

Climate And Resource Awareness is Imperative to Achieving Sustainable AI (and Preventing a Global AI Arms Race)

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Abstract

Sustainability encompasses three key facets: economic, environmental, and social. However, the nascent discourse that is emerging on sustainable artificial intelligence (AI) has predominantly focused on the environmental sustainability of AI, often neglecting the economic and social aspects. Achieving truly sustainable AI necessitates addressing the tension between its *climate awareness* – the need to mitigate AI’s environmental impacts – and its social sustainability, which hinges on equitable access to AI development resources. The concept of *resource awareness* advocates for broader access to the infrastructure required to develop AI, fostering equity in AI innovation. Yet, this push for improving accessibility often overlooks the environmental costs of expanding such resource usage. In this position paper, we argue that reconciling climate and resource awareness is essential to realizing the full potential of sustainable AI. We use the framework of base-superstructure to analyze how the material conditions are influencing the current AI discourse. We also introduce the Climate and Resource Aware Machine Learning (CARAML) framework to address this conflict and propose actionable recommendations spanning individual, community, industry, government, and global levels to achieve sustainable AI.

1 Introduction

The capabilities of artificial intelligence (AI) methods are demonstrably diverse and multi-faceted with the potential to help us as a global society to reach many of the Sustainable Development Goals (SDGs) (Vinuesa et al., 2020). Availability of large-scale datasets and computational resources has been essential in the recent accelerated development of deep learning (DL) that is driving most of the AI methods (LeCun et al., 2015; Schmidhuber, 2015).

The computational resources required to develop AI methods have doubled every 3.4 months for some salient DL methods (Amodei and Hernandez, 2018; Sevilla et al., 2022). This trend has maintained for over a decade starting around 2012. This startling trend of doubling the compute resources required to develop AI models every few months has disparate effects on *holistically* sustainable AI.

Environmental sustainability of AI: The growing computational demand has led to a proportional increase in the energy consumption of AI. As energy production is still one of the largest green house gas (GHG) emitters in the world (Bruckner et al., 2014; Sevilla et al., 2022), the resulting carbon footprint of AI has been of increasing concern (Strubell et al., 2019; Anthony et al., 2020; Selvan et al., 2022). Furthermore, the specialized hardware required to develop AI models such as graphics processing units (GPUs), the e-waste generated due to these electronics (Wang et al., 2024), building infrastructure that houses these data-centers, and the water required to cool the data-centers (Li et al., 2023a) are adversely impacting the *environmental sustainability* of AI methods (Li et al., 2023a; Wright et al., 2025; Tannu and Nair, 2023).

Social sustainability of AI: The large-scale resource requirements in terms of compute, energy, and other raw materials, have given rise to a new access barrier to AI methods risking the de-democratization of AI (Ahmed and Wahed, 2020). The resource barrier is reducing the participation of stakeholders from several regions of the world, primarily from low- and middle- income countries (LMICs) compared to high-income countries (HICs). The availability of large-scale compute capacity in different countries is shown in Figure 1, and the distribution of AI research publications in 2022 country-wise is visualized in Figure 2 which captures a clear under-representation of LMICs

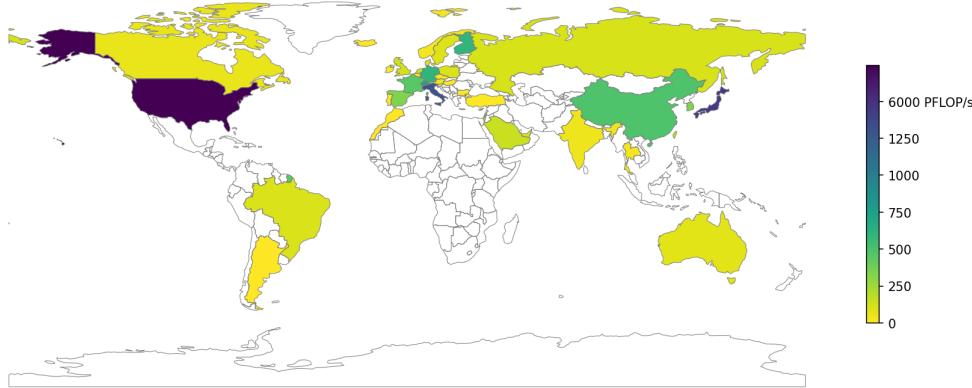


Figure 1: Compute capacity in different countries based on the Top500 listing of supercomputers using data from November, 2024 ([Top500-Org., 2024](#)). Vast regions in the world, primarily in LMICs have almost no large-scale compute capacity which have grown to become necessary for developing latest AI research.

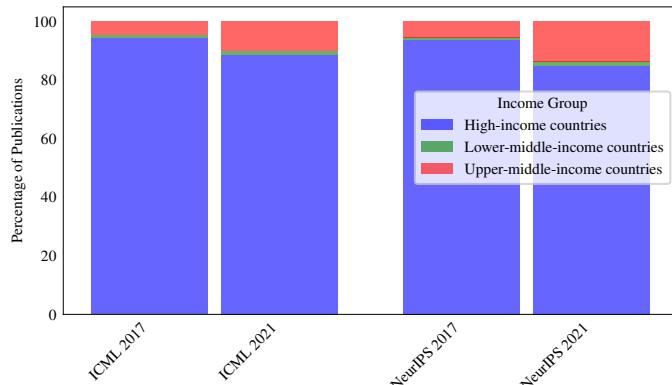


Figure 2: (left) Proportion of authors based on the geographic location of their affiliations. The plot shows this based on publications at two ML conferences (ICML and NeurIPS) in 2017 and 2022. The countries are classified based on their income groups as defined by World Bank. We notice that HICs dominate these conferences compared to LMICs. Details on the data preparation is provided in [Appendix A](#).

in several regions. Disenfranchisement of communities due to the steep resource costs is also aggravating the already existing biases in AI methods ([Ricci Lara et al., 2022](#); [Farnadi et al., 2024](#)).

Improving the environmental sustainability of AI primarily focuses on *climate awareness* as the guiding principle ([Bartoldson et al., 2023](#); [Schwartz et al., 2020](#)), whereas *resource awareness* is used to grapple with improving the social sustainability of AI ([Ahmed and Wahed, 2020](#)). In this position paper, we argue that the joint consideration of **climate and resource awareness is a prerequisite to achieve sustainable AI**. We present the standpoint that the sole focus on climate awareness or on resource awareness leads to a tension that can negatively affect the ambitions of achieving sustainable AI.

AI methods have demonstrated significant potential in advancing the SDGs, for example, in climate change adaptation and improving healthcare access. However, the accelerated expansion of AI infrastructure (fx: data-centers) by big corporations and HICs, often without serious sustainability considerations, presents a critical challenge. An unregulated *global AI arms race* that disregards sustainability is not a strategic or responsible trajectory for the future of AI and the world.

To address these contradictions when pursuing sustainable AI, we present a paradigm of climate and resource aware ML (CARAML). Just as AI models grow in complexity, so too must the actions we need to take. In line with this view, the CARAML framework presents recommendations and actions that evolve across individual, community, industry, government, and global levels.

1.1 Preliminaries and Definitions

Before proceeding further, we define the key terms with their intended use in this work.

Sustainable AI: The definition of Sustainable AI that we adhere to considers all the three facets of sustainability, i.e., economic, environmental, and social. This definition is from [Van Wynsberghe](#)

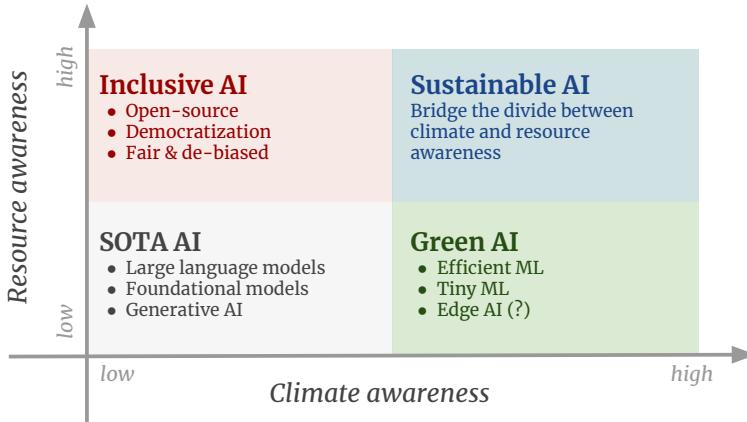


Figure 3: Contextualizing Sustainable AI using the two axes of climate awareness and resource awareness. The position of this paper is that Sustainable AI should be in the top right quadrant where both climate and resource awareness are high. In case of Edge AI, there is some ambiguity in if it actually is climate aware; so we have marked it with a question mark.

(2021), where the author explains that Sustainable AI is about “*how to develop AI that is compatible with sustaining environmental resources for current and future generations; economic models for societies; and societal values that are fundamental to a given society.*”

This is to contrast with the looser use of the term Sustainable AI in the literature, which can conflate energy efficiency with carbon efficiency, carbon efficiency with environmental sustainability, and environmentally sustainable AI to Sustainable AI as pointed out by Wright et al. (2025).

Climate awareness: By this, we will mean the recognition, understanding, and integration of climate impact considerations of AI development and deployment. This awareness enables practitioners to optimize the energy efficiency, carbon footprint, and other broader environmental impacts of AI. The class of methods which result from this can be grouped into the *Green AI* quadrant in Figure 3.

Resource awareness: By this, we focus on the effort to bridge the AI divide by making it more accessible (United Nations (UN), 2024). The recognition here is not only of the resource consumption of AI models, but also of the resource availability of the people who develop and use AI solutions. The class of methods that promote *Inclusive AI* either by arguing for more accessibility and democratization in the top-left quadrant in Figure 3 are examples of resource awareness.

An overview of current developments within AI research are mapped using the axes of climate awareness and resource awareness in Figure 3.

1.2 Tension between Climate awareness and Resource Awareness

Achieving Sustainable AI necessitates a balanced approach that includes both climate awareness and resource awareness. The two are complementary but can sometimes be at odds with each other. We present two concrete examples to highlight this contradiction.

1.2.1 Social sustainability of low-carbon data centers

The push towards powering data-centers with renewable energy, or generally known as green computing (Yang et al., 2022), is a valid approach to reduce *some* of the climate impact of developing large AI models by reducing operational carbon emissions.¹

However, these green computing solutions, such as low-carbon data centers, rely heavily on renewable energy like solar, wind, or hydroelectric power to operate. Many countries still face significant challenges in energy access, with large portions of the population lacking reliable electricity, or relying on cheaper carbon-intensive sources such as fossil fuels. According to the International Renewable Energy Agency (IRENA), renewable energy capacity in many developing countries is still insufficient to meet growing demand (International Renewable Energy Agency (IRENA), 2024), as shown in Fig. 4.

As a result, the demand for clean energy to support greener data-centers for AI not only strains already limited resources (Sukprasert et al., 2024) but also creates a paradox for LMICs.

¹Carbon emissions due to the energy consumption of data centers is just one factor of the climate impact of AI. Embodied emissions, water usage for cooling, mining of rare-earth minerals, e-waste disposal, and other broader environmental impact are not accounted for when only talking about green energy (Wright et al., 2025).

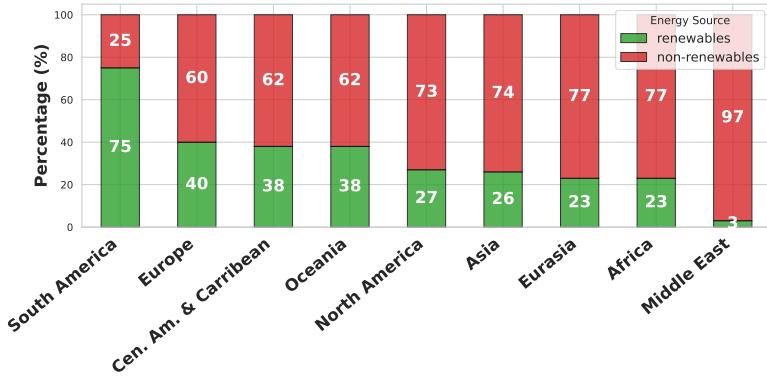


Figure 4: Proportion of non-renewable and renewable energy sources in different regions of the world.
Source: ([International Renewable Energy Agency \(IRENA\), 2024](#))

These countries are being asked to adopt greener technologies while lacking the clean energy infrastructure necessary to power them. This deepens the technological divide and locks out LMICs from participating in the climate aware development of AI. This we argue results in double penalty – once for not having access to the resources, and again for not having access to cleaner resources.

1.2.2 Environmental sustainability of Efficient AI Models

The ML community has acknowledged the growing resource costs of developing recent AI models and has primarily turned towards making them more efficient ([Bartoldson et al., 2023](#)). While this in itself is a meaningful endeavor, as it improves access to a broader community, the larger implications of this resource awareness on the environment are not immediately apparent.

From a climate awareness standpoint, efficiency in computational resource use, though seemingly beneficial in terms of reducing direct energy consumption, could paradoxically be at odds with long-term environmental sustainability when considering the rebound effect ([Alcott, 2005](#)). This effect, rooted in economic and ecological theory, suggests that any technological advancement that improves efficiency often leads to an increase in overall demand for the very resource it was designed to conserve ([Wright et al., 2025](#)).

This paradox has come to the fore with the recent success of DeepSeek models ([DeepSeek-AI et al., 2024; 2025](#)), where they report using a fraction of resources compared to other existing models in the same class.² This claim of efficiency has drawn many more people to use and build with these models i.e, it has improved access which is a key factor in improving social sustainability. For some companies and countries, DeepSeek may be a sign that “AI-sovereignty” (see [section 3](#)) also in reach for them, which may lead to more investments in data centers and model creation.

So, how do we resolve these contradictions between climate awareness and resource awareness?

The short answer we adhere to in this position is that this contradiction can be resolved only by integrating both climate and resource awareness. Only then can we create a Sustainable AI ecosystem that is not only efficient and climate-friendly but also just and equitable.

2 Related Literature

Using Figure 3 as a map, we will provide an overview of the AI literature in relation to climate awareness and resource awareness.

2.1 State-Of-The-Art (SOTA) AI

The advancements in DL methods in the last few years that have ushered in a new class of generative AI that are particularly resource intensive. Text to image models based on diffusion models have shown mind-boggling potential in generating images based on text prompts ([Ho et al., 2020; Rombach et al., 2022](#)). The strides made with the class of large language models (LLMs) has revolutionized multiple domains beyond natural language processing with popular applications such as ChatGPT built on GPT-3/GPT-4 ([Brown et al., 2020; Achiam et al., 2023](#)) and open-source alternatives built on models such as LLaMA ([Touvron et al., 2023](#)). Other recent classes of models that fall under the umbrella term of foundational models are also extremely powerful in modelling

²We note that even this “smaller” resource cost is exorbitant. DeepSeek-V3 used about 2.8M GPU hours on Nvidia-H800s, compared to say 30.8M GPU hours on Nvidia-H100s for a comparable model Llama-3-405B.

complex, and diverse, data distributions with versatile capabilities. For instance, the segment anything model has proven to be quite powerful in solving segmentation problems across image types (Kirillov et al., 2023; Ma et al., 2024).

While the astonishing capabilities of these SOTA models are one common aspect between them, the other commonality is their extreme reliance on large-scale resources (Sevilla et al., 2022). All the aforementioned classes of models require massive amounts of data to train extremely large models (with several billion parameters) for several hundred GPU days. All these resources amount to an increase in their underlying energy consumption and carbon emissions (Lucioni and Hernandez-Garcia, 2023). Further, questions on how to address the ethical usage of these models, and measures to mitigate bias are still being explored (Bender et al., 2021; Ricci Lara et al., 2022). These features are captured in Figure 3 in the bottom-left quadrant wherein the SOTA AI methods are shown to have low climate and resource awareness.

2.2 Green AI

The life-cycle of a typical deep learning model consists of several stages: dataset curation, model selection, model training, model development, and model deployment.

Each of these steps can be resource intensive due to the storage, compute, and energy consumption requirements. Recent works demonstrate the benefit of data, work, and hardware resource sharing when reducing the CPU needs of data loading and preprocessing steps of model training (Xu et al., 2022; Audibert et al., 2023; Mohan et al., 2021; Robroek et al., 2024a) and the GPU needs of actual training computations (Espenshade et al., 2024; Robroek et al., 2024b; Strati et al., 2024a; Wang et al., 2021). Reducing the reliance of model deployment on large-scale resources is also an active area of investigation within the domains of resource-efficient ML (Sze et al., 2017). Some works in this domain target using existing hardware resources more effectively in data centers (Strati et al., 2024b; Yu et al., 2022), thereby reducing the need for more, or building hardware specifically tailored for deep learning (Jouppi et al., 2023). Others investigate model deployment on resource-constrained platforms (Bayer et al., 2024; Hojjat et al., 2024), enabling TinyML (Dutta and Bharali, 2021) or EdgeML/EdgeAI (Zhao et al., 2021). For such cases, the model deployment and inference is performed closer to the data sources (satellites, under-water monitoring, phones, etc.), i.e., at the edge, rather than in the cloud. This brings several benefits thanks to the reduced data movement: lower dependency on a powerful network connection and cloud hardware, higher privacy and security, and faster and more energy-efficient end-to-end inference. Other classes of methods comprising quantization (Dettmers et al., 2021), model compression (Cheng et al., 2018), efficient model selection (Bakhtiarifard et al., 2024), tensor decomposition (Memmel et al., 2024), knowledge distillation (Sanh et al., 2019), dataset condensation (Cui et al., 2022) or a combination of these steps are being studied to address the question of improving resource efficiency in other steps in the DL life-cycle (Schwartz et al., 2020; Bartoldson et al., 2023). There are no existing theoretical paradigms that can holistically improve the resource efficiency of the entire DL pipeline.

On the other hand, it has been shown in multiple recent works that the techniques that improve the resource efficiency of AI methods can hamper the social sustainability of AI methods by making them more biased or reducing their fairness (Hooker et al., 2020; Stoychev and Gunes, 2022; Ramesh et al., 2023). Furthermore, deploying billions of resource-constrained devices for utilizing TinyML/EdgeAI creates both a resource availability challenge and increases the end-to-end environmental footprint of these methods (Prakash et al., 2023). Finally, specialized hardware for ML tends to be at the hands of a few big companies rather than a wider variety of institutions. As a result we position the class of Green AI methods in the lower right quadrant in Figure 3 with high climate awareness but low resource awareness.

2.3 Inclusive AI

The nebulousness of social sustainability results in a broad and multi-faceted understanding of the social sustainability of AI. In this work, we narrow down to the factors that will positively improve the equitable use of AI. Topics related to the ethical use of AI models (Jobin et al., 2019), ensuring user privacy (Abadi et al., 2016), fairness (Ricci Lara et al., 2022), and bias mitigation strategies (Bender et al., 2021) are considered to be under the purview of the social sustainability of AI.

Measuring and optimizing for factors that affect the equitable use of AI methods such as privacy, fairness and bias is not straightforward. Consider fairness, for instance, which is difficult to optimize for when performing standard deep learning (Corbett-Davies et al., 2023). Existing approaches enforce additional optimization criteria which could be at odds with the task-specific performance

measures (Li et al., 2023b). Furthermore, the computational overhead due to these can reduce the environmental sustainability of AI methods. This is most clearly captured with differentially private deep learning which is notorious for the additional computational overheads (Bu et al., 2023). Given these factors, we place the Equitable AI in the upper-left quadrant in Figure 3 indicating the trade-off between resource awareness and climate awareness.

Given these, we want Sustainable AI to be in the upper-right quadrant of Figure 3 which has high climate and resource awareness.

3 Democratization of AI

Democratizing AI – ensuring widespread access and participation in its development and use – is a necessary step towards equitable technological advancement. This can improve the social sustainability of AI, as it can improve participation in the development of AI (Berditchevskaia et al., 2021) to match the local needs instead of *trickle-down AI* solutions.

Jensen Huang, CEO of NVIDIA, captures the essence of *AI sovereignty* by emphasizing that AI codifies a society’s culture, intelligence, and history, asserting that nations should “own their own data.” (NVIDIA, 2024). We agree with this aspiration, however, are wary of the monopoly held by NVIDIA over global AI infrastructure (Cusumano, 2024), and would push for AI sovereignty that also includes the hardware capabilities.

The pursuit of AI sovereignty, wherein nations develop and control their AI capabilities, stands in contrast to what could be termed *Factional AI* – a scenario where AI development is concentrated among a few powerful entities with disproportionate influence (Ahmed et al., 2023). While AI sovereignty promises a more democratized and inclusive technological future, it is also a driver of the global competition for computational resources, exacerbating existing inequalities.

This divide between the *GPU-rich* and *GPU-poor* clearly reflects the contrasting abundance and scarcity mindsets shaping AI development. Countries and corporations with vast computational resources can push the frontiers of AI, while others struggle with limited access to hardware, data, and expertise. Unequal access to AI skews its development, reinforcing biases that cater to specific groups while neglecting or misinterpreting others. As AI research becomes increasingly dominated by industry interests (Ahmed et al., 2023), the risks of a widening technological divide grow more pronounced, leading to cascading disparities that further marginalize underrepresented communities (Farnadi et al., 2024).

Despite these concerns, calls for AI democratization remain strong. Joe Biden, in his farewell address as the 46th President of the United States, declared AI to be “the most consequential technology of our time, perhaps of all time,” while cautioning against “the potential rise of a tech-industrial complex that could pose real dangers.” (Biden, 2025). His assertion that “in the age of AI, it’s more important than ever that the people must govern” underscores the necessity of a grassroots approach to AI governance and development, ensuring that AI remains a tool for collective progress rather than corporate or geopolitical dominance.

However, as we have discussed earlier in this position, democratization by emphasizing resource awareness alone is insufficient. The expansion of AI infrastructure – large-scale data centers, energy-intensive training processes, and resource-intensive hardware manufacturing – places enormous pressure on the environment. The pursuit of AI sovereignty and universal AI access risks accelerating ecological degradation unless sustainability considerations are embedded within AI policies and practices. Without careful intervention, AI development risks deepening its alienation from nature, individuals, and broader societal well-being (Marx, 1844/1965).

4 The Material Basis for AI

Training one of the Llama-3 models with 405B parameters on a dataset consisting >15 trillion tokens required 30.84M GPU hours (AI@Meta, 2024). The corresponding energy consumption only based on the GPU usage can be estimated to be 21.5 GWh, with a total of 8,930 tons CO₂e in emissions. This is the cost for one *open-source* model, but exorbitant resources at this or higher scales are being used to develop wide array of recent AI models. While one can argue that open-source models can be used by a broader community³, majority of the resources being spent are for proprietary models. This is because the material infrastructure required to develop models at this scale is currently available only with a handful of private actors operating in HICs.

³Meta reported that the Llama models have been downloaded more than 350M times between Feb. 2023-Jul. 2024.

Kate Crawford characterizes AI not as an algorithmic advancement but an embodied infrastructure. Crawford writes, "*artificial intelligence is both embodied and material, made from natural resources, fuel, human labor, infrastructures, logistics, histories, and classifications*" ([Crawford, 2021](#)). The unequal access to this embodied infrastructure shapes not only the types of AI models that are created but also how these models are used.

The material basis for AI's development forming the embodied infrastructure – knowledge, labour, investments, and raw materials – do not merely exist in isolation; they also shape the ethics, policy, cultural narratives, and educational frameworks that govern AI and beyond. The dominant ethical frameworks, policy decisions, cultural narratives, and educational systems are all shaped to maintain the concentration of control over the material base. This interplay ensures that AI is deployed in ways that maintains existing power imbalances, rather than challenging them ([Pasquinelli, 2023](#)). This framework of viewing a material base that is interacting with a superstructure stems from historical materialism, pioneered by [Marx \(1844/1965\)](#), illustrated in Figure 5, and is particularly relevant in this era of large-scale AI development and the risks posed by climate change.

Illustration of the Base-Superstructure Interplay in AI

Consider a *hypothetical* scenario where an advanced AI hardware producer faces export restrictions due to political and economic tensions. These restrictions, justified under national security and technological leadership narratives, exemplify how the superstructure – through policy, regulation, and strategic discourse – can exert control over the material base, shaping the trajectory of AI development.

In response, the restricted entity must rapidly reconfigure its supply chains, invest in alternative semiconductor manufacturing, and develop domestic expertise to regain technological independence. However, this forced adaptation is constrained by existing dependencies controlled by the dominant actors forming the superstructure. The initial effect is technological deceleration, increased production costs, and fragmentation of global AI development efforts, reinforcing existing asymmetries rather than dismantling them.

Meanwhile, the controlling superstructure uses these constraints to strengthen its own material dominance. By limiting access to critical AI hardware, it dictates the pace and direction of innovation elsewhere, ensuring that alternative ecosystems develop under more challenging conditions. At the same time, narratives around security, ethical AI governance, and responsible innovation are deployed to justify these material restrictions, further legitimizing the existing power structure.

This feedback loop illustrates how the superstructure does not passively reflect material conditions but actively intervenes to maintain and reshape them. Even as new production centers emerge, they do so within a landscape already defined by the controlling actors, reinforcing a cycle where technological dependencies persist under a different guise ([Pappachen and Ford, 2023](#)). Thus, the ability to withhold access to essential AI components becomes not just an economic tool but a structural mechanism for maintaining global technological hierarchies.

The question we pose in this position is, can we steer the base-superstructure interplay towards more Sustainable AI? This, we argue, can happen only if climate and resource awareness start to shape the superstructure to adjust its relationship with the material base. But, it has to start from the material base, as the labour layer in AI – all of us – are part of the material base. In the next section we present some action points that can steer the base-superstructure towards Sustainable AI.

5 Climate and Resource Aware Machine Learning (CARAML)

The process of scaling up AI models typically involves the transition from small, specialized models to large, generalizable ones with progressively increasing effort and resources ([Kaplan et al., 2020](#)). Similarly, achieving Sustainable AI requires one to *scale up actions* at multiple levels that work together toward a unified goal of building CARAML systems.

We outline some ideas that are already prevalent in literature, and chalk out other new suggestions, within the CARAML framework that evolves across individual, community, industry, government and global levels.

1. Individual Researchers

- (a) *Redefining Metrics of AI Success:* Performance measures of models should account for sustainability, as focusing only on task-specific measures like accuracy obfuscate climate

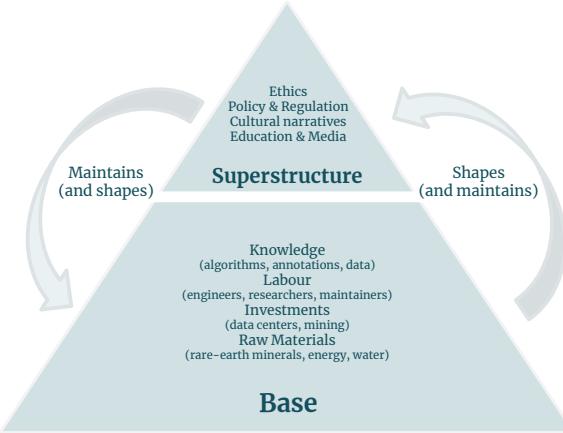


Figure 5: The material basis for developing AI consists of raw-materials, monetary investments, labour, and knowledge commodities. This base forms the foundation of AI as an infrastructure which also shapes the socio-political identity of AI – manifested through policy, regulation, cultural narratives, media and education – which can be considered the superstructure. The material base shapes the superstructure, which in turn maintains and shapes the base. Both the base and superstructure are not static; they influence each other. This base-superstructure view, developed as part of historical materialism (Marx, 1844/1965), when applied to AI offers useful insights into how we can influence the combined entity to become more sustainable.

and resource awareness. Performance that is normalised to account for resource costs is more useful in this regard (Evchenko et al., 2021; Selvan et al., 2025).

- (b) *Pareto Sustainable AI:* Multi-objective optimization that actively strives to balance performance, climate awareness and resource awareness will be important in pursuing Sustainable AI. Pareto optimization offers tools here to obtain set of solutions with varying trade-offs (Miettinen, 1999).
- (c) *Commit to Open-Source and Transparent Reporting:* Publishing trained models and datasets to foster reproducibility can go a long way in improving how we conduct AI sustainably. This can reduce repeated investment of resources to redo experiments and help improve access to expensive models (Eiras et al., 2024). Additionally, documenting useful negative results in publications can be important in reducing resources being spent on ideas that have been shown to be unsuccessful (Schein et al., 2021).

2. ML Community

- (a) *Pre-Registering Experiments and Accountability:* Large-scale AI experiments should be pre-registered as it enhances transparency and accountability. It can also prevent wasted resources on flawed or misleading research, ensuring investments in AI contribute to long-term, ethical progress rather than short-term hype. Finally, it can help prioritize responsible experiments that justify their resource costs, discouraging redundant or wasteful computations (Albanie et al., 2021).
- (b) *Encourage Transparency and Self-reporting:* Many ML conferences already have a broader impact statement. Expanding these statements to include a comprehensive sustainability impact statement can be useful. Providing tools to measure this impact can help standardise reporting resource costs, using interfaces like MLCO2 Impact Calculator (Lacoste et al., 2019), carbontracking tools (Henderson et al., 2020; Anthony et al., 2020), and model cards (Mitchell et al., 2019; Strubell et al., 2019).
- (c) *Hybrid Conferences for Sustainable AI:* Transitioning to hybrid conferences can enhance accessibility by allowing researchers from diverse backgrounds, including those with financial, geographic, or mobility constraints, to participate. They reduce travel costs for attendees while broadening the audience. Significantly lower the carbon footprint of conferences by reducing the need for extensive air travel (Epp et al., 2023; Editorial@Nature, 2024). Some ML conferences are already doing this. To take this forward, in-person participation should be limited and spots should be either randomly allocated⁴, or allotted to optimize for improving diversity, equity, and inclusion amongst the

⁴NeurIPS 2024 had to resort to a lottery-based participation as the number of spots were fewer than the expected number of participants. Source: <https://blog.neurips.cc/2024/10/29/neurips-2024-registration-changes/>

participants. On the other hand, the hybrid conferences may increase the costs of the conference due to the need to ensure reliably streaming the conference talks to everyone, lead to an unpredictable conference budget due to difficulties of estimating the number of people who will join the conference in-person, and amplify the burden on the conference organizers.

3. AI Industry

- (a) *Synergy with Academia:* Collaborations between industry and academia can help address AI's societal challenges – such as bias, fairness, and inclusivity – by combining resources from industry (data and other infrastructure). It can also help avoid redundant efforts, enabling efficient and responsible resource allocation ([Ahmed et al., 2023](#)).
- (b) *Sustainability Impact Disclosures:* Handful of industrial entities control vast infrastructure in the AI sector. Estimating the embodied emissions is next to impossible due to the opacity in how many industries conduct business ([Luccioni et al., 2023](#)). Mandating these disclosures in standardized reporting can help assess the actual sustainability impact of AI industry ([Luccioni and Hernandez-Garcia, 2023](#); [Wright et al., 2025](#)).
- (c) *Carbon Cap for AI:* A regulatory limit on the total carbon emissions due to AI should be endorsed by industry. Given the skyrocketing energy demands of large-scale AI training and deployment ([Sevilla et al., 2022](#)), this approach would force the industry to prioritize sustainability and accountability.

4. Governments

- (a) *Redefining Metrics for AI Impact:* Governments could require mandatory AI Impact Assessments (AIAs) similar to Environmental Impact Assessments (EIAs) ([Reisman et al., 2018](#)). These would evaluate potential AI impacts on employment, social structures, privacy, and environmental sustainability, ensuring projects are aligned with public welfare.
- (b) *Reverse Innovation from LMICs:* Implement programs that not only transfer AI technologies to LMICs but also create mechanisms for reverse innovation, where solutions developed in LMICs are brought back to HICs. This model ensures that AI development is truly inclusive and reflects diverse challenges, as has been argued for in domains like healthcare ([Ahmed et al., 2017](#)).
- (c) *Ethics, Policy and Governance:* Each country faces unique challenges based on its socio-political context, economic development, technological infrastructure, and cultural values. This would entail pursuing regional AI sovereignty. However, the core challenges surrounding Sustainable AI are shared globally. Governments must recognize both the commonalities and the specifics to create effective frameworks that are adaptable yet robust across contexts ([Mügge, 2024](#)).

5. Global Action

- (a) *Coordinated Global Standards:* Governments, in collaboration with international organizations (like the UN or OECD), could establish global standards for AI ethics, safety, and performance. These standards would provide guidelines for ensuring Sustainable AI. Efforts like the EU-AI Act ([EU, 2024](#)) are initial attempts at this which need support from all levels in the CARAML framework to help it evolve in the fast-paced AI sector.
- (b) *Addressing the Digital Divide Through Global Access:* Governments and international organizations should make AI tools, infrastructure, and knowledge accessible to all. This could involve providing affordable cloud-based AI platforms, open-source models, and training programs to build local AI expertise ([Sastry et al., 2024](#)). The question of "Right to Compute" is already being raised ([Shearer et al., 2024](#)) which needs to be adjusted to the "Right to Sustainable Compute".
- (c) *Coordinated Research on Global Challenges:* Establish international consortia that bring together AI stakeholders from across the world to work on solving pressing global challenges, such as climate change, pandemic response, poverty, and sustainable development. By pooling resources, knowledge, and expertise, these collaborative efforts would ensure that AI solutions are developed with global impact in mind, particularly for solving problems that span the planet ([Kaack et al., 2022](#)). This would be the antidote to the rhetoric that encourages a global AI arms race.

To develop Sustainable AI in a way that benefits everyone, we must embrace climate and resource awareness. The recommendations presented here at the different scales in the CARAML framework can be used to sway the dynamics in the AI base-superstructure towards improving the sustainability of AI.

Alternative views

The key alternative views to the position presented in this paper have been argued against from only climate or on resource aspects. To the best of the authors knowledge, there are no widely held views that dispute our stance of identifying the contradictions between climate awareness and resource awareness and/or the recommendations proposed within the CARAML framework.

The caution we ask the community to have about the growing climate impact of AI has been disputed in some important papers. For example, [Patterson et al. \(2022\)](#) claim that the carbon footprint of ML will plateau, and then shrink. All the authors in this work were affiliated with Google, and was seen as a rebuke to some works like [Strubell et al. \(2019\)](#) that had estimated the carbon footprint of training AI models. Ironically though, Google had “a 13% year-over-year increase and a 48% increase” in their 2024 carbon emissions compared to their 2019 target base year. This is primarily attribute to increases in data center energy consumption ([Google, 2024](#)) indicating that the carbon footprint is neither plateauing nor shrinking.

Another line of argument that is presented is that the carbon footprint of ICT sector has largely remained constant due to the efficiency improvements of hardware. For example, [Malmodin et al. \(2024\)](#) show this to some degree according to their estimations. While efficiency improvements are important, and can certainly reduce the corresponding carbon footprint, it is not enough to achieve Sustainable AI as argued by [Wright et al. \(2025\)](#).

6 Conclusion

We are at the precipice of massive changes in our world. Climate change is at our doorstep and we – as a global community – are lagging behind on the effort required to meet any reasonable planetary warming targets. These effects have a disproportionate impact on poorer and disadvantaged communities ([Hallegatte and Rozenberg, 2017](#)).

And concurrently, we are also at the verge of creating one of the most promising technological capability with the recent advancements in AI. The hype and doom around “general AI” is detrimental to a meaningful discourse ([Hanna and Bender, 2024](#)). And also viewing AI as a panacea to all problems including climate change adaptation and climate change mitigation is naive ([Klein, 2014](#)). However, when faced with a planetary-scale problem, we should have all the tools at our disposal – including AI methods, except with a key difference. We have argued in this position that it should be Sustainable AI that we should strive for. The discourse around democratization of AI, AI sovereignty, green AI, and inclusive AI, are all inter-related. We as a community should resist the forces that pit us against each other in a global AI arms race. We have more important problems that are actually threatening our existence, like climate change to address. For the AI solutions we develop to have a net positive impact, we have to be both aware of its climate impact and resource costs.

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A Data Collection and Processing

We scraped the data from a public repository⁵ covering ICML (2017–2023), NeurIPS (2006–2022), and ICLR (2018–2023 except 2020). The year 2020 is missing for ICLR because their one-off virtual format was hosted on a webpage incompatible with the scraping tool. After extracting paper titles, authors, and affiliations, we geocoded each affiliation to determine its country, marking unresolved affiliations as “Unknown” and removing them. We then assigned each country to a World Bank income group ([World Bank, with major processing by Our World in Data, 2024](#)) based on the publication year.

For ICML, we scraped a total of 1588 entries in 2017 (434 unique), which included 1029 high-income affiliations, 52 upper-middle-income, and 11 lower-middle-income, plus 496 unknown. Similarly, in 2021 we obtained 4844 entries (1183 unique), comprising 3166 high-income, 365 upper-middle-income, 47 lower-middle-income, and 1266 unknown.

For NeurIPS, 2497 entries were retrieved in 2017 (679 unique), with 1754 mapped to high-income countries, 104 to upper-middle-income, 13 to lower-middle-income, and 626 unknown. In 2021, we gathered 9931 entries (2334 unique), of which 6470 were high-income, 1052 upper-middle-income, 106 lower-middle-income, and 2303 unknown.

Limitations. A single paper may have multiple affiliations listed, so our scraped dataset can include multiple entries per publication – one for each affiliation. This inflates the total number of entries relative to unique papers. In addition, some affiliations cannot be successfully geocoded, potentially skewing the distribution if certain regions are more prone to geocoding failure. Nevertheless, preliminary checks suggest that these unresolvable affiliations are not disproportionately associated with any single income group, preserving the overall regional balance in our analyses.

B Algorithms for CARAML

In Section 5, we presented the CARAML framework with a set of recommendations that start from the individual and evolve into global action. As ML practitioners, there are some algorithmic research we can pursue to push the agenda of CARAML forward.

B.1 Frugal innovation theory for ML

Frugal innovation theory, often associated with emerging markets and resource-constrained environments, emphasizes the development of products, processes, or solutions that are cost-effective, resource-efficient, and simple yet effective ([Prabhu, 2017](#)). During the COVID pandemic, there was an urgent need for innovation with limited resources to alleviate risks in developing countries, and frugal innovation theory was useful in this setting, as shown in ([Harris et al., 2020](#)). Although not as urgent as a global pandemic, there is also a need for frugal innovation within ML. AI model development currently is rife with redundancies that are hogging up resources that could be put to better use.

Frugal innovation theory, when applied to AI methods, is a concept that centers on optimizing and simplifying DL models and practices to make them more resource-efficient, cost-effective, and adaptable to various environments. This is currently expressed through methods such as model parameter compression ([Cheng et al., 2018](#)), quantization ([Hubara et al., 2016; Nagel et al., 2021](#)), employing knowledge distillation ([Sanh et al., 2019](#)), promoting sparsity in model weights ([Louizos et al., 2018](#)), and applying efficient training strategies ([Dettmers et al., 2021](#)). These approaches aim to make DL more resource-efficient and cost-effective at *individual steps* of its life-cycle while maintaining performance.

These formulations on frugal techniques are based on existing, disconnected solutions that act on individual steps of the DL model life-cycle. An all-encompassing frugal innovation theory for DL needs to emerge to serve as a guiding framework for researchers and practitioners. This can help them make informed decisions about model design, resource allocation, and obtaining meaningful performance trade-offs.

B.2 Scaling laws and Sustainable AI

The current class of upscaled deep learning ([Sevilla et al., 2022; Kaplan et al., 2020](#)) has garnered immense attention and resources in recent years, often overshadowing theoretical rigor and in-depth

⁵<https://github.com/martenlienien/icml-nips-iclr-dataset>

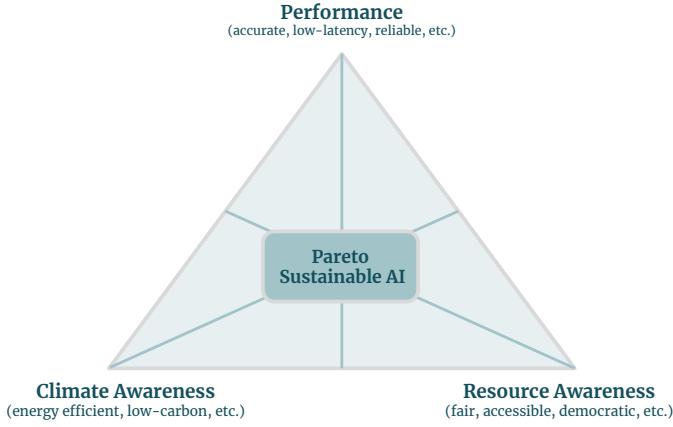


Figure 6: Pareto Sustainable AI seeks to perform multi-objective optimization between performance measures, climate awareness, and resource awareness.

understanding. We argue that the rush towards larger and more complex models has led to a neglect of fundamental theoretical underpinnings of these models, and limit propagation of novel ideas from related domains such as theoretical computer science, neuroscience (Friston, 2010) or physics (Memmel et al., 2024; Brehmer et al., 2024). The theoretical foundations of DL can become obscured by the enthusiasm for scale, making it difficult to fully explain why certain architectures or techniques work.

The notion of “bigger is better” has its limitations; as models scale up, the incremental improvements in performance tend to diminish. The extraordinary computational costs associated with large models may not always justify the modest gains achieved. This diminishing return on investment is a point of concern from a theoretical perspective, challenging the wisdom of extreme scaling. Investigating stronger theoretical foundations of DL can not only benefit in reducing their resource consumption, but can also have implications on improving their interpretability, better generalization, and mitigation of biases (Roberts et al., 2022).

Bridging the gap between learning theory by developing frameworks to include large-scale DL models that encompass current AI methods will be critical in the coming years with implications on improving the overall sustainability of AI.

B.3 Pareto sustainable AI

“Pareto sustainable AI” extends the concept of sustainability to include a trade-off between three critical dimensions: environmental sustainability, social sustainability, and performance. Pareto sustainable AI is based on multi-objective optimization (Miettinen, 1999) and treats performance, environmental sustainability and social sustainability as objectives to be jointly optimized, illustrated as the three axes in Figure 6.

This involves optimizing energy consumption, minimizing carbon emissions, and using eco-friendly hardware and infrastructure. Efforts are made to reduce the environmental footprint, considering the entire life-cycle of AI systems, from data center operations to end-user devices. Pareto sustainable AI ensures that AI technologies contribute positively to society. This includes addressing issues like bias in AI algorithms, ensuring accessibility for all users, and respecting privacy and human rights. Ethical AI development and deployment practices are prioritized to create a socially sustainable AI ecosystem. All the same, the performance dimension remains crucial in Pareto sustainable AI. AI systems must continue to deliver high-quality results and meet the intended objectives. However, this is done in a balanced way that does not excessively compromise environmental and social sustainability. The focus is on optimizing the key performance aspects that matter most, as identified by the Pareto principle. In this framework, achieving Pareto sustainable AI involves making informed trade-offs among these three dimensions:

Performance vs. Environmental Sustainability: The trade-off here implies optimizing AI systems for performance while minimizing their environmental impact. This might involve using energy-efficient hardware, data center cooling solutions, and energy-conscious algorithms to maintain high performance while reducing carbon emissions (Tan and Le, 2019; Selvan, 2021; Bakhtiarifard et al., 2024).

Performance vs. Social Sustainability: This trade-off emphasizes delivering high-performance AI solutions while ensuring ethical and socially responsible use. Ethical considerations may lead to

avoiding certain applications or use cases, even if they promise superior performance, to align with societal values and principles (Bender et al., 2021).

Environmental Sustainability vs. Social Sustainability: Balancing environmental and social sustainability may involve choices that optimize both while not necessarily maximizing either. For instance, ensuring fair and unbiased AI systems may require additional computational resources for fairness testing and bias mitigation, which can impact environmental sustainability to some extent (Bu et al., 2023).

Pareto sustainable AI recognizes that trade-offs are inevitable, but seeks to find the right balance. By posing this as a multi-objective optimization, trade-offs between these axes can be meaningfully explored. This concept of Pareto sustainable AI reflects a holistic approach to AI that considers not only technical excellence, but also its broader societal and environmental implications.