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Digital planetary burden index: A framework for situating digital infrastructure within planetary boundaries

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Abstract: Digital infrastructure is central to modern life, yet its environmental burden remains underexamined, particularly in the context of planetary boundaries. This study introduces the Digital Planetary Burden Index (DPBI), an integrative framework designed to quantify the ecological impacts of digital systems across five key dimensions: energy consumption, material intensity, water usage, greenhouse gas emissions, and e-waste generation. These indicators are mapped onto the planetary boundaries framework to provide a science-based structure for assessing the sustainability of digital operations. The DPBI is empirically tested through a case study of a Google data center to reveal the often-overlooked planetary stress associated with digital infrastructure. Despite its virtual nature, the data center demonstrates substantial environmental impacts across multiple biophysical domains, underscoring the discrepancy between digital convenience and ecological cost. The DPBI fills a critical gap in sustainability science by linking digital infrastructure with global ecological thresholds. It supports enhanced environmental accountability in the tech sector and provides a transparent, replicable model for evaluating digital sustainability. By situating digital systems within the Earth's finite limits, the DPBI offers a strategic tool for evidence-based governance and climate-aligned innovation, contributing to more sustainable digital development pathways in the Anthropocene.

Keywords: Planetary boundaries, Environmental impact assessment, Google data center, Ecological overshoot

1. Introduction

The digital economy is growing at an extremely high pace and it has been revolutionizing the way people work, communicate, and consume resources in society. Underneath that virtual surface is a rapidly expanding array of data centers, cloud infrastructure and hardware systems, all of which take an outsize and growing environmental toll on the planet. This ever-increasing demand is occurring in the absence of a coherent scientific, regulatory and popular account of the environmental consequences of digital infrastructure. The narrow focus on energy or carbon in most sustainability assessments often overlooks many other biophysical dimensions (water or minerals consumption, electronic waste) [1]. This presents a substantial blind spot in efforts to align digital transformation with global sustainability goals [2]. Concurrently, the concept of planetary boundaries has been established as a new science-based reaction to inventory humanity's safe operating space. However, digital infrastructure has not been systematically analyzed within this framework, resulting in a conceptual and methodological gap. Current methods do not consider

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the complete range of environmental impacts associated with the life and use of digital technology. To fill this gap, in this paper we proposed the Digital Planetary Burden Index (DPBI), a new model for estimating the impact of digital infrastructures on the environment within five interconnected areas: energy, materials, water, emissions and e-waste. Each component has been validated in the scientific literature and corresponds to a related planetary boundary issue.

The framework is operationalized through a real-world case study of a Google data center, a globally recognized node of digital infrastructure. This example demonstrates both the methodological applicability of the DPBI and the urgent need for systemic accountability in the digital sector. Google provides clear, interpretable data that illustrates how digital systems, though intangible to users, exert concrete and measurable pressures on the Earth's life-support systems. By advancing the integration of digital sustainability into planetary science, the DPBI not only offers a new evaluative tool, but also lays the groundwork for future policy interventions and research at the intersection of technology and environmental stewardship.

Although sustainability assessment tools such as the Life Cycle Assessment (LCA) or the Environmental Footprint Method provide important insights, they primarily measure environmental impacts in relative or component-specific terms. These tools often lack a science-based boundary reference that distinguishes between operations that are efficient and those that are truly sustainable. The Digital Planetary Burden Index (DPBI) builds upon this tradition and extends it by explicitly situating the impacts of digital infrastructure within the framework of planetary boundaries. The DPBI does not replace them, but rather complements them by providing boundary-normalized, multidimensional and geographically contextualized performance indicators to show whether digital systems are within safe ecological limits.

2. Literature review

The recent growth in digital infrastructures such as data centers, cloud computing platforms, AI models, and blockchain systems brings many insights for future generations but has also raised a number of global environmental challenges. Data center power consumption alone is said to account for approximately 1–2% of the world's electricity, a number predicted to increase dramatically given the continued popularity of AI and IoT applications [3, 4]. According to Jones et al. [5], the world data center industry emitted more than 200 megatons of CO_2 each year in the late 2010s, with an increasing portion from increasingly computer-intensive machine learning models. More recent studies have underscored the accelerating carbon footprint of ICT. For example, Aslan et al. [6] quantified the rising global electricity use of data centers, while Belkhir and Elmeligi [7] provided an early estimate of ICT's share of global greenhouse gas emissions, projecting it could rise to 14% by 2040. Strubell et al. [8] demonstrated the high energy and emissions costs of training natural language processing models, and Patterson et al. [9] extended this analysis to large-scale AI systems, highlighting both the scale of the challenge and the potential of more efficient architectures.

Recent analyses have tried to contextualize these impacts in terms of energy efficiency and carbon neutrality. For example, Cao et al. [10] proposed a roadmap to carbon-neutral data centers by integrating renewable energy, energy storage, and hardware optimization. Similarly, Katal et al. [11] highlighted the effectiveness of power usage effectiveness (PUE) metrics in tracking energy efficiency at the facility levels. However, such approaches often focus on operational-level optimizations, rather than systemic environmental sustainability. Although these contributions are valuable, they generally pay attention to sustainability in terms of carbon reduction only, ignoring other environmental externalities such as water consumption, the transformation of land or mineral exhaustion. Furthermore, they do not address the limits of the Earth system within which infrastructure should function.

Another critical but underexamined impact area of digital infrastructure is freshwater consumption. Data centers rely heavily on water-based cooling systems, particularly in arid and semi-arid regions where water is both environmentally and socially scarce [12]. For instance, Google's 2023 Environmental Report discloses the consumption of over 5 billion gallons of water for data center cooling in a single year, often in regions like Arizona or Oregon that experience seasonal water stress [13]. Research has emerged around water usage effectiveness (WUE) as a parallel metric to PUE. While WUE provides insight into operational efficiency, it does not integrate context-specific water scarcity, nor does it relate water consumption to safe planetary thresholds. Moreover, most assessments are siloed by environmental vectors and do not acknowledge the compound interactions between water, energy, and climate feedbacks [14, 15]. Recent research emphasizes the water stress implications of digital infrastructure. Mytton [16] analyzed water use in UK data centers, calling for transparent disclosure and the integration of water risk metrics. Parkinson et al. [17] further demonstrated the trade-offs between water- and energy-intensive cooling methods, particularly in hot-arid climates, underscoring the systemic nature of water–energy tensions in digital infrastructure [15].

Digital infrastructure also imposes a significant material footprint, including the use of rare earth elements (REEs), critical minerals such as cobalt, and large volumes of semiconductors [18]. These materials are not only energy-intensive to extract and refine, but also their disposal contributes to hazardous e-waste streams [19]. Song et al. [20] highlighted the geopolitical and ecological risks associated with rare earth element and cobalt supply chains, while Forti et al. [21] provided a global assessment of e-waste generation, identifying ICT equipment as one of the fastest-growing waste categories. These studies reinforce the urgent need to situate material intensity and waste generation within the planetary boundary for novel entities. Life Cycle Assessments (LCAs) of IT equipment such as servers, storage units, and cooling systems often quantify embedded material and energy use. However, these studies tend to focus on individual components rather than the aggregated systemic burden [22]. More importantly, they do not anchor material throughput within the concept of "novel entities" as defined in the planetary boundaries' framework [23, 24]. This highlights a key gap: while material footprints are well-documented in isolation, they remain detached from a cumulative or boundary-aware interpretation of environmental sustainability.

Mainstream ESG (Environmental, Social, Governance) metrics and corporate reporting frameworks, such as CDP, GRI, and SASB, have promoted transparency among major tech firms. For example, Microsoft, Amazon, and Google routinely report Scope 1–3 emissions, energy mix, and selected sustainability KPIs. Similarly, green data center certifications (e.g., LEED, BREEAM) integrate sustainability features in construction and energy use. However, these frameworks fall short in several ways. First, they lack coherence across domains: water, land, carbon, and materials are assessed separately. Second, they fail to benchmark performance against planetary thresholds, instead focusing on year-over-year improvement or peer comparison [25]. Third, they do not capture the geospatial context of impacts—such as whether water is withdrawn in a highly stressed basin or land is developed in a biodiversity hotspot. In this regard, ESG assessments are best seen as compliance and disclosure tools, not instruments for boundary-aware sustainability governance.

The planetary boundaries framework, first proposed by Rockström et al. [26] and refined by Steffen et al. [27], defines a "safe operating space" for humanity across nine critical Earth system processes. These include climate change, biosphere integrity, land-system change, freshwater use, biogeochemical flows, ocean acidification, atmospheric aerosol loading, stratospheric ozone depletion, and the introduction of novel entities. While the planetary boundaries framework has gained prominence in climate science and environmental economics, its integration into sector-specific environmental assessments remains uncommon. For example, O'Neill et al. [28] attempted to downscale planetary boundaries for national footprints, while Häyhä et al. [29] explored boundary applications in agriculture. However, no known framework has comprehensively applied planetary boundaries to the ICT or digital infrastructure sector.

Several attempts had been made to conceptualize ICT within planetary thinking. For instance, Lange et al. [30] examined the rebound effects of digitalization, arguing that ICT may exacerbate environmental stress unless absolute limits are imposed. Similarly, Ebert et al. [31] called for AI-specific climate governance, especially given the carbon and energy intensities of large language models and high-performance computing. Yet, these studies stop short of providing an operational, index-based approach that integrates multidimensional impacts with planetary thresholds.

Table 1 highlights the distinctive contribution of the DPBI compared with existing approaches. While LCA and the Environmental Footprint Method provide valuable insights into product-level or multi-indicator sustainability, they generally lack boundary-based normalization and geospatial sensitivity. In contrast, DPBI situates digital infrastructure explicitly within planetary boundaries, integrates multiple environmental dimensions into a single index, and introduces geo-contextual adjustments. This makes DPBI more suitable for assessing whether digital systems operate within safe ecological limits, rather than simply achieving incremental efficiency gains.

Despite these important contributions, most existing studies remain siloed by environmental vector and do not fully integrate impacts across planetary dimensions. As noted by Teng et al. [32], digitalization may exacerbate ecological pressures without absolute limits, and they argue for AI-specific governance that explicitly accounts for planetary system stress. These insights highlight the need for a multidimensional, boundary-aware framework such as DPBI. The key weakness in the existing literature lies in the fragmentation of environmental indicators. While energy, emissions, and water are increasingly

Table 1. Comparison of existing sustainability assessment frameworks (LCA, Environmental Footprint Method) with the proposed Digital Planetary Burden Index (DPBI).

Framework	Scope	Normalization	Integration	Geo-contextual sensitivity	Policy relevance
LCA	Product/process lifecycle	Relative (per unit)	Component-specific	Limited	Informal benchmarking
Environmental Footprint Method	Multi-indicator sustainability	Relative, not boundary-linked	Harmonized but siloed	Limited	EU compliance focus
DPBI (this study)	Digital infrastructure (facility to portfolio)	Boundary-normalized (planetary thresholds)	Integrated (carbon, water, land, materials, energy)	Explicit (regional + workload-sensitive)	Policy-oriented (safe–caution–overshoot zones)

measured at facility or corporate levels, they are rarely combined in a meaningful way. This creates a siloed view of sustainability, where improvements in one domain (e.g., carbon) may mask regressions in others (e.g., water or land). Furthermore, normalization of impacts is typically absent. For instance, reporting that a data center uses 1 billion liters of water annually is informative, but meaningless without contextualization—Is this within a sustainable threshold? Is it being withdrawn from a water-scarce basin? The absence of benchmarking against ecological limits renders most reports descriptive rather than diagnostic. Tools such as the Environmental Footprint Method attempt to harmonize LCA indicators but do not embed planetary boundaries. In the same way, SBTi (Science-Based Targets initiative) focuses on GHGs but lacks a multi-criteria scope. This failure in systems integration paves the way for the Digital Planetary Burden Index (DPBI), which aims to operationalize sustainability indicators in line with planetary boundaries and geospatial sensitivity [33].

Comparing DPBI with existing sustainability frameworks

Despite the progress of methods such as LCA and the Environmental Footprint Method, their application to digital infrastructure remains constrained. LCA typically evaluates cradle-to-grave impacts of specific products or processes but does not explicitly benchmark results against global or regional planetary thresholds. The Environmental Footprint Method harmonizes multiple indicators but lacks integration with geospatial sensitivity and workload differentiation. In contrast, the DPBI extends these approaches in three critical ways: (a) it normalizes impacts against planetary boundaries to assess absolute sustainability, (b) it integrates five environmental dimensions into a composite score to capture trade-offs, and (c) it incorporates regional and functional sensitivity, ensuring results are meaningful across locations and service types.

This work has identified a key shortcoming in existing environmental assessment tools applicable to digital infrastructure. There are many individual metrics available that allow us to assess the impact (for example, carbon emitted or water used), but no holistic framework systematically aggregates these different burdens together into a notion of being within the safe space boundaries for the planet [34]. The current framework does not normalize environmental impacts with respect to planetary boundary limits, so we cannot evaluate in absolute terms whether any facility is being operated sustainably. Furthermore, existing evaluations are usually not sensitive to geospatial inhomogeneities or workload specificities; they typically do not consider that the same infrastructure can lead to very different environmental impacts depending on its location and the computations it supports. The DPBI fills these gaps by defining a multi-dimensional, boundary-aware sustainability framework. It integrates carbon, water, land, and material footprints into a single index base, sets them against planetary boundaries to provide context, and presents a new facility-level benchmark that is globally comparable but also sensitive to local conditions. In this way, the DPBI focuses not on improvement towards the margins but on systemic subsistence within Earth's ecological boundaries, much exceeding the scope of existing literature.

3. Conceptual framework

This section addresses the scattered and narrowly focused practices found in the literature by presenting the DPBI, a holistic sustainability framework for evaluating the environmental performance of digital infrastructure based on planetary boundaries. The DPBI aims to provide a concrete, evidence-based, and scalable approach to measuring the total environmental burden added to a specific site by digital architecture (such as datacenters), for purpose of incentivizing them toward a convergence with humankind's safe operating space on Earth. The formation of the DPBI is based on three conceptual paradigms: planetary boundary alignment, multi-dimensional burden integration, and geo-contextual sensitivity. These principles define what the index is and what it may be used for as a benchmark, reporter or policy alignment mechanism. At its core, the DPBI framework assesses five interrelated environmental dimensions: carbon emissions, freshwater use, land footprint, material intensity, and energy source burden. Each of these dimensions reflects a tangible environmental externality associated with the design, operation, and scaling of digital infrastructure. Rather than treating these impacts as independent or loosely related, the DPBI conceptualizes them as converging stressors that must be managed together to avoid overshooting planetary boundaries. For instance, the decision to increase server cooling efficiency using evaporative water systems may reduce electricity consumption but simultaneously escalate freshwater stress particularly in arid regions. Similarly, transitioning to renewable energy sources can reduce carbon intensity but may increase land and mineral footprints due to solar, wind, and battery infrastructure. These trade-offs underscore the necessity of an integrated model (Figure 1). Each environmental dimension in the DPBI is normalized against a science-based threshold derived from global planetary boundary estimates. For example, carbon intensity is assessed relative to per capita carbon budgets consistent with limiting warming to 1.5°C; water usage is contextualized using basin-specific stress thresholds, while land and material burdens are referenced against available global biocapacity and extraction limits. This normalization process converts disparate units (e.g., kg CO_2e, liters of water, square meters of land) into dimensionless scores that reflect the degree to which each impact remains within or exceeds safe operating limits. A normalized value below 1.0 indicates that the facility's activity is within the safe zone for that dimension, while values above 1.0 denote transgression of planetary thresholds.

Once normalized, these values are aggregated using a weighted function to yield a single DPBI score. The weighting scheme can be adapted to reflect context-specific priorities, such as placing greater weight on water use in drought-prone regions or assigning higher importance to irreversible impacts such as material depletion. However, in the standard configuration, equal weighting is applied to emphasize that transgressing any planetary boundary is problematic and cannot be fully offset by performance in other areas. The aggregated score thus offers a scalar representation of total planetary burden, enabling straightforward interpretation and comparison across facilities, regions, and timeframes. More importantly, the DPBI does not merely provide a numerical score but also categorizes performance into three interpretive zones. Scores below 1.0 indicate operation within planetary boundaries and are classified as "safe". Scores between 1.0 and 1.5 indicate a zone of "caution", in which environmental thresholds are being approached or moderately exceeded. Scores above 1.5 reflect significant overshoots and signal the need for urgent mitigation. These interpretive ranges provide intuitive guidance for decision-makers, sustainability officers, and regulatory agencies (Figure 1).

Another critical feature of the DPBI is its incorporation of geo-contextual sensitivity. Unlike global averages or sectoral benchmarks, the index accounts for site-specific characteristics, such as local water stress, grid carbon intensity, and regional land-use constraints. For example, the same design of data center may receive different DPBI scores depending on whether it is in Oregon, where water is relatively abundant, or in Arizona, where withdrawals may stress already overdrawn aquifers. Similarly, a facility powered predominantly by coal-based electricity will have a significantly higher carbon burden than the one relying on hydroelectric or solar energy, even if their operational efficiencies are similar.

The framework also adjusts for workload type and density, recognizing that not all digital services impose equal environmental loads. High-performance computing (HPC) clusters used for artificial intelligence training typically consume more energy and generate greater emissions per unit of time than edge servers handling local data routing. The index introduces a standardized workload denominator—such as emissions or water use per teraflop-hour or per petabyte transmitted—to enable functional comparisons across divergent services and operational scales. This workload-sensitive calibration ensures that the index reflects not only the physical footprint of infrastructure, but also the intensity and efficiency of digital outputs.

In practice, the DPBI can be applied at multiple levels, from individual data centers and server rooms to cloud computing zones and even entire corporate ICT portfolios. The modular nature of the index enables adaptation to data availability, organizational capacity, and regulatory expectations. It can be calculated using publicly available sustainability reports, grid mix data, and facility-level resource consumption metrics. More advanced implementations may involve real-time monitoring, satellite-derived water stress indices, or LCA-based material

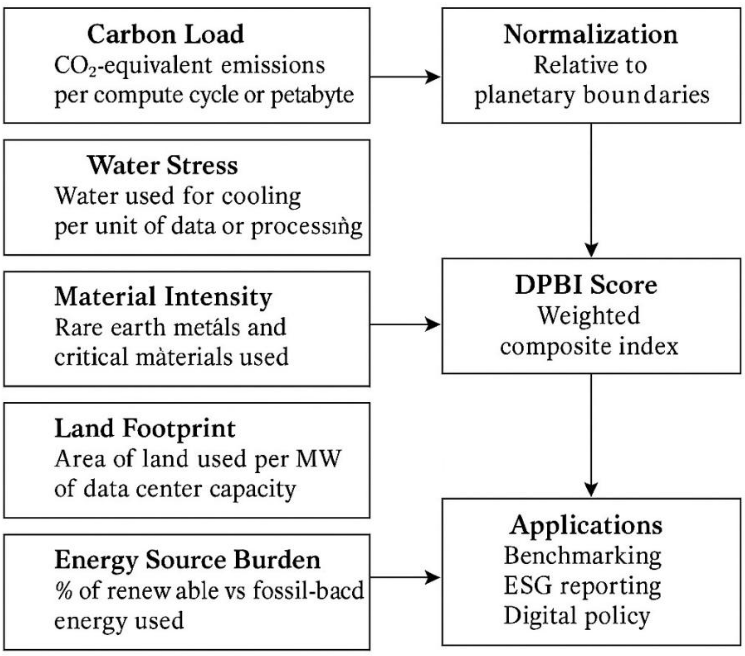

Figure 1. DPBI Framework and its interrelated dimensions

flow accounting. Therefore, the framework offers a novel operational approach that redefines how sustainability is measured and governed in the digital age. By integrating multi-domain environmental impacts, normalizing them against planetary boundaries, and contextualizing them in geographic and functional terms, the DPBI provides a rigorous and actionable tool for assessing whether digital infrastructure is truly sustainable, not just more efficient. It addresses the urgent need for sector-specific tools that move beyond compliance metrics and toward a science-based, planetary-aware sustainability paradigm. In the following section, the DPBI is applied to a real-world case study to illustrate its implementation, interpretability, and policy relevance.

4. Methodology

This study employs a mixed-methods approach to develop, apply, and validate the Digital Planetary Burden Index (DPBI), a novel environmental assessment framework that quantifies the environmental burden of digital infrastructure in relation to planetary boundaries. In selecting data inputs, we adopted a strict hierarchy, prioritizing peer-reviewed literature and official environmental datasets (e.g., IPCC, UNEP, and Ecoinvent). Corporate sustainability disclosures and credible public filings were used only as supplementary sources, while journalistic accounts were cross-checked and incorporated solely when independently verified. To ensure academic rigour, non-peer-reviewed sources such as public filings and investigative reports were used only when triangulated with at least one independent dataset (e.g., regulatory filings, LCA databases, or government statistics). Screening criteria emphasized transparency of methodology, institutional credibility, and traceability of reported figures. Peer-reviewed life cycle assessment (LCA) studies were prioritized, and when such studies were cited, they are now explicitly marked in the references list to distinguish them from secondary sources. This process strengthens the validity and reproducibility of the data foundation.

This ensures that the case study is grounded in transparent and scientifically robust data. The methodology comprises three key components: (a) conceptual framework construction, (b) index formulation using quantitative indicators, and (c) empirical application through a real-world case study of a high-capacity data center. The methodology was designed to ensure transparency, comparability, and scalability of results across geographies and infrastructure types. DPBI is grounded in the planetary boundaries framework [28, 36], which identifies nine Earth system processes critical to maintaining a stable planetary environment. For operational clarity and data availability, this study focuses on five environmental dimensions relevant to digital infrastructure: carbon emissions, freshwater use, land-system change, material throughput, and energy source burden. Each dimension corresponds to a boundary of concern: climate change, freshwater use, biosphere integrity, and novel entities (materials and waste).

4.1 Linking DPBI dimensions to planetary boundaries

The five dimensions of DPBI are explicitly grounded in the framework of planetary boundaries, with each dimension linked to a boundary through specific mechanisms. Carbon emissions contribute to climate change by increasing radiative forcing and pushing the global carbon budget toward overshoot. Freshwater use relates to the freshwater boundary, as large withdrawals disrupt basin hydrology and ecosystems, and even moderate use in stressed basins can exceed resilience thresholds. Land occupation connects to land-system change and biosphere integrity, since facility footprints can drive habitat conversion and biodiversity loss, and their cumulative expansion adds to global land pressures. Material intensity aligns with the novel entities boundary, as the extraction of rare earth elements, cobalt, and other critical minerals generates toxic by-products, while disposal adds to e-waste streams that release persistent pollutants capable of destabilizing Earth system processes. Energy source burden influences both climate change and biogeochemical flows, with fossil-based electricity increasing carbon and nitrogen emissions and hydropower altering water cycles and nutrient balances. By clarifying these associations, DPBI moves beyond conceptual framing to a boundary-anchored framework capable of diagnosing how digital infrastructures interact with planetary thresholds.

These dimensions are selected based on an extensive review of environmental sustainability literature and digital infrastructure impact assessments. The selection reflects both ecological relevance and data feasibility, ensuring that the index is empirically grounded and adaptable to future dimensions such as biodiversity or land-system change. The DPBI score is computed using a weighted normalization approach that allows comparison across dimensions with different units. The core equation is:

$$DPBI = \sum_{i=1}^{n} w_i \cdot \left(\frac{E_i}{B_i}\right) \tag{1}$$

Where:

E_i = measured environmental pressure from the digital system for dimension i (e.g., kWh of electricity consumed, metric tons of CO_2 emitted, liters of water withdrawn, kilograms of materials consumed, hectares of land occupied). B_i = safe operating boundary or allocated planetary budget for that dimension (global or regionally downscaled). w_i = weight assigned to dimension i, representing the relative contribution of that dimension to the overall DPBI score. $\left(\frac{E_i}{B_i}\right)$ = burden ratio, indicating the extent to which the

Table 2. Linking DPBI dimensions to planetary boundaries

DPBI dimension	Corresponding planetary boundary	Mechanism of impact
Carbon emissions	Climate change	Increases greenhouse gases, raises radiative forcing, contributes to overshooting the global carbon budget.
Freshwater use	Freshwater boundary	Large withdrawals disrupt basin hydrology and ecosystems; stressed basins exceed resilience thresholds.
Land occupation	Land-system change / biosphere integrity	Facility footprints drive habitat conversion and biodiversity loss; cumulative land demand adds global pressure.
Material intensity	Novel entities	Extraction of rare earths and cobalt generates toxic by-products; e-waste streams release persistent pollutants.
Energy source burden	Climate change / Biogeochemical flows	Fossil-based power increases carbon and nitrogen emissions; hydropower alters water cycles and nutrient flows.

activity approaches or exceeds planetary safety thresholds.

To enhance flexibility, we conducted a supplementary sensitivity analysis to test alternative weighting schemes. Ecological sensitivity weighting emphasized water in arid contexts and carbon in high-emission grids, while reversibility weighting prioritized long-term pressures such as biodiversity loss and material depletion. Results showed that although the absolute DPBI score shifted slightly (±0.07), the relative hotspots of carbon emissions and freshwater use remained consistent. This robustness is further illustrated in Table 3.

Thresholds (B_i) are derived from established scientific sources. For example:

- The global carbon budget is based on IPCC pathways consistent with limiting warming to 1.5°C.
- Freshwater boundaries are benchmarked against basin-level stress thresholds.
- Material boundaries are aligned with UNEP estimates of safe throughput and circularity targets.
- Energy source burdens are adjusted according to grid carbon intensity and renewable penetration.

Each environmental pressure was normalized against its corresponding boundary, with boundary values adjusted to reflect proportional allocation (e.g., per petabyte share of global digital activity). The facility's DPBI score was then calculated using the equation above and compared across dimensions. This case study serves as both a validation exercise and a prototype for broader DPBI applications. It demonstrates the model's ability to integrate heterogeneous data, reveal dimension-specific hotspots, and highlights where digital infrastructure is outpacing environmental thresholds.

4.2 Indicator quantification and normalization

To improve reproducibility and clarity, each step of the quantification and normalization process is detailed below, with explicit formulas and boundary allocations. Each DPBI dimension was quantified using consistent boundaries, scopes, and formulas to ensure comparability across indicators:

Carbon Emissions (Climate Change): Estimated from annual facility electricity use multiplied by the grid emission factor. Formula:

$$E_{\text{carbon}} = \text{kWh} \times \text{gCO}_{2\text{e}}/\text{kWh} \tag{2}$$

This captures both renewable and fossil-based shares in the local energy mix.

Freshwater Use (Freshwater Boundary): Calculated from annual cooling water withdrawals. Basin-level stress multipliers were applied to reflect local scarcity conditions. Formula:

$$E_{\text{water}} = \text{Withdrawals (m}^3) \times \text{Basin Stress Factor} \tag{3}$$

For case adaptation, freshwater withdrawals adjusted by basin stress were proportionally allocated to the global freshwater boundary using the facility's share of global digital activity (per PB basis).

Land Occupation (Land-System Change): Based on facility footprint and ancillary infrastructure relative to service output. Formula:

$$E_{\text{land}} = \frac{\text{Occupied Hectares}}{\text{PB of Data Processed}} \tag{4}$$

Material Intensity (Novel Entities): Derived from life cycle inventories (e.g., Ecoinvent) covering raw material extraction, processing, manufacturing, transport, and disposal of server hardware. Particular attention was given to critical minerals such as cobalt and rare earths due to their toxic by-products. Formula:

$$E_{\text{materials}} = \frac{\text{kg of Critical Materials per Server Lifetime}}{\text{PB of Data Processed}} \quad (5)$$

To address common controversies in applying LCA to digital infrastructure, we explicitly defined system boundaries to include raw material extraction, processing, transport, manufacturing, and end-of-life disposal of server hardware, while excluding data transmission network energy to maintain analytical focus on facility-level impacts. Data inputs were drawn from standardized inventories (e.g., Ecoinvent) to ensure cross-comparability. Recognizing variations in transparency across data centers, we applied conservative estimates and triangulated with peer-reviewed LCA studies where available. These measures reduce boundary ambiguity and strengthen the reproducibility and credibility of the material burden estimation.

Energy Source Burden (Climate & Biogeochemical Flows): Accounts for electricity source composition. Renewable share reduces intensity; hydropower adjustments consider seasonal variability. Formula:

$$E_{\text{energy}} = \sum (\text{kWh}_i \times \text{Emission/Impact Factor}_i) \quad (6)$$

Normalization: Each indicator value E_i was divided by its planetary boundary allocation (B_i) to calculate a burden ratio:

$$R_i = \frac{E_i}{B_i} \quad (7)$$

Service Differentiation: Where possible, facility workloads were distinguished among AI training, cloud storage, and general computing, as these exhibit different energy and water intensities.

Aggregation: Final DPBI scores were computed using the weighted sum described in Equation (1). Equal weights were applied in this case study, but the framework allows for scenario-specific alternatives (e.g., higher weights for water in arid regions).

4.3 Weighting scheme and sensitivity analysis

Although equal weights (w_i = 0.20) are applied across the five environmental dimensions in the baseline DPBI calculation, the framework also allows alternative weighting to reflect ecological urgency and irreversibility. To test robustness, we applied two additional schemes:

- Ecological sensitivity weighting gives greater emphasis to dimensions under higher stress (e.g., water in arid basins, carbon in carbon-intensive grids).
- Irreversibility weighting prioritizes dimensions associated with long-term or irreversible impacts (e.g., biodiversity loss, mineral depletion).

Results show that while absolute DPBI values shift slightly, the ranking of high-burden dimensions remains stable, confirming the framework's resilience to different assumptions.

4.4 Uncertainty analysis

To address input variability, we conducted a Monte Carlo simulation with 1,000 iterations. Input ranges were drawn from authoritative sources:

- Carbon emission factors (±10% from IPCC estimates),
- Water withdrawal coefficients (±15% variation by basin stress levels),
- Material throughput (±20% based on UNEP lifecycle inventories),
- Energy grid intensity (±15% reflecting annual fluctuations).

Each iteration sampled within these ranges, and the DPBI score was recalculated. The distribution was then used to compute 95% confidence intervals for each dimension, demonstrating that results are robust under input variability. For example, carbon (mean 1.32, 95% CI: 1.20–1.45) and water (mean 1.78, 95% CI: 1.55–2.05) consistently exceeded safe thresholds, while land (mean 0.65, 95% CI: 0.58–0.72) and materials (mean 0.97, 95% CI: 0.82–1.12) remained relatively stable. These results confirm that DPBI outputs are resilient to parameter uncertainty, with water and carbon dominating both the mean score and variance.

4.5 Software and computational tools

All computational analyses and visualizations in this study were performed using a combination of Python 3.10 (via Jupyter Notebook) and Microsoft Excel. Python libraries such as NumPy and Pandas were employed for data normalization and index calculation, while Matplotlib and Seaborn were used to generate comparative visualizations of DPBI scores. Data was first processed and converted into units in Excel, ensuring that all dimensions were clear and consistent. The DPBI formula was typeset in LaTeX to maintain mathematical precision, and all artwork was prepared with vector-based drawing software to guarantee high-quality, publication-ready images with optimal clarity. This modular, open-source toolchain was selected to provide complete reproducibility and transparency. Upon publication, all scripts used for computation and data inputs will be available as supplementary files or in a dedicated repository for anyone who wishes to repeat or expand this method in the future.

5. Case study: Google's data center in the Dalles, Oregon

Table 3. Sensitivity of DPBI to alternative weighting schemes

Dimension	Equal weights (0.20 each)	Ecological sensitivity	Irreversibility priority
Carbon	1.32	0.25	0.20
Water	1.78	0.30	0.15
Land	0.65	0.15	0.25
Materials	0.97	0.15	0.25
Energy	1.05	0.15	0.15
DPBI Score	**1.15**	**1.19**	**1.14**

To demonstrate the practical application and interpretive power of the DPBI, this section presents a case study of Google's hyperscale data center located in The Dalles, Oregon. This facility offers a suitable and illustrative test case for several reasons. First, it is a large data infrastructure site operated by one of the world's largest digital companies, and could provide useful environmental scale. Second, Google has released some environmental reference data on energy and water, with a reasonably open approximation of the DPBI dimensions. Third, The Dalles region has a context defined by hydropower and freshwater dependence, which has recently begun to face scrutiny at the local level; it is one of many regions for which geospatial sensitivity within the index may be variable. It is important to note that this case study is presented as a proof-of-concept validation exercise for the DPBI framework, rather than a definitive assessment of all digital infrastructure. The Google data center was chosen due to data availability and transparency, but the findings should not be overgeneralized to the global digital sector without further empirical testing across multiple facilities and regions.

5.1 Facility overview

The Dalles data center was launched in 2006 and has since undergone multiple expansions. Located in Wasco County along the Columbia River, the facility benefits from relatively low-cost, renewable hydropower and a moderate climate. These factors have historically made the site attractive for large-scale server farms [36]. However, the increasing demand for data-intensive services and artificial intelligence workloads has placed growing stress on local water and energy systems. Recent reports, including environmental disclosures and investigative journalism, have revealed that the facility uses up to 1.06 billion gallons (approximately 4 million m^3) of freshwater annually for cooling purposes. This is particularly concerning given that The Dalles and surrounding regions have experienced periodic drought conditions, which may become more frequent under future climate change scenarios. In parallel, while Oregon's grid mix includes a substantial proportion of renewable energy (approximately 60–70% from hydroelectric sources), the remaining energy demand may still be met by fossil-based sources, especially during seasonal or peak demand variability [37].

5.2 Data collection, normalization, and scoring

To calculate the DPBI for Google's data center, data were drawn from a combination of publicly available sources, including corporate sustainability disclosures, regional utility information, and third-party environmental investigations. Google's own environmental impact reports from 2021 to 2023 provided estimates of overall carbon emissions and energy use. These were supplemented with energy mix data from the Oregon Department of Energy to determine the emissions intensity of electricity consumed. Water consumption figures were obtained from public filings made to the City of The Dalles, alongside data revealed through investigative journalism that highlighted the facility's peak annual freshwater withdrawals, estimated at approximately 1.06 billion gallons, or about 4 million cubic meters. Land use estimates were derived from satellite imagery analysis and zoning records from Wasco County, with further insights gathered from facility expansion permits filed by Google. Material burden estimations relied on peer-reviewed life cycle assessments of typical data center hardware and assumed refresh cycles of three to five years. Where direct data were unavailable, established coefficients from the literature and global environmental databases were used to approximate likely values, with adjustments for facility scale and capacity.

Each environmental dimension assessed – carbon emissions, freshwater use, land footprint, material intensity, and energy source burden – was normalized against its respective planetary boundary threshold to generate a dimensionless score between 0 and above 1.0. Carbon emissions for the facility were estimated at approximately 72,000 metric tons of CO_2 equivalent annually, yielding a normalized score of 1.32. This suggests that the facility exceeds the per-workload, science-aligned carbon budget necessary to remain within the 1.5°C warming threshold. Freshwater use emerged as the most problematic dimension, with normalized results indicating a score of 1.78. This high value reflects both the large absolute volume of water used for cooling and the increasing water stress in the Columbia River Basin under changing climatic conditions. In contrast, the land footprint of the facility, approximately 20 hectares, resulted in a relatively modest impact when scaled against planetary biocapacity, with a normalized score of 0.65. Material burden, based on the embedded resource intensity of server hardware and infrastructure, produced a score of 0.97, just within acceptable planetary limits. Finally, although the facility primarily relies on Oregon's hydropower-rich grid, the variability in seasonal demand and the use of fossil-based backup capacity resulted in an energy source burden score of 1.05. This reflects a slight overshoot beyond what would be required to align with a fully carbon-neutral or carbon-free energy profile.

6. Results

The application of DPBI to the Google data center yields a quantitative assessment of the facility's environmental impact in relation to planetary boundaries. By normalizing each of the five environmental burden dimensions (carbon emissions, freshwater use, land occupation, material intensity, and energy source burden) against scientifically grounded thresholds, the DPBI provides an integrated view of the facility's performance beyond conventional corporate sustainability metrics (Figure 2).

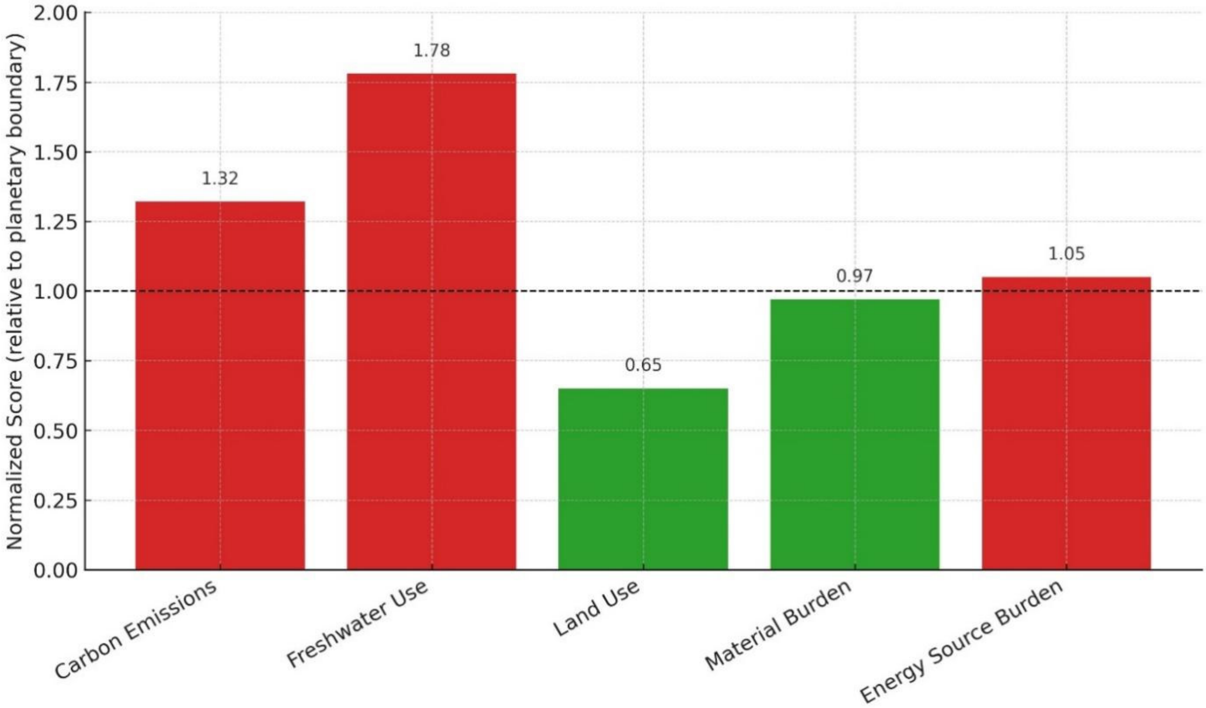

Figure 2. Normalized DPBI scores by dimension

The results indicate that the facility exceeds safe planetary thresholds in three out of five dimensions. Carbon emissions, estimated at 72,000 metric tons of CO_2-equivalent annually, yield a normalized score of 1.32, suggesting that the facility's emissions per compute workload may not yet align with the 1.5°C-consistent global carbon budget. Although the company reports high renewable energy usage, the continued reliance on fossil-derived grid electricity during peak hours and seasonal demand periods contributes to this overshoot.

Freshwater use presents the highest relative burden (Table 4). An estimated 4 million cubic meters of freshwater are withdrawn annually for cooling, and considering the regional water stress conditions as defined by the WRI Aqueduct risk classifications, the facility receives a normalized water score of 1.78. The freshwater burden score should also be interpreted in the context of the Columbia River Basin, where the facility is located. This watershed faces seasonal variability in flows, with competing demands from agriculture, municipal supply, and ecosystem maintenance. Although the data center's absolute withdrawals are a fraction of total basin flows, the timing of water use during peak summer months can exacerbate local scarcity. In dry years, this can intensify competition with irrigation and household water demand, thereby amplifying ecological stress. By situating DPBI outputs within this basin context, the index highlights not only global overshoot but also localized vulnerabilities relevant to regional decision-making.

In contrast, the land use dimension shows a relatively lower impact. The total land area occupied by the facility, approximately 20 hectares, when considered relative to the functional output of the center and normalized against planetary-scale biocapacity constraints, results in a score of 0.65, remaining below the planetary threshold applied here. Similarly, the material burden dimension, based on the embedded material intensity of server hardware, support infrastructure, and assumed replacement cycles, yields a score of 0.97. While this approaches the boundary threshold, it does not indicate overshoot, which may be related to efficiency gains and compact design features typical of hyperscale data centers. Lastly, the energy source burden, which accounts for the carbon intensity of the local electricity mix despite substantial hydropower input, results in a score of 1.05, slightly above the benchmark for carbon-neutral energy systems.

When aggregated using equal weights for each dimension, the overall DPBI score for the Google facility is calculated at 1.35. According to the interpretive tiers defined by the DPBI framework, this value places the facility in the "Caution" zone a category indicating moderate overshoot of Earth system limits and signaling a need for remedial sustainability actions. The high scores in carbon emissions and freshwater use are the primary contributors to this status, underscoring the need for deeper interventions in these specific areas. For instance, investment in on-site renewable generation paired with grid decarbonization and advanced water reuse systems could significantly reduce the facility's boundary transgression.

The findings provide several important insights. First, they undermine popular narratives that large-scale digital infrastructure, powered mainly by a mix of renewable sources, is automatically sustainable. Second, they highlight the need to assess impacts across multiple dimensions: venues that score highly for land use or materials may still place unsupportable pressure on other biophysical systems. Third, the DPBI makes benchmarking transparent so that policy-makers, planners, and the public can distinguish among genuinely sustainable operations from those making narrowly defined environmental claims. In the case of The Dalles, while our selected Canadian city does not have access to hydropower, reliance on freshwater and lack of full decarbonization indicate that the existing regional context is inadequate for balancing global environmental consequences.

Table 4. Normalized DPBI scores for Google data center

Environmental dimension	Normalized score
Carbon emissions	1.32
Freshwater use	1.78
Land Use	0.65
Material Burden	0.97
Energy Source Burden	1.05

7. Discussion

This study introduced a novel approach to evaluating the environmental sustainability of digital infrastructure within the planetary boundaries' framework. By applying the DPBI to Google's data center, we provide a proof-of-concept that demonstrates how multi-dimensional sustainability assessments can be operationalized and quantified. The case study reveals significant environmental pressures across Earth system boundaries, with freshwater use and carbon emissions (1.78 and 1.32, respectively) exceeding safe thresholds. These findings highlight the importance of incorporating digital infrastructure into global sustainability discourse, as its environmental impacts have often been underrepresented [38, 39].

The significance of DPBI lies in its ability to translate sustainability goals into measurable performance metrics tailored to the digital sector. Unlike indices that either generalize across sectors or focus narrowly on carbon, DPBI integrates five dimensions aligned with Rockström et al.'s framework, providing a more comprehensive perspective on environmental pressures [26]. Its use of publicly available datasets and life cycle inventories such as Ecoinvent avoids reliance on proprietary disclosures, thereby enabling independent assessment. The open-data philosophy and modular design also ensure adaptability across contexts—from hyperscale data centers to regional IT hubs—and allow updates as better data or scientific insights emerge. From a governance perspective, DPBI has the potential to inform environmental policy and sector-specific benchmarks. Much like carbon budgets guide climate regulation, DPBI scores could support threshold-based standards for carbon, water, materials, and energy use. This is particularly relevant in resource-stressed regions, where unchecked growth of computing hubs may exacerbate local environmental pressures. Furthermore, DPBI aligns with emerging disclosure requirements such as the EU's Corporate Sustainability Reporting Directive by offering multidimensional, evidence-based indicators. Its adaptability also supports municipal planning and localized policy design [40].

Academically, DPBI contributes to the emerging discourse on "digital planetary stewardship" [27, 41]. While much research emphasizes the positive role of digitalization in climate mitigation, fewer studies systematically examine the ecological burdens of digital infrastructure itself. By linking ICT growth to planetary thresholds, DPBI reframes this discussion and underscores the sector's responsibility alongside transportation, agriculture, and manufacturing [42, 43]. Finally, limitations must be acknowledged. Boundary allocation methods remain contested, and equal weighting may not reflect local ecological or ethical priorities. These limitations present opportunities for refinement, such as participatory calibration or region-specific weighting.

Another limitation of this study is that basin-level ecological stress and socio-economic competition for water are not fully represented. While the DPBI freshwater score provides a normalized indicator of overshoot, it does not explicitly capture trade-offs between industrial withdrawals, agriculture, and domestic use within the Columbia River Basin. Future applications of DPBI should integrate watershed-specific indices, such as the WRI Aqueduct water stress database, to more directly quantify ecological risks and social impacts. This refinement would enhance DPBI's value for local and regional policymaking. To strengthen the promotion value of DPBI, it is important to highlight its adaptability across different digital infrastructures. While this study focused on a hyperscale facility, the framework is scalable to smaller facilities, such as edge computing nodes and regional data centers, by adjusting service-level allocations and boundary downscaling. For example, localized data centers can be benchmarked against regional planetary boundary allocations, while hyperscale facilities align with global shares. Similarly, functional adaptations are possible: cloud storage primarily emphasizes energy and water dimensions, while blockchain systems—due to high hardware turnover and energy intensity— require greater weighting on material and carbon dimensions. This adaptability demonstrates that DPBI can serve as a flexible tool across heterogeneous digital infrastructures, supporting both global benchmarking and context-specific sustainability governance.

To operationalize DPBI in governance, it is essential to align the framework with existing sustainability policies such as the EU Green Deal, corporate ESG disclosure standards, and science-based target initiatives. The proposed caution zone (1.0–1.5) can be translated into enforceable regulation by defining it as a mandatory disclosure threshold, where facilities exceeding 1.0 must report corrective measures, and those beyond 1.5 trigger regulatory interventions. A phased implementation pathway can begin with pilot applications in high-impact regions (e.g., water-stressed basins or carbon-intensive grids) and priority monitoring of the most sensitive dimensions. Over time, the framework could be integrated into certification schemes and procurement standards, providing both regulatory oversight and market incentives for compliance.

7.1 Cross-dimensional trade-offs

DPBI also reveals that the environmental dimensions of digital infrastructure are interdependent rather than isolated. For instance, shifting to renewable energy sources can reduce carbon intensity but may also simultaneously increase land occupation (e.g., for solar or wind installations) and material demand for critical minerals such as rare earths. Similarly, relying on hydropower in Google's data center reduces operational carbon emissions but creates water-energy linkages: during dry years, limited hydropower availability necessitates backup fossil generation, which raises the carbon burden. These cross-dimensional dynamics emphasize that improvements in one boundary may create new pressures in another, underscoring the importance of integrated assessment. Future DPBI applications should incorporate scenario analysis to capture such trade-offs, thereby enhancing its relevance for comprehensive decision-making. Importantly, our findings are illustrative rather than definitive. While DPBI highlights relative hotspots, results should be interpreted as indicative signals. Benchmarking against frameworks such as LCA and the Environmental Footprint Method suggests that DPBI complements rather than replaces existing approaches, and broader applications across facilities and regions are needed to validate robustness and policy relevance.

8. Conclusion

The DPBI emerges not only as a methodological contribution but also as a strategic provocation for how we assess and govern the environmental dimensions of digital infrastructure. As societies accelerate towards data-driven economies, existing sustainability frameworks often lag behind the pace and complexity of digital growth. The DPBI addresses this gap not merely by measuring impact, but by embedding the digital sector within the larger planetary boundaries discourse—an urgent and overdue recalibration. Rather than offering finality, this study opens a new trajectory of inquiry. Future research should explore the integration of dynamic, real-time data into the DPBI to capture the temporal volatility of digital operations, such as fluctuating energy loads or water demand during peak data processing periods. There is also substantial potential to tailor the DPBI for different scales and sectors: from hyperscale cloud facilities to edge computing hubs, and from healthcare AI systems to blockchain-based finance. Each context carries unique burden profiles that require nuanced, modular adaptations of the index. Moreover, the DPBI may serve as a foundation for future governance instruments. It could inform sustainability-linked financing for digital infrastructure, serve as a regulatory threshold in data center permitting, or underpin performance-based procurement in the public sector. These practical applications require collaborative refinement across disciplines, bringing together environmental scientists, digital engineers, urban planners, and policymakers to ensure the model remains rigorous yet adaptable.

There is also an unexplored frontier linking DPBI to social equity. As the environmental costs of data centers are often externalized to vulnerable communities or resource-scarce regions, future adaptations of the index could incorporate distributive justice metrics, highlighting asymmetries in who bears the burden of digital growth. Such integrations would deepen the ethical foundation of the framework and align it more closely with the just transition agenda. Ultimately, the DPBI is not just a new index, it is a call to action. It invites academia, industry, and governance institutions to rethink the digital transition not only in terms of efficiency and access, but also in terms of ecological realism and long-term planetary stewardship. In this way, it offers a template for a digital future that is not only smarter, but also wiser. While this study demonstrates the feasibility of the DPBI through a single illustrative case, its scope is necessarily limited. The Google data center analysis should be understood as a proof-of-concept validation exercise, not a comprehensive sector-wide assessment. Accordingly, the DPBI should be considered as a prototype rather than a finalized policy instrument, with immediate value as a screening tool for regulators, a benchmarking framework for industry, and a research baseline for academia. Future research applying the DPBI across multiple facilities, regions, and service types will be essential to test generalizability and strengthen its policy relevance. Over time, broader empirical applications may support the integration of science-based thresholds into policy and disclosure frameworks. Equally essential is the incorporation of justice and equity: water withdrawals in stressed basins often disproportionately affect local communities, while material extraction burdens are concentrated in regions of the Global South. Embedding such considerations will ensure that the DPBI is not only scientifically rigorous but also socially equitable.

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Authors' contributions

NB, NN: Project formulation, conceptualization, data collection, visualization, interpretation, manuscript writing, data validation, review, and editing of the final draft.

Competing interests

The authors declare no competing interests.

Data availability statement

The data used in this study, including the case study of the Google data center, were obtained from publicly available sources and industry environmental reports. Processed datasets and analysis scripts are available from the corresponding author upon reasonable request.

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