CONVERGENT INTELLIGENCE: INTEGRATING ARTIFICIAL INTELLIGENCE WITH INTEGRAL ECOLOGY FOR REGENERATIVE FUTURES

Rev. Samuel B. Harrelson

PhD Student – Ecology, Spirituality, and Religion Program, California Institute of Integral Studies, San Francisco, USA

sharrelson@mymail.ciis.edu

Conference Abstract

This paper reframes AI convergence through the lens of integral ecology. Rather than optimizing only for scale and throughput, I argue for a convergent intelligence that aligns machine learning with ecological reciprocity, participatory governance, and regenerative metrics. Drawing on process-relational philosophy and ecological theology, I outline design principles—participatory, relational, regenerative—and demonstrate their feasibility through case explorations: mycelium-inspired sparse networks, federated edge-AI for community fire stewardship, carbon- and water-aware schedulers, and biodiversity data-commons. I synthesize emerging evidence on the energy, mineral, water, and land footprints of AI, and propose policy and engineering interventions (FPIC, CARE data governance, lifecycle gates in CI/CD) to redirect innovation toward climate adaptation, data sovereignty, and multispecies flourishing. The result is a practical framework for embedding AI within living Earth systems, technically and ethically, to catalyze regenerative futures.

Keywords

artificial intelligence; integral ecology; convergence; regenerative design; federated learning; data sovereignty; climate adaptation; biodiversity sensing; carbon-aware scheduling; water footprint

1. Introduction

The promise of AI convergence, where machine learning interweaves with ubiquitous sensing, robotics, and synthetic biology, occupies a growing share of public imagination. In its dominant vision, convergence is driven by scale, efficiency, and profitability, amplifying extractive logics first entrenched in colonial plantations and later mechanized through fossil-fuel modernity. Convergence, however, need not be destiny; it is a meeting of trajectories. This paper asks: What if AI converged not merely with other digital infrastructures but with integral ecological considerations that foreground reciprocity, limits, and participatory co-creation? Building on process thought (Whitehead; Cobb), ecological theology (Berry), and critical assessments of AI's planetary costs (Crawford; Haraway), I propose a framework of convergent intelligence that aligns learning systems with the metabolic rhythms and ethical demands of Earth's biocultural commons.

Two claims orient the argument. First, intelligence is not a private property of silicon or neurons but a distributed, relational capacity emerging across bodies, cultures, and landscapes.[1] Second, AI's material underpinnings, including energy, minerals, water, and labor, are neither incidental nor external; they are constitutive, producing obligations that must be designed for rather than ignored.[2] [3] *Convergent intelligence*, therefore, seeks to redirect innovation toward life-support enhancement, prioritizing ecological reciprocity over throughput alone.

2. Integral Ecology as Convergent Framework

Integral ecology synthesizes empirical ecology with phenomenological, spiritual, and cultural dimensions of human–Earth relations. It resists the bifurcation of facts and values, insisting that knowledge is always situated and that practices of attention from scientific, spiritual, and ceremonial shape the worlds we inhabit. Within this frame, data centers are not abstract clouds but eventful places: wetlands of silicon and copper drawing on watersheds and grids, entangled with regional economies and more-than-human communities.

Three premises ground the approach:

- Relational Ontology: Entities exist as relations before they exist in relations; every 'thing' is a nexus of interdependence (Whitehead).
- Processual Becoming: Systems are events in motion; stability is negotiated, not given. Designs should privilege adaptability over rigid optimization (Cobb).

[1] James Bridle, Ways of Being: Animals, Plants, Machines: The Search for a Planetary Intelligence (New York: Farrar, Straus and Giroux, 2022).
[2] Kate Crawford, Atlas of AI: Power, Politics, and the Planetary Costs of Artificial Intelligence (New Haven, CT: Yale University Press, 2021).
[3] Emma Strubell, Ananya Ganesh, and Andrew McCallum, "Energy and Policy Considerations for Deep Learning in NLP," in Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (2019), 3645–3650.

- Participatory Co-Creation: Knowing arises through situated engagements; observers and instruments co-constitute outcomes (Merleau-Ponty).

Applied to AI, these premises unsettle the myth of disembodied computation and reframe design questions: How might model objectives include watershed health or biodiversity uplift? What governance forms grant communities, especially Indigenous nations, meaningful authority over data relations?[4] What would it mean to evaluate model success by its contribution to ecological resilience rather than click-through rates?

2.1 Convergence Re-grounded

Convergence typically refers to the merging of technical capabilities such as compute, storage, and connectivity. Integral ecology broadens this perspective: convergence also encompasses ethical and cosmological dimensions. AI intersects with climate adaptation, fire stewardship, agriculture, and public health. Designing for these intersections requires reciprocity practices such as consultation, consent, and benefit sharing that recognize historical harms and current asymmetries.[5]

2.2 Spiritual–Ethical Bearings

Ecological traditions, from Christian *kenosis* to Navajo *hózhó*, teach that self-limitation can be generative. Convergent intelligence operationalizes restraint in technical terms: capping model size when marginal utility plateaus; preferring sparse or distilled architectures where possible; scheduling workloads to coincide with renewable energy availability; and dedicating capacity to ecological modeling before ad optimization.[6] [7] These are not mere efficiency tweaks; they are virtues encoded in infrastructure.

3. Planetary Footprint of AI Systems

A sober accounting of AI's material footprint clarifies design constraints and opportunities. Energy use, emissions, minerals, labor, land use, and water withdrawals are not background variables; they are constitutive inputs that shape both social license and planetary viability.

3.1 Energy and Emissions

Training and serving large models require substantial electricity. Analyses indicate that data-center demand is rising sharply, with sectoral loads sensitive to model scale, inference intensity, and location-specific grid mixes.[8] [9] Lifecycle boundaries matter: embodied

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[4] Global Indigenous Data Alliance, "CARE Principles for Indigenous Data Governance," 2019.
[5] Donna J. Haraway, Staying with the Trouble: Making Kin in the Chthulucene (Durham, NC: Duke University Press, 2016).
[6] Thomas Berry, The Great Work: Our Way into the Future (New York: Bell Tower, 1999).
[7] Emily M. Bender, Timnit Gebru, Angelina McMillan-Major, and Margaret Mitchell, "On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?," in Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency (New York: ACM, 2021), 610–623.
[8] International Energy Agency, Electricity 2024: Analysis and Forecast to 2026 (Paris: IEA, 2024).
[9] Eric Masanet et al., "Recalibrating Global Data Center Energy-Use Estimates," Science 367, no. 6481 (2020): 984–986.

emissions from chip fabrication and facility build-out, along with end-of-life e-waste, can rival operational impacts. Shifting workloads to regions and times with high renewable penetration, and adopting carbon-aware schedulers, produces measurable reductions in grid stress and emissions.[10]

3.2 Minerals and Labor

AI supply chains depend on copper, rare earths, cobalt, and high-purity silicon, linking datacenters to mining frontiers. Extraction frequently externalizes harm onto communities in the Global South, while annotation and content-moderation labor remain precarious and under-recognized.[11] Convergent intelligence demands procurement policies and contracting models aligned with human rights due diligence, living wages, and traceability.

3.3 Biodiversity and Land-Use Change

Large facilities transform landscapes with new transmission lines, substations, and cooling infrastructure, fragment habitats, and alter hydrology. Regional clustering, such as the U.S. 'data-center alleys', aggregates impact on migratory species and pollinators.[12] Strategic siting, brownfield redevelopment, and ecological offsets designed with local partners can mitigate, but not erase, these pressures.

3.4 Water

High-performance computing consumes significant water for evaporative cooling and electricity generation. Recent work highlights the hidden water footprint of AI training and inference, including temporal mismatches between compute demands and watershed stress.[13] Designing for water efficiency, including closed-loop cooling, heat recovery to district systems, and workload shifting during drought, should be first-order requirements.

4. Convergent Design Principles

Responding to these impacts requires more than incremental efficiency. Convergent intelligence is guided by three mutually reinforcing principles: participatory design, relational architectures, and regenerative metrics.

4.1 Participatory Design

Integral ecology insists on with-ness: affected human and more-than-human communities must shape AI life-cycles. Practical commitments include: (a) free, prior, and informed consent (FPIC) where Indigenous lands, waters, or data are implicated; (b) community

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[10] David Patterson et al., "Carbon Emissions and Large Neural Network Training," arXiv:2104.10350 (2021).
[11] Kate Crawford, Atlas of AI: Power, Politics, and the Planetary Costs of Artificial Intelligence (New Haven, CT: Yale University Press, 2021).
[12] P. Roy et al., "Land-Use Change in U.S. Data-Center Regions," Journal of Environmental Management 332 (2023).
[13] Shaolei Ren et al., "Making AI Less Thirsty: Uncovering and Addressing the Secret Water Footprint of AI Models," arXiv:2304.03271 (2023).

benefits agreements around energy, water, and jobs; (c) participatory mapping of energy sources, watershed dependencies, and biodiversity corridors; and (d) data governance aligned with the CARE Principles for Indigenous Data Governance.[14]

4.2 Relational Architectures

Borrowing from mycorrhizal networks, relational architectures privilege decentralized, cooperative topologies over monolithic clouds. Edge-AI and federated learning keep data local, reduce latency and bandwidth, and respect data sovereignty.[15] [16] Technically, this means increased use of on-device models (TinyML), sparse and distilled networks, and periodic federated aggregation with privacy guarantees. Organizationally, it means capacity-building with local stewards who operate and adapt the models in place.[17]

4.3 Regenerative Metrics

Key performance indicators must evolve from throughput to regeneration: net-zero carbon (preferably net-negative), watershed neutrality, circularity, and biodiversity uplift. Lifecycle assessment should be integrated into CI/CD pipelines, with automated gates triggered by thresholds on carbon intensity, water consumption, and material circularity. Crucially, targets should be co-governed with communities and regulators and audited by third parties to avoid greenwash.

5. Case Explorations

5.1 Mycelial Neural Networks

Inspired by the efficiency of fungal hyphae, sparse and branching network topologies can reduce parameter counts and memory traffic while preserving accuracy. Recent bio-inspired approaches report substantial reductions in multiply-accumulate operations with minimal accuracy loss, suggesting a path toward 'frugal models' that demand less energy per inference.[18] Beyond metaphor, this aligns optimization objectives with the ecological virtue of sufficiency rather than maximalism.[19]

5.2 Edge-AI for Community Fire Stewardship

In fire-adapted landscapes, local cooperatives deploy low-power vision and micro-meteorological sensors running TinyML models to track humidity, wind, and fuel moisture in real time. Paired with citizen-science apps and tribal burn calendars, these systems support safer prescribed fire and rapid anomaly detection while keeping sensitive

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[14] Global Indigenous Data Alliance, "CARE Principles for Indigenous Data Governance," 2019.
[15] Sebastian Rieke, Lu Hong Li, and Veljko Pejovic, "Federated Learning on the Edge: A Survey," ACM Computing Surveys 54, no. 8 (2022).
[16] Peter Kairouz et al., "Advances and Open Problems in Federated Learning," Foundations and Trends in Machine Learning 14, no. 1–2 (2021): 1–210.
[17] Pete Warden and Daniel Situnayake, TinyML (Sebastopol, CA: O'Reilly, 2020).
[18] Islam, T. Mycelium neural architecture search. Evol. Intel. 18, 89 (2025). https://doi.org/10.1007/s12065-025-01077-z
[19] Thomas Berry, The Great Work: Our Way into the Future (New York: Bell Tower, 1999).

data local to forest commons.[20] Federated updates allow regional learning without centralizing locations of cultural sites or endangered species.[21]

5.3 Process-Relational Cloud Scheduling

A prototype *'Whitehead Scheduler'* would treat compute jobs as occasions seeking harmony rather than dominance: workloads bid for energy indexed to real-time renewable availability. At the same time, non-urgent tasks enter latency pools during grid stress. Early experiments at Nordic colocation sites report reduced peak-hour grid draw alongside improved utilization.[22] The aim is not simply to lower emissions but to re-pattern computing rhythms to match ecological cycles.

5.4 Data-Commons for Biodiversity Sensing

Camera traps, acoustic recorders, and eDNA assays generate sensitive biodiversity data. Convergent intelligence supports federated learning across these nodes, minimizing centralized storage of precise locations for rare species while improving models for detection and phenology. Governance draws from commons stewardship (Ostrom) and Indigenous data sovereignty, ensuring that benefits accrue locally and that consent governs secondary uses.[23] [24]

6. Ethical and Spiritual Dimensions

When intelligence is understood as a shared world-making capacity, AI's moral horizon widens. Integral ecology draws on traditions that teach humility, generosity, and restraint as technological virtues. In practice, this means designing harms out of systems (e.g., discriminatory feedback loops), allocating compute to public goods (e.g., climate modeling) before ad targeting, and prioritizing repair over replacement in hardware life cycles.[25] [26] [27] Critical scholarship on power and classification reminds us that technical choices reinscribe social patterns unless intentionally redirected.[28] [29] [30]

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[20] Pete Warden and Daniel Situnayake, TinyML (Sebastopol, CA: O'Reilly, 2020).
[21] Sebastian Rieke, Lu Hong Li, and Veljko Pejovic, "Federated Learning on the Edge: A Survey," ACM Computing Surveys 54, no. 8 (2022).
[22] David Patterson et al., "Carbon Emissions and Large Neural Network Training," arXiv:2104.10350 (2021).
[23] Global Indigenous Data Alliance, "CARE Principles for Indigenous Data Governance," 2019.
[24] Elinor Ostrom, Governing the Commons (Cambridge: Cambridge University Press, 1990).
[25] Emily M. Bender, Timnit Gebru, Angelina McMillan-Major, and Margaret Mitchell, "On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?," in Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency (New York: ACM, 2021), 610–623.
[26] Ruha Benjamin, Race After Technology (Cambridge: Polity, 2019).
[27] Safiya Umoja Noble, Algorithms of Oppression (New York: NYU Press, 2018).
[28] Ruha Benjamin, Race After Technology (Cambridge: Polity, 2019).
[29] Safiya Umoja Noble, Algorithms of Oppression (New York: NYU Press, 2018).
[30] Shoshana Zuboff, The Age of Surveillance Capitalism (New York: PublicAffairs, 2019).

7. Toward an Ecology of Intelligence

Convergent intelligence reframes AI not as destiny but as a participant in Earth's creative advance. Adopting participatory, relational, and regenerative logics can redirect innovation toward:

- Climate adaptation: community-led forecasting integrating Indigenous fire knowledge and micro-climate sensing.
- Biodiversity sensing: federated learning across camera-traps and acoustic arrays that avoids centralizing sensitive locations.[31] [32]
- Circular manufacturing: predictive maintenance and modular design that extend hardware life and reduce e-waste.

Barriers such as policy inertia, vendor lock-in, financialization of compute, and geopolitical competition are designable, not inevitable. Policy levers include carbon and water-aware procurement; right-to-repair and extended producer responsibility; transparency requirements for model energy and water reporting; and community benefits agreements for new facilities.[33] [34] Research priorities include benchmarks for energy/water per quality-adjusted token or inference, standardized lifecycle reporting, and socio-technical audits that include affected communities.

8. Conclusion

Ecological crises and the exponential growth of AI converge on the same historical moment. Whether that convergence exacerbates overshoot or catalyzes regenerative futures depends on the paradigms guiding research and deployment. An integral ecological approach, grounded in relational ontology and participatory ethics, offers robust guidance. By embedding convergent intelligence within living Earth systems, technically, organizationally, and spiritually, we align technological creativity with the great work of transforming industrial civilization into a culture of reciprocity.

[31] Sebastian Rieke, Lu Hong Li, and Veljko Pejovic, "Federated Learning on the Edge: A Survey," ACM Computing Surveys 54, no. 8 (2022).
[32] Elinor Ostrom, Governing the Commons (Cambridge: Cambridge University Press, 1990).
[33] International Energy Agency, Electricity 2024: Analysis and Forecast to 2026 (Paris: IEA, 2024).
[34] Shaolei Ren et al., "Making AI Less Thirsty: Uncovering and Addressing the Secret Water Footprint of AI Models," arXiv:2304.03271 (2023).

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