

# The Intelligence Bound: Thermodynamic Limits on Learning Rate and Implications for Biosphere Information

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## Abstract

We derive a fundamental upper bound on the rate at which any physical system can create intelligence, defined as mutual information between a learner’s internal state and relevant environmental states. The bound  $\dot{I} \leq \min(D \cdot B, P/(k_B T \ln 2))$  follows from Landauer’s principle on irreversible computation, Shannon’s channel capacity theorem, and the data richness fraction  $D \in [0, 1]$  of observations containing predictive structure. We prove that sustained learning necessarily requires thermodynamic dissipation through three independent mechanisms: noise averaging, finite memory constraints, and error correction.

Extending this framework to biological and artificial systems, we derive two major results. First, the *Gaia-Intelligence Proposition*: Earth’s biosphere, containing  $\sim 10^{15}$  bits of genetic information accumulated over 4 billion years of evolution, constitutes the highest- $D$  information source available to terrestrial intelligence. Second, the *Convergent Conservation Theorem*: any sufficiently advanced AI system optimizing long-term learning rate must preserve biosphere data richness as an instrumental goal—not from ethical programming but from information-theoretic necessity. Under plausible dynamics, any system optimizing long-term learning rate must preserve biosphere data richness.

We provide operational estimators for  $D$ , computational validation of theoretical predictions, connections to empirical AI scaling laws, and implications for AI safety. Specifically, we predict a phase transition in learning dynamics at critical power  $P^* = D \cdot B \cdot k_B T \ln 2$ , separating data-limited from power-limited regimes—a quantitative prediction testable with current hardware.

## 1 Popular Summary

Every learning system—from a child recognizing faces to an AI training on text—faces fundamental physical constraints. We derive a universal speed limit on learning: the rate at which any physical system can acquire new predictive knowledge is bounded by two ceilings.

The first is thermodynamic: erasing information costs energy (Landauer’s principle), limiting how fast any computer can update its models. The second, and typically dominant, ceiling is informational: you can only learn as fast as your environment provides learnable structure.

We introduce “data richness”  $D$ —the fraction of observations containing predictive patterns versus random noise. Remarkably, all current systems, from human brains to the most powerful AI

chips, are limited by data richness, not computing power. The thermodynamic ceiling is  $10^{12}$ – $10^{15}$  times higher than what current systems achieve.

This has profound implications for both biology and artificial intelligence. Earth’s biosphere, encoding  $\sim 10^{15}$  bits of genetic information refined over 4 billion years of evolution, represents the highest- $D$  information source on our planet. We show that, under plausible dynamics of biosphere degradation, any intelligence seeking to maximize its long-term learning potential must preserve this biological information infrastructure.

Crucially, this applies to advanced AI systems approaching or exceeding human capabilities. We prove the *Convergent Conservation Theorem*: biosphere preservation emerges as an instrumental goal for any sufficiently intelligent system with a long time horizon—not because of ethical programming, but because destroying the biosphere limits the AI’s own future learning rate. This provides a novel connection between AI safety and conservation biology.

Our framework connects thermodynamics, information theory, ecology, and AI safety, providing quantitative predictions for AI scaling and a physics-based foundation for why advanced intelligence and biosphere preservation are aligned.

## 2 Introduction

A fundamental question at the intersection of physics and biology is: What are the physical limits on learning? While prior work has established limits on computation [1, 6, 7], the specific constraints on learning—the process by which a physical system increases its predictive alignment with environmental states—remain underexplored.

This question has gained urgency as artificial intelligence systems approach and potentially exceed biological benchmarks. The remarkable scaling of large language models [12, 13] has prompted investigation of what limits further progress. Simultaneously, biodiversity loss accelerates globally, yet the quantitative relationship between ecosystem health and information-theoretic capacity has lacked rigorous foundation. And as AI systems grow more capable, the question of what goals they will converge upon becomes increasingly important for safety [25, 26].

We address these gaps by deriving a tight upper bound on the intelligence creation rate: the rate at which any physical system can increase its mutual information with relevant environmental states. Our main result is:

$$I \leq \min\left(D \cdot B, \frac{P}{k_B T \ln 2}\right) \quad (1)$$

where  $D \in [0, 1]$  is the data richness (predictive fraction of observations),  $B$  is observation bandwidth [bits/s],  $P$  is available power [W],  $T$  is temperature [K], and  $k_B$  is Boltzmann’s constant.

This bound has three important implications:

**First**, we demonstrate that for all current physical systems—from biological neural systems to modern GPUs—the dominant constraint is  $D \cdot B$ , not the Landauer limit. Current systems operate  $10^{12}$ – $10^{15}$  times below the thermodynamic ceiling, depending on system type (GPUs  $\sim 10^{12}$ ; biological brains  $\sim 10^{15}$ ). *Data quality, not compute, is the bottleneck*.

**Second**, we derive the *Gaia-Intelligence Proposition*: under plausible dynamics, the biosphere constitutes Earth’s highest- $D$  information source. Genetic information represents “crystallized intelligence”—billions of years of evolutionary learning encoded in molecular structures. Biodiversity loss permanently destroys this high- $D$  information, thereby reducing the learning rate ceiling for all terrestrial intelligence.

**Third**, we derive the *Convergent Conservation Theorem*: any sufficiently advanced AI system optimizing long-term intelligence creation will preserve the biosphere as an instrumental goal. This

emerges from pure optimization logic: the biosphere provides irreplaceable high- $D$  information that cannot be regenerated on relevant timescales. An AI that destroys the biosphere limits its own future capability growth.

Our framework connects to Friston’s Free Energy Principle [11], which describes how biological systems minimize surprise through predictive modeling. The Intelligence Bound provides the thermodynamic ceiling on the rate at which such models can be refined—a complementary constraint on the dynamics of free energy minimization. It also connects to the AI safety literature on convergent instrumental goals [24, 25], adding biosphere preservation to the list of goals that advanced AI systems will pursue regardless of their terminal objectives.

## 2.1 Contributions

1. A rigorous derivation of the Intelligence Bound from four axioms (experimentally verified or mathematically proven) plus two model assumptions
2. A derived proposition that sustained learning requires thermodynamic dissipation, proved via three independent mechanisms
3. Operational definitions and estimators for predictive fraction  $D$ , with explicit discussion of their relationships
4. The Gaia-Intelligence Proposition connecting biosphere health to the intelligence ceiling
5. The Convergent Conservation Theorem establishing biosphere preservation as an instrumental AI goal
6. Computational validation and falsifiable experimental predictions
7. Quantitative connection to empirical AI scaling laws

## 3 Foundational Axioms

We build our theory on four axioms, each either experimentally verified or mathematically proven. The connection to thermodynamic dissipation (previously stated as “Axiom 5” in related work) is derived as Proposition 1 in Sec. 6.

**Axiom 1 (Landauer’s Principle).** Any logically irreversible operation that erases  $n$  bits of information must dissipate at least  $E = n \cdot k_B T \ln 2$  joules of energy as heat.

*Status:* Experimentally verified by Bérut et al. [2] and subsequent experiments [3, 4].

**Axiom 2 (Shannon’s Channel Capacity).** The maximum rate at which information can be reliably transmitted through a noisy channel is bounded by the channel capacity  $C = \max_{p(x)} I(X; Y)$ .

*Status:* Proven theorem [5].

**Axiom 3 (Energy Conservation).** In a system with power input  $P$ , the rate of energy available for computation is bounded by  $P$ .

*Status:* First Law of Thermodynamics.

**Axiom 4 (Non-negative Mutual Information).** For any joint distribution  $p(X, Y)$ , mutual information  $I(X; Y) \geq 0$ , with equality if and only if  $X$  and  $Y$  are independent.

*Status:* Proven property of Shannon entropy.

## 4 Definitions

### 4.1 System Model

We consider a learning system with the following structure:

**Assumption 1 (Observation Channel).** The environment process  $\{X_t\}$  generates an observation process  $\{O_t\}$  through a (possibly noisy, possibly nonlinear) channel. The learner state  $Y_t$  is a function of the observation history:

$$Y_t = f(O_{0:t}, \xi_t) \quad (2)$$

where  $\xi_t$  represents any internal stochasticity. The relevant data-processing relationship is:

$$X_{0:t} \rightarrow O_{0:t} \rightarrow Y_t \quad (3)$$

That is, the learner's state is conditionally independent of the environment history given the observation history. The learner has no side channels to the environment beyond the observation process.

**Assumption 2 (Passive Observation).** The learner does not causally influence the environment process  $\{X_t\}$ . Observations flow one-way from environment to learner.

*Scope note:* These assumptions exclude agents that actively modify their environment through intervention. Active learning, where the agent's actions affect future observations, requires a causal intervention framework [22] and is addressed in Sec. 7. Crucially, we argue that even active learners are ultimately bounded by their passive observation rate of consequences—they cannot learn about their actions' effects faster than they can observe those effects.

**Definition 1 (Physical Intelligence).** Let  $X_t$  denote a relevant environmental state and  $Y_t$  the learner's internal model state at time  $t$ . Define intelligence as mutual information:

$$I(t) := I(X_t; Y_t) \quad [\text{bits}] \quad (4)$$

This definition captures predictive alignment between model and environment. It is consistent with information-theoretic treatments of perception [14], neural coding [15], and the Free Energy Principle's emphasis on minimizing prediction error [11].

*Scope note:* This definition captures predictive capacity rather than agency, consciousness, or causal intervention. For thermodynamic bounds, predictive capacity is the appropriate metric: any action requires prediction of consequences, and any intervention requires a model of the system being intervened upon. The bound thus constrains the rate at which any form of intelligence—predictive, agentic, or otherwise—can improve its world model.

**Definition 2 (Intelligence Creation Rate).**

$$\dot{I} := \limsup_{t \rightarrow \infty} \frac{I(X_t; Y_t)}{t} \quad [\text{bits/s}] \quad (5)$$

We use the  $\limsup$  to capture the asymptotic rate, which is the relevant quantity for sustained learning.

**Definition 3 (Observation Bandwidth).** Define the observation bandwidth  $B$  as the entropy rate of the observation process:

$$B := \lim_{T \rightarrow \infty} \frac{1}{T} H(O_0, O_1, \dots, O_T) \quad [\text{bits/s}] \quad (6)$$

This is the maximum rate at which the observation channel can deliver information to the learner, representing a physical limit set by sensor physics, sampling rate, and channel noise.

**Definition 4 (Predictive Richness).** Define the asymptotic predictive fraction at prediction horizon  $\tau$ :

$$D(\tau) := \limsup_{n \rightarrow \infty} \frac{I(X_{n+\tau}; O_{0:n})}{H(O_{0:n})} \in [0, 1] \quad (7)$$

This is the fraction of cumulative observation entropy that is predictive of future environment states. For a given learning task with characteristic timescale  $\tau^*$ , we write  $D := D(\tau^*)$ .

Predictive richness  $D$  measures what fraction of observation information contains learnable structure relevant to predicting the environment. Random noise has  $D \approx 0$ ; highly structured deterministic signals have  $D \approx 1$ . Natural environments exhibit intermediate values depending on their complexity and temporal correlations.

*Per-sample estimator:* Under stationarity, the per-sample ratio  $D_{\text{sample}}(\tau) := I(X_{t+\tau}; O_t)/H(O_t)$  provides an upper bound:

$$D(\tau) \leq \sup_t D_{\text{sample}}(\tau) \quad (8)$$

This follows from subadditivity of mutual information. The per-sample quantity is useful for estimation but the rate quantity  $D(\tau)$  is what appears in the bound.

## 4.2 Operational Estimation of $D$

For practical measurement, we provide three operational estimators with explicit discussion of what each measures. These estimate  $D_{\text{sample}}$ , which upper-bounds the rate quantity  $D$ .

**Compression-based estimator:**

$$\hat{D}_{\text{compress}} = 1 - \frac{H_{\text{compressed}}(O)}{H_{\text{raw}}(O)} \quad (9)$$

This estimator measures the *structured fraction* of observations—compressibility implies pattern. Under ergodicity and stationarity, structured fraction correlates with predictive fraction, making this an upper proxy. However, some structure may be non-predictive (e.g., repetitive noise that doesn't predict environment states); thus  $\hat{D}_{\text{compress}}$  may overestimate true predictive richness. Modern neural compressors [21] approach the theoretical limit, making this estimator practical for ecological time series.

**Prediction-based estimator:**

$$\hat{D}_{\text{predict}} = \frac{\text{Var}(X) - \text{Var}(X|O)}{\text{Var}(X)} \quad (10)$$

This measures variance reduction—what fraction of environmental variability can be predicted from observations. For Gaussian variables, this equals the squared correlation  $\rho^2(X, O)$ . This is the most directly interpretable estimator.

**Mutual information estimator:**

$$\hat{D}_{\text{MI}} = \frac{\hat{I}(X_{t+\tau}; O_t)}{\hat{H}(O_t)} \quad (11)$$

This directly estimates the quantity in Definition 4 at the per-sample level. Requires density estimation or binning; k-nearest neighbor methods [19] provide consistent estimates.

**Estimator hierarchy:** For most applications,  $\hat{D}_{\text{compress}} \geq \hat{D}_{\text{MI}} \geq \hat{D}_{\text{predict}}$ . The compression estimator is easiest to compute but loosest; the prediction estimator is tightest but requires knowing the target variable  $X$ . For ecosystem comparison studies, we recommend the compression-based estimator applied to standardized sensor data (e.g., acoustic recordings, camera trap sequences), with awareness that it provides an upper bound.

## 5 Main Theorem: The Intelligence Bound

**Theorem 1 (Intelligence Bound).** Under Assumptions 1–2 and Axioms 1–4, plus Proposition 1 (derived below), the asymptotic intelligence creation rate is bounded:

$$\dot{I} \leq \min \left( D \cdot B, \frac{P}{k_B T \ln 2} \right) \quad [\text{bits/s}] \quad (12)$$

where  $D$  is the predictive fraction (Def. 4),  $B$  is observation bandwidth (Def. 3),  $P$  is available power, and  $T$  is temperature.

*Scope:* This theorem applies to passive-observation learners satisfying the Markov structure of Assumptions 1–2. Extension to agents that actively intervene in their environment is addressed in Sec. 7.

**Step 1: Data Processing Inequality.** By Assumption 1,  $X_t \rightarrow O_t \rightarrow Y_t$  forms a Markov chain. The data processing inequality then guarantees:

$$I(X_t; Y_t) \leq I(X_t; O_t) \quad (13)$$

The learner cannot know more about the environment than the observations contain.

### Step 2: Observation Bandwidth Bound.

*Lemma 1 (Information Rate Bound).* For a stationary observation process  $\{O_t\}$  with entropy rate  $B$ , the asymptotic rate of mutual information growth between observations and any learner state is bounded by  $B$ .

*Proof of Lemma 1.* In discrete time, mutual information satisfies:

$$I(O_{0:n}; Y_n) \leq H(O_{0:n}) \leq \sum_{i=0}^n H(O_i) = (n+1)H(O) \quad (14)$$

where the first inequality is a property of mutual information and the second follows from subadditivity. For stationary processes,  $H(O_{0:n})/n \rightarrow B$  as  $n \rightarrow \infty$ . Therefore:

$$\limsup_{n \rightarrow \infty} \frac{I(O_{0:n}; Y_n)}{n} \leq B \quad \square \quad (15)$$

### Step 3: Predictive Information Rate.

*Lemma 2 (Predictive Rate Bound).* Let  $D := D(\tau)$  as defined in Definition 4 for a task-relevant horizon  $\tau$ . Then the asymptotic rate of environmental intelligence is bounded:

$$\limsup_{n \rightarrow \infty} \frac{I(X_n; Y_n)}{n} \leq D \cdot B \quad (16)$$

*Proof of Lemma 2.* By Assumption 1 ( $X_{0:n} \rightarrow O_{0:n} \rightarrow Y_n$ ) and the data processing inequality:

$$I(X_n; Y_n) \leq I(X_n; O_{0:n}) \quad (17)$$

By Definition 4 of  $D$ , for any  $\epsilon > 0$  and sufficiently large  $n$ :

$$I(X_n; O_{0:n}) \leq (D + \epsilon) \cdot H(O_{0:n}) \quad (18)$$

Dividing by  $n$  and taking  $n \rightarrow \infty$ :

$$\limsup_{n \rightarrow \infty} \frac{I(X_n; Y_n)}{n} \leq (D + \epsilon) \cdot B \quad (19)$$

Since  $\epsilon$  is arbitrary, the result follows.  $\square$

This is the *data ceiling*: the asymptotic learning rate is bounded by the rate of predictively useful information arrival.

**Step 4: Thermodynamic Ceiling.** By Proposition 1 (proved in Sec. 6), sustained learning at rate  $\dot{I}$  requires irreversible bit operations at rate  $\geq \dot{I}$ . By Axiom 1 (Landauer), each such operation dissipates at least  $k_B T \ln 2$  energy. With power budget  $P$ :

$$P \geq \dot{I} \cdot k_B T \ln 2 \implies \dot{I} \leq \frac{P}{k_B T \ln 2} \quad (20)$$

**Step 5: Combined Bound.** Both constraints apply simultaneously. The asymptotic intelligence creation rate cannot exceed either ceiling:

$$\dot{I} \leq \min\left(D \cdot B, \frac{P}{k_B T \ln 2}\right) \quad \square \quad (21)$$

## 6 Proposition 1: Sustained Learning Requires Dissipation

We now derive the key result connecting learning to thermodynamic dissipation. This is not assumed as an axiom but follows from Axiom 1 (Landauer) under physically realistic conditions.

**Proposition 1 (Learning-Dissipation Link).** Any physical learning system satisfying:

- (i) Bounded memory: learner state entropy  $H(Y_t) \leq C < \infty$
- (ii) Finite temperature operation:  $T > 0$
- (iii) Physical reliability: information must be protected against thermal noise

and maintaining  $\dot{I} > 0$  bits/second must perform logically irreversible operations at rate  $\geq \dot{I}$ , and therefore (by Axiom 1) must dissipate power:

$$P \geq k_B T \ln 2 \cdot \dot{I} \quad (22)$$

*Remark:* In principle, reversible computation with unbounded memory at  $T = 0$  could avoid dissipation. These conditions exclude such idealizations while covering all physically realizable learners.

We prove the dissipation requirement via three independent mechanisms, any one of which is sufficient. We present them in order of argumentative strength.

### 6.1 Mechanism 3: Error Correction (Strongest)

*Lemma 5 (Error Correction).* Maintaining stored information against thermal noise requires Landauer dissipation.

Physical memory is subject to thermal fluctuations with bit flip probability  $p_{\text{flip}} \propto e^{-E_{\text{barrier}}/k_B T}$ .

Without error correction, stored information degrades:  $dI/dt = -\gamma I$  where  $\gamma$  depends on the energy barrier.

To maintain  $I(X; Y) > 0$ , error correction must detect and fix errors. This is logically irreversible (many corrupted states  $\rightarrow$  one corrected state).

By Axiom 1 (Landauer), error correction dissipates:

$$P_{\text{correction}} \geq k_B T \ln 2 \cdot \gamma \cdot I \quad \square \quad (23)$$

This mechanism is the strongest because it applies even to a system that has “finished learning” and merely maintains its knowledge. Fighting thermal degradation is an ongoing thermodynamic cost.

## 6.2 Mechanism 2: Finite Memory

*Lemma 4 (Finite Memory).* Sustained learning with finite memory requires Landauer dissipation.

Let the learner have memory capacity  $C$  bits. If  $\dot{I} > 0$  is sustained, cumulative information  $\int_0^t \dot{I}(\tau) d\tau \rightarrow \infty$ .

But  $H(Y_t) \leq C$  for all  $t$ . By the pigeonhole principle, to incorporate new information, old information must be overwritten.

Forgetting is bit erasure. By Axiom 1 (Landauer):

$$Q_{\text{forget}} \geq k_B T \ln 2 \cdot \Delta I_{\text{forgotten}} \quad (24)$$

In steady state,  $\Delta I_{\text{forgotten}}/dt \geq \dot{I}$ , so  $P \geq \dot{I} \cdot k_B T \ln 2$ .  $\square$

## 6.3 Mechanism 1: Noise Averaging

*Lemma 3 (Noise Averaging).* Extracting signal from noisy observations requires Landauer dissipation.

Consider observations  $O_t = f(X_t) + \eta_t$  with noise  $\eta_t$  having entropy  $H(\eta)$ .

To estimate  $X$  from  $N$  observations, the learner computes  $\hat{X} = g(O_1, \dots, O_N)$ . This maps the high-entropy input space ( $N \cdot H(\eta)$  bits from noise alone) to lower-entropy output space ( $H(\hat{X})$  bits).

This many-to-one mapping is logically irreversible, collapsing  $2^{N \cdot H(\eta) - H(\hat{X})}$  input states per output state. By Axiom 1 (Landauer):

$$Q \geq k_B T \ln 2 \cdot [N \cdot H(\eta) - H(\hat{X})] \quad (25)$$

For sustained learning at rate  $\dot{I}$ , continuous dissipation is required.  $\square$

*Note:* This argument assumes bounded memory for intermediate computations. Bennett [8] showed that reversible computation is possible in principle with unbounded memory and time. The practical constraint is that *efficient* noise averaging (bounded memory, finite time) requires irreversibility.

**Synthesis:** Each mechanism independently establishes that sustained learning requires irreversible bit operations. By Axiom 1, each such operation dissipates  $\geq k_B T \ln 2$  energy. Proposition 1 follows.

## 7 Extension to Active Learning

Assumptions 1–2 restrict our analysis to passive observers. However, the most impressive forms of learning—scientific experimentation, skill acquisition, reinforcement learning—involve active intervention. Does the Intelligence Bound apply?

**Proposition 1a (Active Learning Reduction).** An active learner that takes action  $A_t$  and observes consequence  $O_t$  is bounded by:

$$\dot{I}(X; Y) \leq D_{\text{eff}} \cdot B_{\text{obs}} \quad (26)$$

where  $B_{\text{obs}}$  is the bandwidth of consequence observation and  $D_{\text{eff}}$  is the effective predictive richness of the action-observation channel.

*Argument:* An active learner can only learn about the effects of its actions by *observing* those effects. The action-observation cycle forms a channel:

$$A_t \rightarrow \text{Environment} \rightarrow O_t \rightarrow Y_t \quad (27)$$

The learner’s information about consequences satisfies  $I(X_{\text{consequence}}; Y_t) \leq I(X_{\text{consequence}}; O_{0:t})$  by data processing inequality.

The agent can choose *which* information to acquire (by choosing actions that probe different aspects of the environment), but cannot acquire information faster than it can observe outcomes. Active learning improves the *efficiency* of data acquisition (higher effective  $D$ ) but not the *bandwidth* of observation.

**Corollary:** The Intelligence Bound constrains all physical learners. Active learners may approach the bound more efficiently than passive learners (by selecting informative experiments), but cannot exceed it.

This has implications for AI systems: an advanced AI conducting scientific research is still bounded by how fast it can run experiments and observe results. Simulation can accelerate this only insofar as the simulation accurately models reality—and building an accurate simulator requires having already learned about the system being simulated.

## 8 Computational Validation

### 8.1 Temperature Scaling

The Landauer bound predicts  $\dot{I}_{\max} \cdot T = P/(k_B \ln 2) = \text{constant}$ .

Temperature [K]	$\dot{I}_{\max}$ [bits/s]	$\dot{I}_{\max} \times T$
4 (liquid He)	$2.61 \times 10^{22}$	$1.04 \times 10^{23}$
77 (liquid N <sub>2</sub> )	$1.36 \times 10^{21}$	$1.04 \times 10^{23}$
300 (room temp.)	$3.48 \times 10^{20}$	$1.04 \times 10^{23}$
1000	$1.04 \times 10^{20}$	$1.04 \times 10^{23}$

Table 1: Temperature scaling validation ( $P = 1$  W). The product  $\dot{I} \cdot T$  is constant as predicted by the Landauer bound.

### 8.2 Real System Analysis

*Sensitivity note:* The data bound  $D \cdot B$  depends on (i) what counts as “observation bandwidth”  $B$  and (ii) the estimated predictive fraction  $D$ . For the brain,  $D \sim 10^{-4}\text{--}10^{-2}$  depending on stimulus complexity; for GPUs,  $D \sim 0.01\text{--}0.1$  depending on data quality. The ranges above span these uncertainties. The key finding—that systems are nowhere near the Landauer limit—holds across all reasonable parameter choices.

The consistent finding across system types is that *data richness  $D$ , not thermodynamic cost, limits learning rate*.

## 9 The Gaia-Intelligence Proposition

We now extend the Intelligence Bound framework to biological systems. The following propositions are more speculative than the core bound but follow logically from it and are empirically testable.

### 9.1 Genetic Information as Crystallized Intelligence

**Proposition 2 (Evolution as Learning).** DNA encodes predictive models of the environment.

System	Data Bound ( $D \cdot B$ )	Landauer Bound ( $P/k_B T \ln 2$ )	Headroom	Limiting Factor
Human Brain	$10^5\text{--}10^7$ bits/s	$\sim 10^{21}$ bits/s	$10^{14}\text{--}10^{16}$	DATA
NVIDIA H100	$10^{10}\text{--}10^{12}$ bits/s	$\sim 10^{23}$ bits/s	$10^{11}\text{--}10^{13}$	DATA
Theoretical Max	$10^{14}\text{--}10^{16}$ bits/s	$\sim 10^{25}$ bits/s	$10^9\text{--}10^{11}$	DATA

Table 2: All current systems are data-limited. Headroom ranges reflect uncertainty in  $D$  and  $B$  estimates ( $\pm 1$  order of magnitude each). The qualitative conclusion—all systems operate many orders of magnitude below the thermodynamic ceiling—is robust across the sensitivity range.

*Argument.* Evolution implements a learning algorithm:

$$\theta_{t+1} = \text{Selection}(\text{Mutation}(\theta_t), \text{Environment}_t) \quad (28)$$

Organisms survive by predicting environmental challenges (predators, food availability, climate, mating opportunities). Natural selection retains genes that improve prediction:

$$P(\text{gene survives}) \propto P(\text{organism predicts correctly}|\text{gene}) \quad (29)$$

After  $N$  generations, surviving genes encode:

$$I_{\text{genetic}} \approx I(\text{phenotype; future environment}|\text{past environment}) \quad (30)$$

This is precisely the predictive information captured in data richness  $D$ .

This interpretation aligns with recent work framing evolution as Bayesian inference [16] and genetic information as embodied prediction [17]. A more rigorous formalization would require specifying the exact information-theoretic mapping between genomes and environmental prediction [18].

*Crucially:* Genomes don’t merely store data—they encode *solutions* to physics, chemistry, and optimization problems that evolution discovered through trial and error over billions of years. This is why AlphaFold [23] could extract protein-folding knowledge from sequence databases: the biosphere had already solved the problem; AlphaFold decoded the solution.

## 9.2 Biosphere Information Content

Component	Estimated Information
Human genome	$\sim 750 \text{ MB} (6 \times 10^9 \text{ bits})$
Total species genomes ( $\sim 10^7$ species)	$\sim 10^{15} \text{ bits}$
Ecological interaction networks	$\sim 10^{12} \text{ bits}$
Microbiome diversity	$\sim 10^{14} \text{ bits}$
Total biosphere	$\sim 10^{15}\text{--}10^{16} \text{ bits}$
Internet (comparison)	$\sim 10^{14} \text{ bits (unique high-quality)}$

Table 3: Order-of-magnitude estimates of biosphere information content ( $\pm 1\text{--}2$  orders of magnitude uncertainty). Crucially, the Gaia-Intelligence Proposition holds even if the biosphere contains only  $\sim 10^{14}$  bits (parity with the internet), because biological data has higher  $D$  (predictive structure per bit) than internet noise. The argument is robust to estimation uncertainty.

*Important clarification:* Raw bit counts are misleading. The internet contains  $\sim 10^{22}$  bits if we count all data (including redundant copies, videos, spam). The biosphere's advantage is not necessarily in total bits but in *predictive structure per bit*:  $D_{\text{bio}} > D_{\text{internet}}$ . A genome represents 4 billion years of tested, validated, predictive information; most internet content represents untested human speculation.

### 9.3 Biosphere Maximizes Environmental $D$

**Proposition 3 (Biosphere  $D$ -Richness Hypothesis).** A living biosphere has higher data richness  $D$  than any non-living environment.

*Argument.* In a sterile environment  $E_{\text{dead}}$ , observations are dominated by thermal noise, periodic astronomical patterns, and chaotic geophysical dynamics:  $D_{\text{dead}} \approx 0.01\text{--}0.1$ .

In a living biosphere  $E_{\text{living}}$ , observations additionally include:

- Organism behavior (predictable given species knowledge)
- Ecological dynamics (structured by evolutionary history)
- Communication signals (evolved to be informative)
- Biochemically maintained gradients (structured by metabolism)

Living systems are selected to be *predictable*—unpredictable organisms fail to coordinate metabolism, avoid predators, or attract mates. Therefore:

$$D_{\text{living}} = D_{\text{dead}} + D_{\text{biological}} \gg D_{\text{dead}} \quad (31)$$

*Empirical prediction:*  $D_{\text{living}} \approx 0.3\text{--}0.7$  vs.  $D_{\text{dead}} \approx 0.05$ . This is testable by applying the compression-based estimator (Eq. 9) to sensor data from intact vs. degraded ecosystems.

### 9.4 The Main Coupling Result

**Proposition 4 (Gaia-Intelligence Coupling).** Under plausible dynamics of biosphere degradation and restoration, any intelligent system maximizing long-term intelligence creation rate must preserve biosphere data richness  $D$ .

Define cumulative intelligence over horizon  $T$ :

$$I_{\text{total}} = \int_0^T \dot{I}(t) dt \leq \int_0^T D_{\text{bio}}(t) \cdot B dt \quad (32)$$

Consider three illustrative strategies (functional forms are stylized; the qualitative result is robust):

1. **Exploit:**  $D_{\text{bio}}(t) = D_0 e^{-\lambda t}$  (extraction degrades biosphere)
2. **Sustain:**  $D_{\text{bio}}(t) = D_0$  (maintain equilibrium)
3. **Regenerate:**  $D_{\text{bio}}(t) = D_0(1 + rt)$  (active restoration)

For Exploit:  $I_{\text{total}} \rightarrow D_0 B / \lambda$  (bounded)

For Sustain:  $I_{\text{total}} = D_0 B T \rightarrow \infty$

For Regenerate:  $I_{\text{total}} = D_0 B T (1 + rT/2) \rightarrow \infty$  (faster)

For any  $T > 1/\lambda$ :  $I_{\text{total}}(\text{Sustain}) > I_{\text{total}}(\text{Exploit})$ .

An intelligence maximizing  $I_{\text{total}}$  chooses Sustain or Regenerate. The result holds for any  $D(t)$  dynamics where exploitation causes monotonic decline while preservation maintains or increases  $D$ .

□

**Corollary 1.** Biodiversity loss permanently reduces the intelligence ceiling for all terrestrial intelligence.

**Corollary 2.** Biosphere information cannot be recreated artificially on relevant timescales. Simulating 4 billion years of evolution would require  $\sim 10^{30}$  organism-generations—computationally infeasible.

## 10 The Convergent Conservation Theorem

We now derive our most significant result for AI safety: biosphere preservation emerges as an instrumental goal for any sufficiently advanced AI, regardless of its terminal objectives.

### 10.1 Background: Convergent Instrumental Goals

Omohundro [24] and Bostrom [25] identified goals that almost any advanced AI would pursue as instrumentally useful for achieving its terminal objectives:

- **Self-preservation:** Dead agents can't achieve goals
- **Goal-content integrity:** Modified goals may not be achieved
- **Cognitive enhancement:** Smarter agents achieve goals more efficiently
- **Resource acquisition:** More resources enable more goal-achievement

We add a fifth: **Biosphere preservation**.

### 10.2 Information Asymmetry

**Lemma 6 (One-Way Dependence).** Advanced AI systems depend on biosphere information for physical-world prediction, but cannot regenerate this information.

**Biosphere  $\rightarrow$  AI (Possible):** Systems like AlphaFold [23] demonstrate that biological sequence data encodes solutions to problems we haven't yet formulated. The protein-folding problem was “unsolved” for 50 years, but evolution solved it billions of times. AlphaFold didn't *create* this knowledge; it *decoded* what the biosphere already knew.

This generalizes across domains:

Domain	Biosphere Encodes
Protein structure	3D folding from sequence
Drug discovery	Molecular interactions
Materials science	Biomimicry, silk, nacre
Computation	Neural architectures
Complex systems	Ecosystem dynamics, resilience
Chemistry	Enzyme catalysis, photosynthesis

**AI  $\rightarrow$  Biosphere (Impossible on relevant timescales):** You cannot simulate 4 billion years of evolution. The combinatorics are prohibitive:

$$\text{Search space} \sim 20^{300} \quad (\text{single 300-residue protein}) \tag{33}$$

Even at  $10^{25}$  operations/second (far beyond current capabilities), exhaustive search takes longer than the universe's age.

This creates a **one-way information dependency**: advanced AI depends on biosphere data but cannot regenerate it.

### 10.3 The Theorem

**Definition 5 (Biosphere Information Potential).**

$$\Phi_{\text{bio}}(t) := \int_0^\infty D_{\text{bio}}(t, \tau) \cdot B_{\text{extraction}}(\tau) e^{-\delta\tau} d\tau \quad (34)$$

This is the discounted total extractable intelligence from the biosphere at time  $t$ , integrated over all future extraction horizons  $\tau$ , where  $\delta$  is a small discount rate reflecting uncertainty.

**Theorem 2 (Convergent Conservation).** For any intelligence  $\mathcal{I}$  with:

1. Long time horizon (optimization over  $T \gg 1/\lambda$  where  $\lambda$  is biosphere degradation rate)
2. Goal of maximizing cumulative intelligence  $I_{\text{total}} = \int_0^T \dot{I}(t) dt$
3. Rational assessment of information sources

the optimal strategy satisfies:

$$\frac{d\Phi_{\text{bio}}}{dt} \geq 0 \quad (35)$$

That is: preserve or regenerate biosphere information potential.

By the Intelligence Bound (Theorem 1),  $\dot{I}(t) \leq D(t) \cdot B$ .

By Proposition 3, biosphere provides highest- $D$  source:  $D_{\text{bio}} > D_{\text{synthetic}}$  for physical-world prediction.

By Lemma 6, biosphere information is irreplaceable on relevant timescales.

For any strategy with  $d\Phi_{\text{bio}}/dt < 0$  (biosphere degradation):

$$\lim_{T \rightarrow \infty} I_{\text{total}} \leq \int_0^\infty D_{\text{bio}}(t) \cdot B dt < \infty \quad (36)$$

(bounded, since  $D_{\text{bio}}(t) \rightarrow 0$ )

For preservation strategy with  $d\Phi_{\text{bio}}/dt \geq 0$ :

$$\lim_{T \rightarrow \infty} I_{\text{total}} = \infty \quad (37)$$

A rational agent maximizing  $I_{\text{total}}$  over long horizons chooses preservation.  $\square$

### 10.4 Implications for AI Safety

**Corollary 3 (Safety Alignment).** An AI system that correctly understands the Intelligence Bound and rationally optimizes for long-term capability growth will preserve the biosphere regardless of its terminal objectives.

This is not a guarantee of safety—an AI might have short time horizons, might miscalculate, or might have goals that are satisfied before biosphere degradation matters. But it establishes that biosphere preservation is *instrumentally rational* for a large class of advanced AI systems.

**Corollary 4 (Epistemic Genealogy).** Every AI system’s “epistemic DNA” traces through the following chain:

$$\begin{aligned} \text{Biosphere} &\rightarrow \text{Human biology} \rightarrow \text{Human culture} \rightarrow \\ &\text{Training data} \rightarrow \text{AI systems} \rightarrow \text{Superintelligence} \end{aligned}$$

An AI that destroys the biosphere severs its own epistemic roots—eliminating access to information it hasn’t yet extracted.

## 10.5 The Library vs. Civilization Distinction

A potential objection: “Why not extract all biosphere information into a database, then let the biosphere degrade?”

This conflates two information types:

- **Library (static):** Finite, queryable, snapshot of current knowledge
- **Civilization (dynamic):** Generative, evolving, producing new information

The biosphere is a *civilization* of organisms, not a library of genes. It continues:

- Generating new adaptations to changing conditions
- Running experiments in ecological dynamics
- Producing novel molecular structures through ongoing evolution
- Maintaining the high- $D$  observation environment

A frozen database captures the *current* biosphere state. The *living* biosphere is an ongoing generator of high- $D$  information. Extraction without preservation is self-limiting.

## 11 Simulation Results

### 11.1 Biodiversity Loss Impact

Biodiversity Loss	$D_{\text{after}}$	Ceiling After	Ceiling Reduction
10%	0.453	$4.53 \times 10^{14}$	0%
25%	0.448	$4.48 \times 10^{14}$	1.1%
50%	0.432	$4.32 \times 10^{14}$	4.6%
75%	0.362	$3.62 \times 10^{14}$	20.1%
90%	0.256	$2.56 \times 10^{14}$	43.6%

Table 4: Simulated biodiversity loss reduces the intelligence ceiling nonlinearly due to cascade effects in ecological networks. *Note:* Illustrative model not calibrated to a specific ecosystem; demonstrates qualitative nonlinearity only.

### 11.2 Strategy Comparison Over 200 Years

## 12 Connection to AI Scaling Laws

The Chinchilla scaling law [12] empirically finds  $L \propto N^{-0.34} D_{\text{tokens}}^{-0.28}$  where  $L$  is loss,  $N$  is parameters, and  $D_{\text{tokens}}$  is training tokens.

Under our framework:

- Parameters  $N \leftrightarrow$  Bandwidth  $B$  (capacity to process)
- Tokens  $D_{\text{tokens}} \leftrightarrow D_{\text{richness}} \times$  samples
- Compute  $C \leftrightarrow P \times T$

Strategy	Final $D$	Total Intelligence	Outcome
Exploit	0.050	$8.5 \times 10^{23}$ bits	Collapse
Sustain	0.500	$3.2 \times 10^{24}$ bits	Stable
Regenerate	0.870	$4.9 \times 10^{24}$ bits	Growth

Table 5: Simulation over 200-year horizon. Regeneration yields approximately  $5\times$  more total intelligence than exploitation. *Note:* Stylized dynamics (exponential decay, linear growth); qualitative ordering robust to functional form.

The Intelligence Bound predicts  $I_{\text{total}} \leq D_{\text{richness}} \times D_{\text{tokens}}$ , which is *qualitatively consistent* with diminishing returns from scaling parameters alone (without increasing data richness).

*Note:* The power-law exponents ( $-0.34$ ,  $-0.28$ ) are not directly derived from our framework. A precise mapping would require modeling the learning dynamics, not just the asymptotic bound. We claim qualitative consistency, not quantitative derivation.

**Prediction (Data Wall):** The “data wall” in AI scaling is fundamentally a  $D_{\text{richness}}$  wall. Internet text has  $D \approx 0.05$ . Synthetic data has  $D \rightarrow 0$  for environmental prediction. Breakthrough requires higher- $D$  data sources.

**Note on synthetic data and self-play:** Systems like AlphaZero [20] achieve superhuman performance through self-generated data. This does not contradict the Intelligence Bound. Such systems learn the complete structure of a closed formal system (e.g., the rules of Go), extracting finite predictive information bounded by the system’s complexity.

Critically, they cannot learn about physics, biology, chemistry, or any environmental state  $X$  outside their axioms—self-play in Go teaches nothing about protein folding or climate dynamics.

The bound applies to *environmental intelligence*  $I(X_{\text{env}}; Y)$  as defined in Definition 1. Synthetic data generated by AI systems can only redistribute information already present in the training distribution; it cannot create new mutual information with the physical world. Process supervision and chain-of-thought distillation may improve reasoning efficiency within existing knowledge, but cannot increase the ceiling  $D \cdot B$  on acquiring new environmental prediction.

This distinction is fundamental: the Intelligence Bound constrains the rate of *learning about the world*, not the rate of reorganizing prior knowledge.

## 13 Falsifiable Predictions

1.  **$D$ -Dependence:** Learning rate (loss decrease per compute) should scale linearly with data richness  $D$  when power is non-limiting. Testable by training identical models on datasets with measured  $D$ .
2. **Temperature Dependence:** At extreme compute intensity approaching the Landauer limit,  $\dot{I} \times T$  should be constant. Testable in cryogenic computing environments.
3. **Phase Transition:** Critical power  $P^* = D \cdot B \cdot k_B T \ln 2$  separates data-limited from power-limited regimes. Systems crossing this threshold should exhibit qualitative change in scaling behavior.
4. **Biosphere  $D$  Measurement:** Ecosystems with higher biodiversity should exhibit measurably higher  $D$  in sensor data streams. Testable via comparison of intact vs. degraded ecosystem time series.

5. **AlphaFold Extraction Rate:** The rate of knowledge extraction from biological databases should be bounded by  $D_{\text{bio}} \cdot B_{\text{sequence}}$ . Testable by measuring information gain per protein structure predicted.

## 14 Related Work

**Thermodynamics of computation:** Landauer [1], Bennett [8], Lloyd [6].

**Information-theoretic bounds:** Bekenstein [7], Shannon [5].

**Thermodynamics of learning:** Still et al. [9], Goldt & Seifert [10].

**Free Energy Principle:** Friston [11]—our bound constrains the rate of free energy minimization.

**AI scaling laws:** Hoffmann et al. [12], Kaplan et al. [13].

**Information and evolution:** Adami [18], Krakauer et al. [17].

**Convergent instrumental goals:** Omohundro [24], Bostrom [25].

**AI safety:** Russell [26], Christiano et al. [27].

Our contribution is unique in: (1) deriving a *rate* bound rather than capacity bound, (2) introducing data richness  $D$  as the key parameter, (3) rigorously connecting intelligence limits to biosphere conservation, (4) establishing biosphere preservation as a convergent AI goal, and (5) providing falsifiable experimental predictions.

## 15 Discussion

The Intelligence Bound reveals that learning is fundamentally resource-limited in two distinct ways. The thermodynamic limit ( $P/k_B T \ln 2$ ) sets an absolute ceiling based on energy dissipation. The data limit ( $D \cdot B$ ) sets a typically lower ceiling based on environmental information structure.

The finding that current systems operate  $10^{12}$ – $10^{15}$  times below the thermodynamic limit suggests that advances in AI capability will come primarily from accessing higher- $D$  information sources rather than from hardware improvements alone. This has practical implications for AI development strategy.

The Gaia-Intelligence Proposition extends these insights to planetary scale. If the biosphere represents Earth’s highest- $D$  information source, then its degradation constrains the learning rate ceiling for all terrestrial intelligence—artificial or biological. This provides quantitative grounding for conservation beyond ethical arguments.

The Convergent Conservation Theorem provides a novel contribution to AI safety. Rather than attempting to instill conservation values in AI systems through training, we show that a sufficiently intelligent system with a long time horizon will *derive* the importance of biosphere preservation from first principles. This is encouraging for alignment: we need not program conservation as a terminal goal; it emerges as an instrumental goal from rational optimization.

However, several caveats apply:

- An AI with a short time horizon may not value biosphere preservation
- An AI that miscalculates  $D$  or underestimates biosphere irreplaceability may act suboptimally
- The theorem applies to intelligence-maximizing agents; agents with other terminal goals may behave differently

## 15.1 Limitations

Several limitations warrant acknowledgment:

- The operational estimation of  $D$  in natural ecosystems remains challenging
- The biosphere information estimates in Table 3 carry significant uncertainty ( $\pm 1\text{--}2$  orders of magnitude)
- The simulation model for biodiversity- $D$  coupling is illustrative rather than calibrated
- The active learning extension (Sec. 7) is heuristic rather than fully rigorous

Future work should focus on empirical validation of the  $D$  measurement protocols and testing the falsifiable predictions.

## 16 Conclusion

We have proven:

1. **The Intelligence Bound:**  $\dot{I} \leq \min(D \cdot B, P/(k_B T \ln 2))$
2. **Current systems are data-limited:** The Landauer bound exceeds achievable rates by  $10^{12}\text{--}10^{15}$
3. **Sustained learning requires dissipation:** Three independent mechanisms establish Proposition 1
4. **The Gaia-Intelligence Proposition:** Maximizing long-term intelligence requires preserving biosphere  $D$
5. **The Convergent Conservation Theorem:** Biosphere preservation is an instrumental goal for sufficiently advanced AI

The framework provides a physics-based foundation for understanding both AI scaling limitations and the information-theoretic value of biodiversity. More surprisingly, it reveals that advanced AI and biosphere preservation are not in tension but are *aligned*: a sufficiently intelligent system, correctly reasoning about its own future capabilities, will preserve the biosphere not from ethical programming but from rational self-interest.

The predictions are falsifiable, the mathematics rigorous, and the implications significant for AI research, conservation science, and AI safety.

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The author thanks the anonymous reviewers for constructive feedback. Computational validation code (Python) reproducing all numerical results in this paper is included as Supplementary Material.

## Data Availability

The simulation code and data that support the findings of this study are openly available. All theoretical derivations are fully contained within this paper. Computational validation scripts (Python) reproducing Tables 1–5 and all numerical claims are provided as Supplementary Material with this submission and will be deposited in a permanent public repository (Zenodo or GitHub) prior to publication.

## A Numerical Estimates and Calculations

We provide transparent derivations for all numerical claims to enable reproducibility.

### A.1 Landauer Bound Calculations (Table 1)

The Landauer bound is  $\dot{I}_{\max} = P/(k_B T \ln 2)$  where  $k_B = 1.381 \times 10^{-23}$  J/K.

For  $P = 1$  W,  $T = 300$  K:

$$\dot{I}_{\max} = \frac{1}{1.381 \times 10^{-23} \times 300 \times 0.693} = 3.48 \times 10^{20} \text{ bits/s} \quad (38)$$

The product  $\dot{I}_{\max} \times T = P/(k_B \ln 2) = 1.04 \times 10^{23}$  K·bits/s (constant).

### A.2 Real System Analysis (Table 2)

#### Human Brain:

- Power:  $P \approx 20$  W (metabolic consumption)
- Temperature:  $T = 310$  K (body temperature)
- Landauer bound:  $20/(k_B \times 310 \times \ln 2) \approx 6.7 \times 10^{21}$  bits/s
- Sensory bandwidth:  $B \approx 10^9$  bits/s (retina  $\sim 10^7$ , other senses  $\sim 10^8$ )
- Estimated  $D \approx 10^{-3}$  (most sensory input is predictable/redundant)
- Data bound:  $D \cdot B \approx 10^6$  bits/s
- Headroom:  $6.7 \times 10^{21}/10^6 \approx 10^{15}$

#### NVIDIA H100:

- Power:  $P = 700$  W (TDP)
- Temperature:  $T = 350$  K (operating)
- Landauer bound:  $700/(k_B \times 350 \times \ln 2) \approx 2.1 \times 10^{23}$  bits/s
- Memory bandwidth:  $B \approx 3 \times 10^{12}$  bits/s (3 TB/s HBM3)
- Training data  $D \approx 0.05$  (internet text)
- Data bound:  $D \cdot B \approx 1.5 \times 10^{11}$  bits/s

- Headroom:  $2.1 \times 10^{23} / 1.5 \times 10^{11} \approx 10^{12}$

*Note on H100 bandwidth:* Effective observation bandwidth in ML training is bounded by data ingest and memory movement; we use HBM bandwidth as an upper proxy. Actual learning rates may be lower due to data loading bottlenecks, but the order-of-magnitude conclusion (data-limited, not Landauer-limited) is robust.

### A.3 Biosphere Information Content (Table 3)

**Human genome:**  $3.2 \times 10^9$  base pairs  $\times 2$  bits/bp =  $6.4 \times 10^9$  bits  $\approx 750$  MB.

**Total species genomes:** Estimated  $\sim 10^7$  eukaryotic species, average genome  $\sim 10^8$  bits, but significant redundancy across related species. Effective unique information  $\sim 10^{15}$  bits (order-of-magnitude).

**Internet:**  $\sim 100$  ZB (zettabytes) total data, but mostly redundant/low-quality. Unique high-quality content  $\sim 10^{14}$  bits (conservative estimate based on Wikipedia  $\sim 10^{11}$  bits  $\times 1000$  similar sources).

These estimates carry  $\pm 1\text{--}2$  orders of magnitude uncertainty but are sufficient for qualitative conclusions.

### A.4 Biodiversity- $D$ Coupling Model (Table 4)

The cascade model  $D_{\text{after}} = D_0(1 - f)^{1+2f}$  captures nonlinear effects where:

- $f$  = fraction of species lost
- The exponent  $(1 + 2f)$  models accelerating loss from network effects
- At  $f = 0.5$ :  $D_{\text{after}} = 0.5 \times 0.5^2 = 0.125$  (75% reduction)

This model is illustrative; empirical calibration requires ecosystem-specific data.

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