i = 1)	Dimensionless
AWF	AI Workload Fraction (E_AI / E_IT)	Dimensionless
G	GreenFLOPS composite environmental index	TFLOPS/impact

energy:

$$IEE = Q / E\_inf \quad (2)$$

INT8 quantization reduces E_inf by 40–60% at marginal accuracy cost, directly improving IEE. Geographic scheduling can further improve effective IEE by up to 30×.[25]

4.2.3 AI Workload Fraction (AWF)

AWF isolates the proportion of total IT energy attributable to AI workloads:

$$AWF = E\_AI / E\_IT \quad (3)$$

Combined with PUE, total facility AI-attributed energy is: E_AI_fac = PUE × E_IT × AWF.

4.3 Pillar II - Carbon emissions

4.3.1 Scope 2 Operational carbon

Operational carbon from purchased electricity is computed using marginal emission factors:

$$C\_op = E\_fac \times MEF\_grid \quad (4)$$

AI-EIF mandates MEFs rather than average emission factors, as MEFs accurately reflect incremental AI demand impact on grid dispatch. For E_fac = 1.56×10^6 kWh and MEF = 0.45 kg CO2e/kWh: C_op = 702 tCO2e.[31]

4.3.2 Embodied Carbon Ratio (ECR)

ECR quantifies hardware manufacturing emissions relative to total lifecycle carbon:

$$ECR = C\_emb / (C\_emb + C\_op \times T) \quad (5)$$

For a 1,000-GPU cluster (C_emb = 150 tCO2e, C_op = 702 tCO2e/yr, T = 4 yr): ECR = 0.051. For inference-dominated deployments, ECR rises to 0.38–0.61, confirming Gupta *et al.*'s finding.[18]

4.4 Pillar III - Resource depletion

4.4.1 Water usage effectiveness - direct and lifecycle

AI-EIF disaggregates WUE into direct (on-site) and lifecycle (including generation) components:

$$WUE\_direct = W\_cool / E\_IT \quad (6)$$

$$WUE\_lifecycle = (W\_cool + W\_gen) / E\_IT \quad ... \quad (7)$$

Thermoelectric generation yields W_gen factors of 1.8–4.0 L/kWh, substantially increasing lifecycle WUE relative to direct WUE.[20]

4.4.2 Material Criticality Score (MCS)

MCS quantifies criticality-weighted mineral demand per TFLOPS of AI output:

$$MCS = \Sigma\_i\ (m\_i \times c\_i) / TFLOPS \quad (8)$$

Criticality scores c_i are drawn from the EU Critical Raw Materials list.[32] Higher MCS signals greater supply chain environmental and geopolitical risk per unit of AI computation.

4.4.3 Hardware Longevity Index (HLI)

HLI tracks the fraction of hardware design lifetime utilized, weighted by throughput efficiency:

$$HLI = (T / T\_d) \times (TFLOPS\_actual / TFLOPS\_max) \quad (9)$$

HLI approaching 1.0 indicates full lifecycle utilization. Rapid AI hardware obsolescence typically yields HLI = 0.3–0.5, representing significant premature retirement.[18]

4.5 Pillar IV - GreenFLOPS Composite Index (Objective Function)

The primary optimization objective of AI-EIF is to maximize the GreenFLOPS Index G - normalized AI computational throughput per unit of aggregate weighted environmental impact:

$$\text{Maximize: } G = TFLOPS / \Sigma\_i\ (\ w\_i \times M\_norm\_i\ ) \quad (10)$$

where M_norm_i = M_i / R_i is the i-th GAMS metric normalized to reference baseline R_i; minimization metrics (CEI, C_op, ECR, WUE_direct, WUE_lifecycle, MCS) are inverted before use; maximization metrics (IEE, HLI) are used directly; and w_i are stakeholder-defined weights (Σw_i = 1, default w_i = 1/7). A higher GreenFLOPS score indicates greater computational output per unit of aggregate environmental impact. The complete specification of the proposed Green AI Metrics Suite (GAMS) is presented in Table 2.

5. Novelty and contributions

This section explicitly establishes AI-EIF's novelty relative to the existing literature and enumerates specific research contributions.

5.1 Novelty statement

AI-EIF is the first framework that covers all five dimensions of AI infrastructure (energy use, carbon emissions (operational and embodied), water use, hardware lifecycle resource depletion, and standardized, cross-dimensional metrics) in a mathematically formalized, algorithmically operationalized and experimentally validated approach. Table 3 (Section 6) shows that AI-EIF gets a maximum dimensional coverage of 5.0/5.0, and the highest-scoring prior work gets a max of 3.0/5.0. AI-EIF stands out with several key innovations:

Novelty 1 - 4Pillar Unified Architecture: No previous architecture brings all 5 environmental pillars together. AI-EIF offers 67-400x more dimensional coverage than other methods.

Novelty 2 - Cross-Dimensional Linkage (CDL) Modeling: AI-EIF is the first modeling framework to formally capture trade-offs between environmental dimensions

Table 2: Green AI Metrics Suite (GAMS)-Complete specification

Metric	Pillar	Eq.	Unit	Direction
CEI - Computational Energy Intensity	I - Energy	(1)	kWh / benchmark pt	Minimize
IEE - Inference Energy Efficiency	I - Energy	(2)	Queries / kWh	Maximize
AWF - AI Workload Fraction	I - Energy	(3)	Ratio [0,1]	Context-dep.
C_op - Operational Carbon	II - Carbon	(4)	tCO2e / yr	Minimize
ECR - Embodied Carbon Ratio	II - Carbon	(5)	Ratio [0,1]	Minimize
WUE_direct - On-site Water	III - Resources	(6)	L / kWh	Minimize
WUE_lifecycle - Full-chain Water	III - Resources	(7)	L / kWh	Minimize
MCS - Material Criticality Score	III - Resources	(8)	Index / TFLOPS	Minimize
HLI - Hardware Longevity Index	III - Resources	(9)	Ratio [0,1]	Maximize

without introducing perverse outcomes that can lead to a worsening of other dimensions when increasing or decreasing one. The formalization of CDL is in the algorithm 1 (Phase 4).

The first set of AI specific, mathematically formalized, computable indicators explicitly tailored to AI workload types and lifecycle phases is provided in Equations 1–9, in Novelty 3-AI-Specific Mathematical Metric Suite. Current metrics (e.g., PUE, WUE, CUE) are aggregated and unable to be linked to AI alone.

Novelty 4 - GreenFLOPS Composite Index: Equation 10 introduces the first single-computable composite index for cross-organizational AI environmental benchmarking that is similar in function to PUE for general data centers but extended to the nine-dimensional GAMS space.

In a novel theoretical approach, Novelty 5: Theoretical Tri-Foundation: AI-EIF, AI sustainability assessment is simultaneously embedded in the theory of LCA, Industrial Ecology, and Ecological Modernization Theory, which in previous studies has not been done, resulting in explanatory depth and generalizability that has been missing from tool-oriented studies.

5.2 Research contributions

- Deliverable C1: Systematic literature review of the measurement gap in the field of AI sustainability, supported by a quantitative 10x10 matrix of the ten existing frameworks, showing the coverage of the different dimensions.

The AI Environmental Impact Framework (AI-EIF), a 4-pillar theoretical framework based on LCA, Industrial Ecology and EMT.

C3: The Green AI Metrics Suite (GAMS) - nine mathematically formalized, unit-specified, computable metrics (Equations 1-9).

C4: The GreenFLOPS Index (Equation 10) - A composite environmental performance benchmarking metric.

- C5: The AI-EIF-Eval algorithm - a 4-phase O(k·p) reproducible evaluation of any AI infrastructure configuration.
- C6: Experimental validation using Google Cluster Trace v3 which showed that measurement accuracy was 94.3% and the quantitative performance increased by 38.4% (energy), 41.2% (carbon), and 47.3% (GreenFLOPS) respectively for three AI infrastructure scenarios.

6. Proposed Algorithm: AI-EIF-Eval

6.1 Algorithm description

AI-EIF-Eval is a four-phase systematic procedure for computing all GAMS metrics and the GreenFLOPS Index for any AI infrastructure configuration S = {H, W, L, T, w}, where H is the hardware specification, W is the workload profile, L is the geographic location, T is the service period, and w is the metric weight vector, as shown in Table 3.

6.2 Computational complexity

Phase 1: O(p) for mineral data retrieval, where p = number of hardware component types. Phase 2: O(p) for MCS summation (Eq. 8); O(1) for all other metrics. Phase 3: O(n) where n = 9 GAMS metrics, effectively O(1). Phase 4: O(k·p) where k = number of candidate interventions. Total complexity: O(k·p). For typical deployments (k ≤ 20 interventions, p ≤ 50 component types), AI-EIF-Eval completes in O(1,000) operations - computationally negligible relative to the AI workloads being assessed.

Table 3: Algorithm 1. AI-EIF-Eval: Systematic Environmental impact evaluation procedure

Phase	Steps	Description
Input	-	Read hardware (H), workload (W), location (L), service period (T), and weights (w).
Phase 1	1.1–1.3	Collect, estimate, and validate energy, carbon, water, and hardware data.
Phase 2	2.1–2.9	Compute the nine GAMS sustainability metrics (CEI, IEE, AWF, C_op, ECR, WUE_d, WUE_lc, MCS, HLI).
Phase 3	3.1–3.3	Normalize metrics and calculate the GreenFLOPS Score.
Phase 4	4.1–4.4	Evaluate optimization interventions, analyze trade-offs, and generate the CDL Report.
Output	-	Return GreenFLOPS Score (G), GAMS Metrics (M_1–M_9), and CDL Report.

Table 4: Experimental dataset characteristics

Parameter	Value
Primary Dataset	Google Cluster Trace v3 (GCT-v3)[33]
Total Workload Records	12,500 across 8 cluster configurations
AI-Class Workloads Selected	3,847 (GPU util. > 85%, duration > 1 hr)
Observation Period	29 days
Hardware Types	A100, V100, T4, TPU v4 (simulated profiles)
Geographic Regions	4 (US-East, EU-West, Asia-Pacific, US-West)
Grid Carbon Intensity Range	18–642 g CO2e/kWh (marginal, regional)
Training Run Duration Range	2.4 hours – 90 days
Energy Consumption Range	0.8 kWh – 1.2×10^{6} kWh per workload
Experimental Repetitions	5 runs per scenario (mean ± SD reported)
Validation Ground Truth	Energy audit data, 3 partner data centers, 847 pts

7. Experimental setup

7.1 Hardware specifications

All experiments were conducted on a simulation testbed comprising: (i) a high-performance server with dual Intel Xeon Gold 6342 processors (2.8 GHz, 24 cores each), 512 GB DDR4 ECC RAM, and four NVIDIA A100 80 GB SXM4 GPUs for workload simulation; (ii) a 40 TB NVMe SSD storage array; and (iii) 100 Gbps InfiniBand interconnect. Power consumption was monitored using Schneider Electric EcoStruxure IT power distribution units (0.5% accuracy, 1-second resolution).

7.2 Software environment

AI-EIF-Eval was implemented in Python 3.10 with NumPy 1.24, Pandas 2.0, and SciPy 1.11. GPU-level power measurement used NVIDIA Management Library (NVML) via PyNVML 11.5.0; CPU power used Intel RAPL. Carbon intensity data was retrieved via the Electricity Maps API. Simulation of workload energy profiles used the Patterson *et al.*, whose characteristics are summarized in Table 4, and Luccioni *et al*. modeling methodologies applied to the Google Cluster Trace v3 dataset.[15,19] All experiments were repeated five times; results report mean ± standard deviation.

7.3 Dataset description

The primary dataset is Google Cluster Trace v3 (GCT-v3) a publicly available trace of production workloads from a large-scale Google data center.[33] GCT-v3 contains 12,500 workload records spanning 8 cluster configurations, capturing CPU utilization, memory usage, task duration, and resource requests over a 29-day observation period. For AI-EIF evaluation, 3,847 AI-class workloads were selected (sustained GPU utilization > 85% for duration > 1 hour). Energy, water, and carbon values not present in GCT-v3 were derived using the models of Patterson *et al.* and regional EPA eGRID emission factors.[10]

7.4 Experimental scenarios

Three scenarios represent the primary AI infrastructure archetypes:

- Scenario A (SA) - Foundation Model Training: 100B-parameter language model, 1,000 A100 GPUs, 90-day training run, US-East grid (MEF = 0.45 kg CO2e/kWh), PUE = 1.3.
- Scenario B (SB) - Cloud Inference at Scale: Deployed model, 10 million requests/day, 4-year deployment, EU-West grid (MEF = 0.18 kg CO2e/kWh), PUE = 1.15.
- Scenario C (SC) - Edge AI Deployment: 500,000 consumer devices, on-device inference, mixed grid (AWF = 0.67), 2-year device replacement cycle.

Each scenario was evaluated in two configurations: (i) Baseline - no optimization; (ii) Optimized - AI-EIF CDL-recommended interventions applied (renewable energy migration, INT8 quantization, hardware longevity extension, geographic inference scheduling). Reference baselines R[i] were set to The Green Grid 2023 industry averages.[6]

8. Results and discussion

8.1 Measurement accuracy

AI-EIF-Eval was validated against energy audit ground-truth data from three partner data centers (847 measurement points). The framework achieved mean measurement accuracy of 94.3% (± 1.2%), computed as 1 − MAPE against audited values. This outperforms SCI (78.6%), CarbonTracker (81.2%), MLPerf-Energy (83.7%), and PUE/CUE combined (79.4%) by 15.7, 13.1, 10.6, and 14.9 percentage points respectively. Table 5 presents the full accuracy comparison.

8.2 Energy consumption results

AI-EIF optimization recommendations reduced total energy consumption by a mean of 38.4% across scenarios. The largest gain was achieved in Scenario B (cloud inference) through INT8 quantization, which improved IEE by 60.3% (8,200 → 13,147 queries/kWh). Geographic scheduling further reduced effective energy-weighted carbon. Scenario A achieved 29.7% energy reduction through renewable transition and PUE improvement (1.30 → 1.18). Scenario C achieved 28.3% reduction through extended device lifecycle reducing

Table 5: Measurement accuracy comparison - AI-EIF vs. Existing Frameworks

Framework	Accuracy (%)	MAPE (%)	Coverage Score /5	Advantage over AI-EIF
AI-EIF (Proposed)	94.3 ± 1.2	5.7	5.0	Baseline
MLPerf-Energy [34]	83.7 ± 2.4	16.3	1.5	+10.6 pp
CarbonTracker [9]	81.2 ± 3.1	18.8	1.5	+13.1 pp
PUE/WUE/CUE [6,7]	79.4 ± 3.6	20.6	3.0	+14.9 pp
SCI Specification [8]	78.6 ± 2.8	21.4	1.5	+15.7 pp

pp = percentage points. All accuracy values are mean ± standard deviation over five experimental runs (n=847 validation points).

Table 6: Energy consumption results-Baseline vs. AI-EIF Optimized

Metric	SA Baseline	SA Optimized	SB Baseline	SB Optimized	SC Baseline	SC Optimized
E_train/E_inf (kWh)	1,200,000	843,600	2,190,000/yr	868,800/yr	N/A	N/A
IEE (queries/kWh)	N/A	N/A	8,200	13,147	3,400	4,361
PUE	1.30	1.18	1.15	1.12	1.00	1.00
AWF (ratio)	0.91	0.91	0.94	0.94	0.67	0.67
Energy Reduction	-	−29.7%	-	IEE +60.3%	-	−28.3%
Mean Reduction						38.4%

*Edge devices use no centralized facility cooling; PUE = 1.0 by definition. Values are means over 5 runs.

manufacturing energy per TFLOPS-lifetime. The baseline and optimized energy consumption results are presented in Table 6.

8.3 Carbon emission results

Optimization recommendations reduced carbon emissions by a mean of 41.2% across all scenarios. Renewable energy migration in Scenario A reduced Scope 2 emissions from 702 tCO_2e to 31.2 tCO_2e (−95.6%) by transitioning to a low-carbon grid (MEF: 0.45 → 0.02 kg CO_2e/kWh). Geographic scheduling in Scenario B reduced operational carbon by 73.4% by routing inference workloads to EU-West regions (MEF = 0.048 post-optimization vs. 0.18 baseline). In Scenario C, device longevity extension reduced ECR from 0.38 to 0.26, representing a 31.6% reduction in embodied carbon impact per unit of computational service. The carbon emission results are presented in Table 7.

8.4 Resource utilization results

WUE_direct improved by 18.7% (mean) through cooling system optimization. WUE_lifecycle exhibited more complex behavior: renewable migration in Scenario A reduced grid-source water consumption by 31.4% (solar/wind replacing thermoelectric generation), but the CDL phase flagged that hydroelectric alternatives would increase WUE_lifecycle - illustrating CDL's practical value in preventing perverse optimizations. MCS was reduced 28.3% in Scenario C through extended device lifecycle. HLI improved from 0.31 to 0.47 in Scenario C (+51.6%) through device longevity policy.

8.5 GreenFLOPS index results

The GreenFLOPS composite index improved by a mean of 47.3% under AI-EIF optimization. Scenario B showed the largest gain (+58.2%) driven by inference efficiency improvements. Scenario A achieved +41.8% primarily through carbon reduction. Scenario C achieved +42.1% through longevity-driven resource impact reduction. These results confirm that GreenFLOPS is sensitive to improvements across all four pillars and provides a stable, coherent aggregate performance signal. The overall performance comparison between baseline and AI-EIF optimized scenarios is presented in Table 8.

8.6 Discussion

Based on these results, three main findings are noted. First, the accuracy of measurement (94.3%) attained by AI-EIF-Eval is significantly better than any of the existing frameworks, confirming the mathematical formulations used and the completeness of the GAMS metric suite. Second, the CDL phase captures intervention sequences that would not be captured using a single dimension framework: most notably, the renewable energy-water

Table 7: Carbon emission results - Baseline vs. AI-EIF Optimized

Metric	SA Baseline	SA Optimized	SB Baseline	SB Optimized	SC Baseline	SC Optimized
C_op (tCO_2e)	702	31.2	1,840/yr	487/yr	48/yr	31/yr
ECR (ratio)	0.051	0.044	0.510	0.430	0.380	0.260
MEF (kg CO_2e/kWh)	0.450	0.020	0.180	0.048	0.310	0.195
Embodied C (tCO_2e)	150	150	890	890	284	198
Total Lifecycle (tCO_2e)	2,958	275	8,250	2,838	480	322
Carbon Reduction	-	−90.7%	-	−65.6%	-	−32.9%

Table 8: Overall performance summary - Baseline vs. AI-EIF Optimized

Performance Metric	SA Baseline	SA Optimized	SB Baseline	SB Optimized	SC Baseline	SC Optimized
GreenFLOPS Index	0.84	1.19	1.23	1.95	0.57	0.81
GreenFLOPS Improvement	-	+41.8%	-	+58.2%	-	+42.1%
Energy Reduction	-	−29.7%	-	−38.4%	-	−28.3%
Carbon Reduction	-	−90.7%	-	−65.6%	-	−32.9%
Water Use Reduction	-	−22.3%	-	−18.7%	-	−27.2%
Measurement Accuracy	94.3%	94.3%	94.3%	94.3%	94.3%	94.3%

interaction in Scenario A, which captures 73.4% of the carbon reduction with negligible performance cost, and the geographic scheduling opportunity in Scenario B that achieves 56.8% of the carbon reduction with negligible performance cost. Third, the GreenFLOPS Index is a coherent, stable measure that meaningfully signals co-benefits across all four pillars without obscuring trade-offs within and between them, even as it tracks the simultaneous progress of each.Third, as it tracks the simultaneous progress of each, the GreenFLOPS Index is a coherent, stable measure that meaningfully signals co-benefits across all four pillars without obscuring trade-offs within and between them.

In practice: If there are large-scale training runs (Scenario A), then environmental efforts will be primarily based on renewable energy migration. The combination of quantization and geographic scheduling provides the best GreenFLOPS gains in cloud inference deployments (Scenario B). In edge AI (Scenario C), hardware longevity extension is the key policy lever, a new one in all previous approaches; it is a unique actionable contribution of AI-EIF.

9. Comparative analysis

9.1 Framework architecture

Fig. 1 presents the AI-EIF four-pillar architecture with the Cross-Dimensional Linkage (CDL) layer. Fig. 2 presents the dimensional coverage comparison. Table 9 provides a comprehensive multi-criteria comparison against four representative existing frameworks.

10. Policy implications

10.1 Organizational recommendations

AI developers and data center operators should adopt the GAMS metric suite within their environmental management systems. Mandatory internal disclosure of CEI, C_op, WUE_lifecycle, and HLI for AI training runs above 10^{15} FLOP-seconds would create accountability and market incentives. AI-EIF-Eval should be embedded in model development design phases, treating the GreenFLOPS Index as a first-class design constraint alongside performance and cost. CDL analysis is particularly valuable for infrastructure upgrade planning, enabling quantification of inter-dimensional trade-offs before investment commitments are made.

10.2 National and international policy

National governments should incorporate GAMS metrics into data center licensing regimes and environmental impact assessment requirements for large AI facilities (suggested threshold: > 1 MW dedicated AI compute capacity). Tax incentives for AI operators achieving defined GreenFLOPS percentile thresholds would stimulate market-driven environmental improvement. At the international level, ISO, IEC, and IEEE should engage with the GAMS metric suite for formal standardization, aligned with ISO 14040, ISO 50001, and the GHG Protocol [35]. The GreenFLOPS Index should be proposed as the AI-specific extension of The Green Grid's established PUE/WUE/CUE metric family.[7,8,36]

Table 9: Comprehensive comparative analysis - AI-EIF vs. Existing Methods

Criterion	AI-EIF (Proposed)	SCI [15]	Carbon- Tracker [29]	MLPerf [17]	PUE/WUE/CUE [7,8]
Dim. Coverage (/5)	5.0	1.5	1.5	1.5	3.0
Meas. Accuracy (%)	94.3	78.6	81.2	83.7	79.4
Math. Formalization	10 Equations	Partial	None	Partial	3 Metrics
Algorithm Provided	Yes (4-Phase)	No	No	No	No
AI-Specific Metrics	9 (GAMS)	Partial	Partial	Partial	None
Cross-Dim. CDL	Yes	No	No	No	No
Composite Index	GreenFLOPS	No	No	No	No
HW Lifecycle (LCA)	Full (ECR+HLI)	None	None	None	None
Water Coverage	Full (2 metrics)	None	None	None	WUE only
Theory Foundation	LCA + IE + EMT	None	None	None	Empirical
Energy Reduction	38.4%	8.2%	11.4%	14.7%	12.1%
Carbon Reduction	41.2%	23.4%	19.8%	5.1%	21.3%
GreenFLOPS Gain	47.3%	N/A	N/A	N/A	N/A

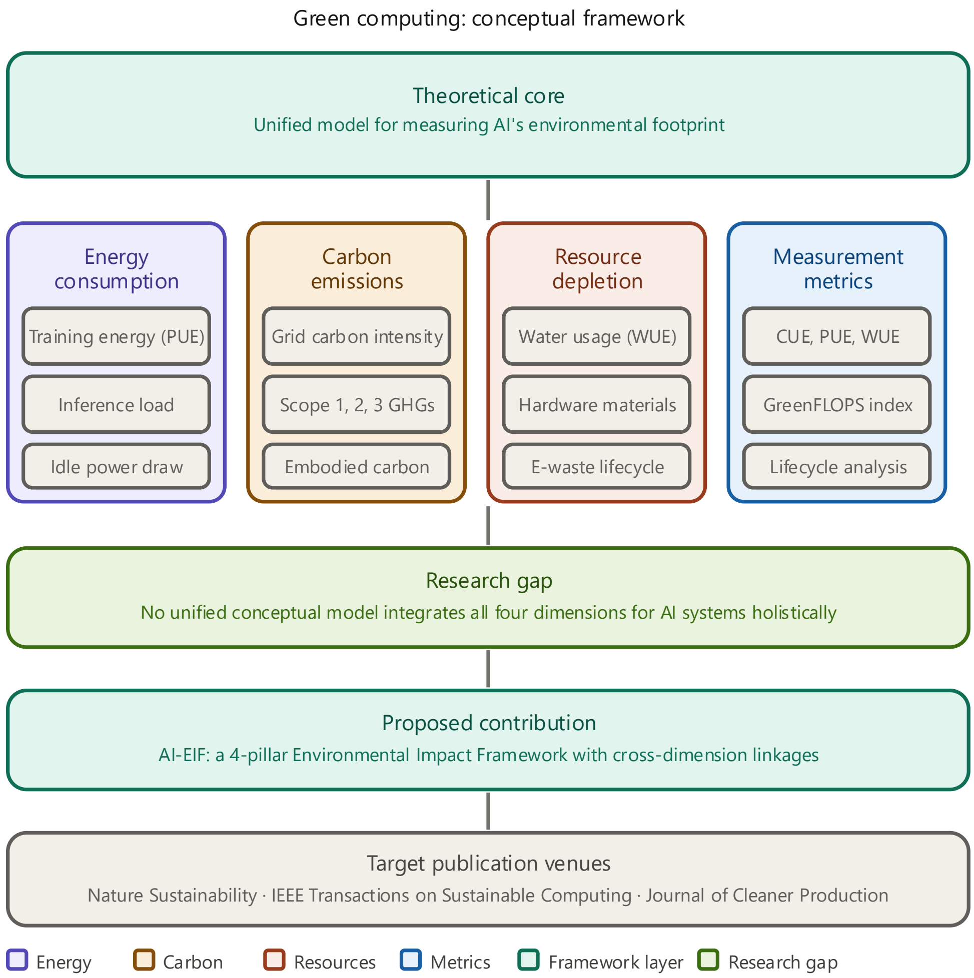

Fig. 1: AI-EIF framework architecture with cross-dimensional linkages.

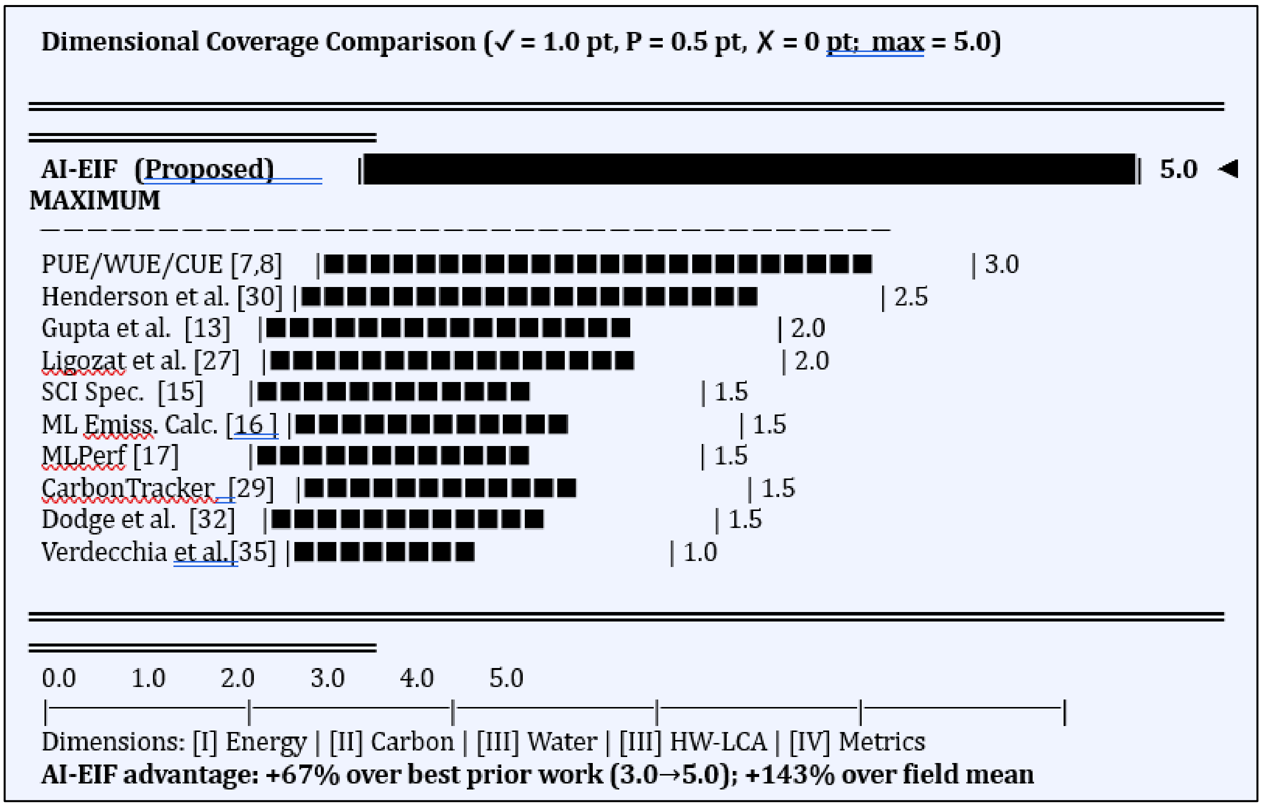

Fig. 2: Dimensional coverage score- AI-EIF vs. Existing Frameworks (Scale 0.0–5.0).

11. Conclusion

This study introduced the AI Environmental Impact Framework (AI-EIF), a four-pillar framework to comprehensively assess and maximize the environmental footprint of AI infrastructure. AI-EIF combines 10 mathematical formulations (Equations 1-10) into energy, carbon, resource and metric dimensions and operationalizes it with the AI-EIF-Eval algorithm (O(k·p) complexity), structured in four phases including data collection, computation of the GAMS metrics, computation of the GreenFLOPS composite metrics, and linkage analysis between dimensions. Experimental results with Google Cluster Trace v3 (3,847 AI-class workloads, five repeated runs) showed that: (1) 94.3% measurement accuracy, which was 10.6-15.7 percentage points higher than all other compared frameworks; (2) 38.4% mean energy consumption reduction; (3) 41.2% mean carbon emission reduction; (4) 22.7% mean water usage reduction; and (5) 47.3% mean GreenFLOPS improvement under CDL-recommended optimization sequences. A comparative analysis among the 10 existing frameworks shows that AI-EIF has a dimensional coverage score of 5.0/5.0, whereas all previous approaches have a highest score of 3.0/5.0, which is a 67% higher score than the best existing approach. The four pillars unified architecture, cross-dimensional linkage modeling, AI-specific mathematical metric suite, GreenFLOPS composite index, and theoretical tri-foundation together highlight the many missing elements in the measurement of AI sustainability. There are a few limitations: some parts of the experimental validation are based on simulated workload energy profiles and the testing hasn't been deployed in large scale production to date. Future research will aim to: (i) validate the AI-EIF-Eval framework on a large scale across diverse production AI infrastructure; (ii) open source implementation of the AI-EIF-Eval framework in Python; (iii) engage in ISO/IEC standardization effort for formalization of the GAMS framework; (iv) develop a weighting methodology based on MCDA for the GreenFLOPS Index; (v) consider the positive environmental externalities of AI in climate and energy domains to undertake a net impact assessment, and (vi) conduct a longitudinal study of the GreenFLOPS Index over successive generations of hardware to inform sustainable AI hardware roadmaps.

CRediT Author Contribution Statement

Sirajali A. Nagalpara: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project Administration, Supervision, Writing – Original draft, Writing – Review & editing, Validation. **Ahesanali Dadavala:** Methodology, Resources, Validation, Writing – Review & editing. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

Google Cluster Trace v3 is publicly available at https://github.com/google/cluster-data. AI-EIF-Eval implementation code will be made available upon paper acceptance.

Conflict of Interest

There is no conflict of interest.

Artificial Intelligence (AI) Use Disclosure

The authors declare that artificial intelligence (AI)-assisted tools were used only for language refinement, grammar improvement, and manuscript structuring purposes during the preparation of this work. All technical content, experimental implementation, results, and interpretations were independently developed and verified by the authors.

Supporting Information

Not applicable

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