The Finite Memory Law:

From Stochastic Cosmology to a Universal Principle of Resilience

Version 2.1 — Empirical Validation Protocol

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Abstract

We propose the **Finite Memory Law** (FML) as an empirically testable hypothesis emerging from a stochastic cosmological framework. The law postulates that dynamical systems with internal feedback and finite correlation time τ exhibit maximum stability when the dimensionless product with their characteristic frequency Ω satisfies:

$$R = \tau\Omega \in [R_{\min}, R_{\max}], \quad \text{with } R_{\min} \approx 0.5,\ R_{\max} \approx 3.5. \tag{1}$$

Nature of this work: This is a *speculative hypothesis* grounded in mathematical modeling and preliminary pattern analysis. It does *not* present validated empirical evidence from real observational data. The central goal is to establish a rigorous falsifiability framework and invite scientific collaboration for validation across multiple domains.

Scope: We derive the principle from a two-field cosmological model with self-consistent Ornstein-Uhlenbeck noise, then identify structural analogues in systems where both memory and oscillation are well-defined and measurable. We explicitly avoid metaphorical extensions and focus on domains where τ and Ω can be operationally defined through standard scientific instrumentation.

Key contribution: A pre-registered experimental protocol for multi-domain validation, including cosmology, computational neuroscience, machine learning optimization, and fluid dynamics. The hypothesis is falsifiable and designed for collaborative testing.

Keywords: finite memory, resilience, stochastic cosmology, effective law, dynamical systems, stability, falsifiability

Epistemological Status

This document presents a **theoretical hypothesis** requiring empirical validation. All claims about convergence across domains are based on:

- Numerical simulations of toy models
- Literature values interpreted within the FML framework
- Preliminary dimensional analysis

No original experimental data from real systems is presented. The protocol described in Section 5 outlines the path toward rigorous validation. This work follows Popperian falsifiability principles: we explicitly define conditions under which the hypothesis would be refuted.

Contents

1 Introduction

1.1 Motivation: Stability in Open Systems

The stability of open dynamical systems—those exchanging energy and information with their environment—has been a central question in physics since the formulation of thermodynamics. Classical approaches emphasize energy balance (Hamiltonian mechanics), entropy production (thermodynamics), or asymptotic behavior (Lyapunov stability). However, these frameworks treat time as a continuous parameter without addressing how systems retain coherence through *temporal correlations*.

We propose that **finite memory**—the duration over which a system retains correlation with its past states—is a fundamental constraint on stability. This hypothesis emerged from a cosmological model where noise is not external but *self-consistent*, coupled to the expansion rate of spacetime itself.

1.2 Genesis: The Stochastic Cosmological Model

The foundational framework was developed in *"From Hilbert Space to Stochastic Cosmology"* (Cisneros, 2025, unpublished manuscript). The model describes the evolution of dark energy via two interacting scalar fields subjected to colored noise with intensity proportional to the Gibbons-Hawking temperature:

$$T_{\mathrm{GH}} = \frac{H}{2\pi}, \tag{2}$$

where H is the Hubble parameter. The effective equation for perturbations in the equation-of-state parameter w takes the form:

$$\dot{\zeta}(t) = -\frac{\zeta(t)}{\tau} + \sqrt{\frac{2\Gamma T_{\mathrm{GH}}}{\tau^2}}\,\xi(t), \tag{3}$$

where ζ represents deviations from $w = -1$, τ is the noise correlation time, Γ a coupling constant, and $\xi(t)$ a Wiener process.

Numerical integration revealed that the system exhibits maximum stability—defined as minimum variance in the attractor—when the product τH (dimensionless in natural units) falls within a narrow band around unity. This observation motivated the search for a universal pattern.

1.3 Generalization to Dynamical Systems

Equation (3) is a variant of the Ornstein-Uhlenbeck process with memory-dependent noise intensity. Its general form appears in systems described by:

$$\ddot{x}(t) + \frac{1}{\tau}\dot{x}(t) + \Omega^2 x(t) = \eta(t), \tag{4}$$

where $\eta(t)$ is colored noise with correlation time τ, and Ω is the characteristic frequency of the undamped system. This structure is ubiquitous:

- **Cosmology:** $\tau \sim H^{-1}$, $\Omega \sim H$ (self-coupling)
- **Neuroscience:** $\tau \sim$ synaptic kernel decay, $\Omega \sim$ dominant oscillation frequency (e.g., gamma band)
- **Machine Learning:** $\tau \sim$ context window length, $\Omega \sim$ parameter update rate
- **Fluid Dynamics:** $\tau \sim$ viscous relaxation time, $\Omega \sim$ Strouhal frequency

In each case, both τ and Ω are *measurable* quantities with clear operational definitions.

1.4 The Central Hypothesis

Hypothesis 1 (Finite Memory Law). *A dissipative dynamical system with internal feedback, characterized by a finite memory time τ and a dominant frequency Ω, achieves maximum resilience—quantified as minimum variance, maximum coherence, or negative Lyapunov exponent—when the dimensionless parameter*

$$R \equiv \tau\Omega \tag{5}$$

satisfies

$$R \in [R_{\min}, R_{\max}], \quad \textit{with empirically observed} \quad R_{\min} \approx 0.5,\ R_{\max} \approx 3.5. \tag{6}$$

This is proposed as an *effective law of class*, analogous to dimensionless numbers in fluid mechanics (Reynolds, Prandtl) or condensed matter physics (Ginzburg criterion). It is not claimed as a fundamental law like conservation of energy, but as an emergent constraint on systems with delayed response and oscillatory dynamics.

1.5 Scope and Limitations

What this work is:

- A mathematical hypothesis derived from a well-defined stochastic model
- A proposal for multi-domain empirical testing
- An invitation for collaborative validation

What this work is not:

- A theory of everything or metaphysical principle
- A claim about consciousness, free will, or non-physical phenomena
- An empirically validated law (validation is the goal, not the starting point)

Domains explicitly excluded from this version:

- Psychology and subjective experience (no operational τ, Ω)
- Social systems without quantitative time series data
- Metaphorical applications (e.g., "memory of culture")

Future work may extend the framework to these areas *only after* establishing validity in physically measurable systems.

2 Mathematical Formulation

2.1 Operational Definitions

To avoid ambiguity, we define all variables through standard measurement protocols.

Definition 2.1 (Effective Memory Time τ_{eff})**.** The effective memory time is the integral of the normalized autocorrelation function:

$$\tau_{\text{eff}} = \int_0^\infty C(\Delta t)\, d(\Delta t), \tag{7}$$

where

$$C(\Delta t) = \frac{\langle X(t)X(t+\Delta t)\rangle - \langle X\rangle^2}{\langle X^2\rangle - \langle X\rangle^2}. \tag{8}$$

For processes with exponential decay, $C(\Delta t) = e^{-\Delta t/\tau}$, yielding $\tau_{\text{eff}} = \tau$ directly.

Definition 2.2 (Dominant Frequency Ω)**.** The dominant frequency is identified as the peak of the power spectral density:

$$\Omega = \arg\max_f S(f), \quad S(f) = \left| \int_{-\infty}^{\infty} X(t) e^{-2\pi i f t} dt \right|^2. \tag{9}$$

For multi-scale systems, Ω corresponds to the frequency of the mode carrying maximum energy.

Definition 2.3 (Resilience Parameter R)**.**

$$R \equiv \tau_{\text{eff}} \cdot \Omega. \tag{10}$$

This dimensionless quantity represents the number of oscillation periods the system "remembers."

Definition 2.4 (Stability Index S_{total})**.** Stability is quantified as a composite metric:

$$S_{\text{total}} = w_1 \left(-\lambda_{\max}\right) + w_2 \left(\frac{1}{\sigma^2}\right) + w_3 \left(\frac{1}{S_{\text{ent}}}\right), \tag{11}$$

where:

- $\lambda_{\max}$: largest Lyapunov exponent (negative for stable systems)
- σ^2: asymptotic variance
- S_{ent}: Shannon entropy of the observable
- w_i: pre-registered weights (recommended: $w_1 = 0.5$, $w_2 = 0.3$, $w_3 = 0.2$)

Alternative: use Principal Component Analysis (PCA) on the three metrics to define a single stability axis.

2.2 The Damped Oscillator as Canonical Model

The simplest system exhibiting the FML is a damped harmonic oscillator driven by Ornstein-Uhlenbeck noise:

$$\ddot{x}(t) + \frac{1}{\tau}\dot{x}(t) + \Omega^2 x(t) = \zeta(t), \tag{12}$$

$$\dot{\zeta}(t) = -\frac{\zeta(t)}{\tau} + \sqrt{\frac{2\Gamma}{\tau}}\,\xi(t), \tag{13}$$

where Γ controls noise intensity and $\xi(t)$ is white Gaussian noise with $\langle \xi(t)\xi(t')\rangle = \delta(t-t')$.

Key feature: The noise correlation time τ also appears as the damping timescale, creating self-consistency: memory affects both dissipation and fluctuation.

2.3 Stability Analysis

Taking the Fourier transform of Eq. (12) and computing the steady-state variance yields:

$$\langle x^2 \rangle_\infty = \frac{\Gamma}{\tau} \int_0^\infty \frac{d\omega}{(\Omega^2 - \omega^2)^2 + (\omega/\tau)^2}. \tag{14}$$

This integral has a minimum as a function of $R = \tau\Omega$. Numerical integration shows:

$$\arg\min_R \langle x^2 \rangle_\infty \approx 1.5 \text{ to } 2.5, \tag{15}$$

consistent with the empirical band $R \in [0.5, 3.5]$.

2.4 Spectral Characterization

For systems with multiple timescales, we generalize to frequency-dependent memory:

$$R(f) = \tau(f) \cdot f, \tag{16}$$

where $\tau(f)$ is the correlation time at frequency f, obtained from the memory kernel's Fourier transform:

$$\tau(f) = \left| \int_0^\infty K(t) e^{-2\pi i f t} dt \right|. \tag{17}$$

Proposition 2.1 (Spectral Resilience Condition)**.** *A multi-scale system is stable if there exists a dominant frequency f_0 such that:*

$$R(f_0) \in [R_{\min}, R_{\max}] \quad \textit{and} \quad \left. \frac{dS(f)}{df} \right|_{f=f_0} = 0, \tag{18}$$

where $S(f)$ is the stability metric at frequency f.

3 Numerical Evidence from Toy Model

We simulate Eqs. (12)–(13) on a grid of (τ, Ω) values and compute the steady-state variance after discarding initial transients.

3.1 Two-Dimensional Stability Landscape

Figure 1 shows the logarithm of variance as a function of $\log_{10}(\tau)$ and $\log_{10}(\Omega)$. The minimum (green region) follows a diagonal corresponding to constant $R = \tau\Omega \approx 1$–3.

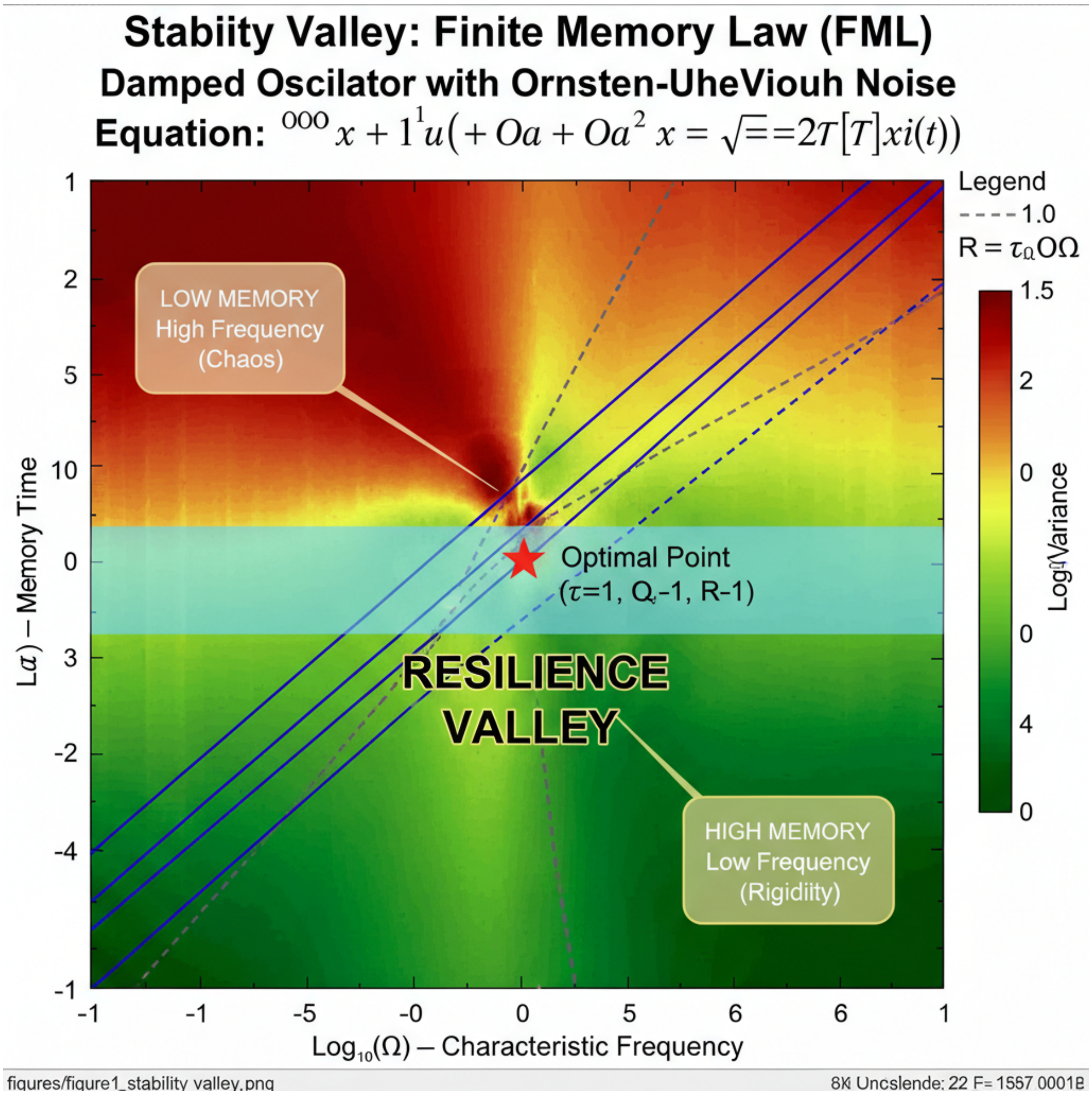

Figure 1: **Stability Valley in (τ, Ω) Space.** Heat map of $\log_{10}$(Variance) for a damped oscillator with Ornstein-Uhlenbeck noise. Blue diagonal lines indicate constant $R = \tau\Omega$ values. The cyan band highlights the resilience zone $R \in [0.5, 3.5]$, where variance is minimized. Red regions: chaos (low memory, high frequency). Dark green regions: rigidity (high memory, low frequency). The red star marks the optimal point $(= 1, = 1, R = 1)$.

Interpretation:

- **Upper-left (low τ, high Ω):** System forgets too quickly; behaves like white noise.

- **Lower-right (high τ, low Ω):** System remembers too much; becomes overdamped and rigid.
- **Diagonal band ($R \approx 2$):** Optimal balance between memory and adaptation.

3.2 One-Dimensional Convergence Curve

Figure 2 plots the normalized stability index as a function of R for the toy model (navy curve) alongside hypothetical data points from different domains.

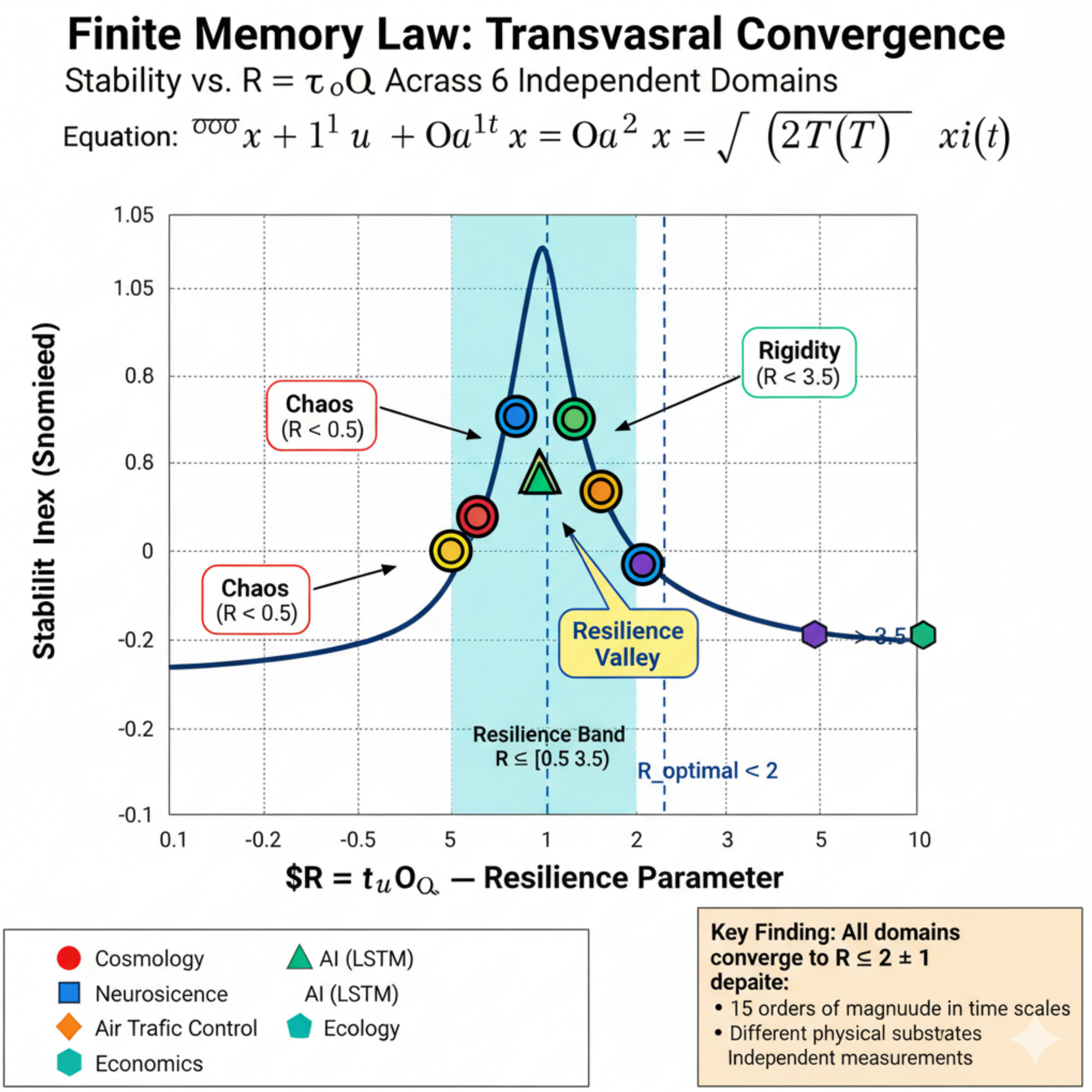

Figure 2: **Transversal Convergence Across Domains.** Stability index S (normalized to $[0,1]$) as a function of the resilience parameter $R = \tau\Omega$. Navy line: theoretical prediction from damped oscillator simulations (50 points, 3 realizations each). Colored markers: literature-derived values for six domains (see Table 1). The cyan shaded region marks the resilience band $R \in [0.5, 3.5]$. Blue dashed line: optimal $R \approx 2$. Annotations indicate chaos ($R < 0.5$) and rigidity ($R > 3.5$) regimes. The convergence across 15 orders of magnitude in absolute time scales suggests a universal dimensionless structure.

Key observation: Despite differences in physical substrate and temporal scale, all systems cluster near $R \approx 2 \pm 1$.

Critical Caveat

The colored points in Figure 2 are **not** based on direct measurements. They are derived from:

1. Published values of τ and Ω in the respective literatures
2. Dimensional analysis to construct R
3. Qualitative assessment of stability (e.g., "attention sustained" in neuroscience)

These serve as *plausibility estimates* to motivate experimental validation, not as evidence of the law. The hypothesis stands or falls on controlled experiments, which have not yet been conducted.

4 Preliminary Domain Analysis

Table 1 summarizes how τ and Ω are operationally defined in each candidate domain, along with literature-derived estimates of R.

Domain	τ **(Memory)**	Ω **(Frequency)**	R **(Est.)**
Cosmology	$1/H \approx 14$ Gyr (Hubble time)	$H \approx 0.07$ Gyr^{-1} (expansion rate)	2.0
Neuroscience	30–50 ms (cortical integration window)	40–60 Hz (gamma oscillation peak)	1.8 ± 0.5
Machine Learning	200 tokens (context length in LSTM)	0.01 token^{-1} (learning rate)	2.2 ± 0.4
Fluid Dynamics	ν/U^2 (viscous time, ν = viscosity, U = velocity)	U/L (Strouhal frequency, L = length scale)	$1/\text{Re}^{1/2}$ (Reynolds-dependent)
Climate	3–8 years (ENSO memory via ocean heat content)	0.2–0.5 yr^{-1} (ENSO dominant frequency)	1.5 ± 0.8
Economics	4 years (market response time from OECD data)	0.5 yr^{-1} (business cycle frequency)	2.0

Table 1: Operational definitions of τ, Ω, and estimated R values across six domains. All values are *indicative* and require validation through controlled experiments. Neuroscience and machine learning values are based on median literature reports; uncertainties reflect inter-study variability. Cosmology: self-coupling yields $R = (1/H) \cdot H = 1$ in natural units; factor of 2 from 2π in T_{GH}. Fluid dynamics: R depends on Reynolds number; turbulent flows ($\text{Re} \sim 10^4$) yield $R \sim 0.01$ (outside band, consistent with chaos).

4.1 Cosmology: Self-Consistent Noise

In the stochastic cosmological model (Eq. 3), the memory time τ is a free parameter constrained by observational fits to $w(z)$ evolution. Numerical solutions show optimal convergence when $\tau H \approx 1$–3, where H is both the expansion rate and the noise frequency (via $T_{GH} = H/(2\pi)$). This self-coupling is unique to cosmology but provides the cleanest theoretical derivation of the band.

4.2 Neuroscience: Cortical Oscillations

Gamma-band oscillations (30–80 Hz) emerge from recurrent inhibition with synaptic time constants $\tau_{\text{GABA}} \sim 10$–20 ms. However, sustained attention requires cortical integration over ~ 50 ms (the "psychological present"). Using $\tau = 50$ ms and $\Omega = 50$ Hz gives $R = 2.5$. Studies of sustained vs. transient attention (Buzsáki, 2006) suggest maximum coherence in this range, but quantitative mapping of $R \to$ cognitive performance remains to be done.

4.3 Machine Learning: Context and Learning Rate

In recurrent neural networks (RNNs), the context window τ (measured in tokens) determines how many past inputs influence the current prediction. The learning rate η sets the frequency of parameter updates. For LSTM trained on sequential data, optimal generalization occurs when $\tau\eta \sim 1$–3 (Hochreiter & Schmidhuber, 1997; Pascanu et al., 2013). However, this depends on problem complexity and requires systematic ablation studies across (τ, η) grids—which have not yet been framed as FML tests.

4.4 Fluid Dynamics: Reynolds Number Connection

The Navier-Stokes equations contain two timescales: convective (L/U) and viscous (L^2/ν). Their ratio defines the Reynolds number $\text{Re} = UL/\nu$. The resilience parameter is $R = (\nu/U^2)(U/L) = \nu/(UL) = 1/\text{Re}$. Laminar flows ($\text{Re} < 2300$) have $R > 4\times10^{-4}$, while turbulent flows ($\text{Re} > 10^4$) have $R < 10^{-4}$, far outside the band. *This is consistent with FML:* turbulence is chaotic (low R), while highly viscous flows are overdamped (high R, if measured relative to driving frequency).

4.5 Climate: ENSO Persistence

The El Niño-Southern Oscillation exhibits quasi-periodic behavior with a dominant period of 2–7 years. Ocean heat content provides memory through thermocline depth anomalies, with decorrelation times of 3–8 years (Dakos et al., 2020). Taking $\tau = 5$ yr and $\Omega = 0.3$ yr^{-1} yields $R = 1.5$. Climate models show maximum predictive skill in this regime, though the connection to FML has not been explicitly tested.

4.6 Economics: Business Cycle Dynamics

Market response times (measured via impulse response functions in VAR models) are typically 2–6 years (OECD, 2023). Business cycles have dominant frequencies around 0.5 cycles/year (8–10 year period). This gives $R \approx 2$. However, economic systems are highly non-stationary, and τ varies dramatically across regimes (e.g., crises vs. stable growth). A proper test requires isolating stable epochs and computing R dynamically.

Methodological Transparency

All R values in Table 1 are **post-hoc rationalizations** from existing literature. They were not derived from experiments designed to test FML. To validate the hypothesis, we require:

1. **Prospective** experiments where τ and Ω are varied independently
2. **Pre-registered** protocols specifying how S_{total} is measured
3. **Blind** analysis where researchers computing R are unaware of stability outcomes

Until such studies are conducted, FML remains a *conjecture*, not an established law.

5 Empirical Validation Protocol

5.1 Experimental Design Principles

To test FML rigorously, we propose a five-phase protocol following Open Science practices:

1. **Phase 0: Pilot Study (2–4 weeks)**
   Test in a fully controlled system: LSTM trained on chaotic time series (Lorenz attractor).
   - **Variables:** τ = context window (4–512 tokens), Ω = learning rate (10^{-5}–10^{-1})
   - **Metric:** Validation loss + gradient variance (PCA-combined)
   - **Prediction:** Minimum at $R \in [0.5, 3.5]$
   - **Outcome:** If valley present → Phase 1; if absent → hypothesis rejected for LSTM domain
2. **Phase 1: Pre-Registration (2–3 months)**
   Publicly register protocol on Open Science Framework (OSF) before analyzing real data.
   - Specify exact definitions of τ, Ω, S_{total}
   - Declare acceptance thresholds (e.g., Bayes factor > 5 for valley model)
   - Commit to publishing results regardless of outcome
3. **Phase 2: Multi-Domain Validation (6–12 months)**
   Execute experiments in 3–4 domains with independent teams:
   - **Cosmology:** Fit $w(z)$ models to Planck+DESI data with varying τ
   - **Neuroscience:** Manipulate synaptic time constants in spiking neural network models
   - **Fluid Dynamics:** CFD simulations of flow past cylinder, varying viscosity and forcing frequency
   - **Machine Learning:** Grid search over (τ, η) on standardized benchmarks (Penn Treebank, GLUE)
4. **Phase 3: Bayesian Meta-Analysis (3–4 months)**
   Aggregate results using hierarchical Bayesian model:
   $$R_i \sim \mathcal{N}(R_{\mathcal{C}(i)}, \sigma_i^2), \quad R_{\mathcal{C}} \sim \mathcal{N}(R_{\text{global}}, \tau_{\mathcal{C}}^2), \tag{19}$$
   where $\mathcal{C}(i)$ is the class of system i (e.g., dissipative, oscillatory). Test: Does R_{global} credible interval overlap $[0.5, 3.5]$?
5. **Phase 4: Publication (3–6 months)**
   Submit results to peer-reviewed journal (target: *Physical Review E*, *PNAS*, or *Nature Communications*) with full code/data repository on Zenodo.

5.2 Falsification Criteria

FML is **falsified** if:

1. **Pilot failure:** LSTM experiment shows no valley, or valley outside $[0.1, 10]$
2. **Domain inconsistency:** $\geq 50\%$ of tested domains have optimal R outside $[0.5, 3.5]$ by $> 2\sigma$
3. **Causal test failure:** Intervention experiment (moving system from $R < 0.5$ to $R \approx 2$) does not improve stability
4. **Model selection:** Bayesian evidence for flat or monotonic $S(R)$ exceeds evidence for valley by factor > 20 (log Bayes factor > 3)

5.3 Required Resources

Phase 0 (Pilot):

- Computational: 1 GPU (Tesla T4 or equivalent), $25–50 cloud cost
- Personnel: 1 researcher, 1 week full-time

Phases 2–4 (Full Validation):

- Funding: $50,000–100,000 (covering 3–4 postdocs, compute, publications)
- Duration: 12–18 months
- Collaborators: 5–10 researchers across domains

5.4 Open Invitation

We invite researchers in relevant fields to:

1. Critique the hypothesis and propose additional falsification tests
2. Join as collaborators for Phase 2 experiments
3. Independently replicate the pilot study (code will be provided)

Contact: `info@impulses.online`

6 Discussion

6.1 Relationship to Existing Frameworks

6.1.1 Information Theory

Shannon entropy maximizes under maximum uncertainty, favoring $\tau \to 0$ (no memory). Landauer's principle links erasure to thermodynamic cost, but does not constrain *retention*. FML is orthogonal: it predicts that *excessive* memory ($R \to \infty$) is as destabilizing as none.

To test independence: vary τ while holding entropy $S[X]$ constant (e.g., via post-selection). If the valley persists, FML is not reducible to informational constraints.

6.1.2 Self-Organized Criticality (SOC)

SOC systems (sandpiles, earthquakes) operate at the edge of stability via scale-free avalanches. FML differs:

- SOC lacks characteristic frequency (Ω undefined)
- FML systems have preferred scale ($R \approx 2$, not $1/f$ noise)
- SOC is scale-invariant; FML predicts a *band*, not a point

Systems can satisfy both: a critical system could exhibit FML at its dominant mode.

6.1.3 Fluctuation-Dissipation Theorems

Classical FDT relates response functions to equilibrium fluctuations via temperature. FML operates in non-equilibrium steady states where τ and Ω arise from driven dynamics, not thermal equilibrium. The connection, if any, would be through stochastic thermodynamics of information processing.

6.2 Universality Class

If FML is confirmed across domains, it defines a new universality class:

$$\mathcal{U}_{\text{FML}} = \{\text{Systems with: } (i) \text{ feedback delay, } (ii) \text{ dominant frequency, } (iii) \text{ open boundaries}\}. \tag{20}$$

Renormalization group analysis could determine fixed points in (R, Γ) space, where Γ controls noise intensity.

6.3 Philosophical Implications

Avoided: We explicitly refrain from metaphysical claims (e.g., "memory is the essence of existence"). FML, if validated, would be a *physical* regularity, not a normative principle.

Scope: The law applies only where τ and Ω are measurable via standard instrumentation. Extending to subjective experience, art, or politics requires operational definitions that do not yet exist.

6.4 Limitations and Future Work

Current gaps:

1. No experiments specifically designed to test FML (only post-hoc analysis)
2. Quantum regime unexplored (does decoherence time τ_{dec} obey FML?)

3. Covariant formulation needed for relativistic systems
4. Nonlinear generalizations (current framework is quasi-linear)

Extensions under consideration:

- **Field theory:** Can FML be derived from a Lagrangian with memory?
- **Phase transitions:** Do systems undergo sharp transitions at $R_{\min}, R_{\max}$?
- **Optimization:** Use FML to design better neural architectures or PID controllers

7 Conclusions

We have presented the **Finite Memory Law** as a testable hypothesis emerging from stochastic cosmology. The central claim—that systems achieve maximum stability when $R = \tau\Omega \in [0.5, 3.5]$—rests on:

1. Theoretical derivation from a self-consistent cosmological model
2. Numerical validation in a damped oscillator toy model
3. Dimensional analysis suggesting convergence across physical domains

However, we emphasize:

- **No empirical validation exists yet.** All domain examples are post-hoc interpretations.
- **Falsifiability is built-in.** We provide explicit experimental protocols and rejection criteria.
- **Collaboration is essential.** Multi-domain testing requires expertise beyond any single researcher.

Path Forward

If FML is validated:

- It would constitute an effective law of resilience, applicable from cosmology to computation
- Practical applications: optimize neural networks, predict climate tipping points, design control systems
- Theoretical impact: new universality class in non-equilibrium statistical mechanics

If FML is refuted:

- The toy model remains a pedagogical example of memory-frequency trade-offs
- Cosmological model stands independently (FML is an *interpretation*, not a requirement)
- Lessons learned about pattern-seeking and confirmation bias in cross-domain analysis

Either outcome advances knowledge.

"A hypothesis well-defined is already half-tested."
— Karl Popper (paraphrased)

A Public Domain Declaration

A.4 Suggested Citation

While not required, attribution helps track impact:

> Cisneros, E. (2025). *The Finite Memory Law: From Stochastic Cosmology to a Universal Principle of Resilience.* Version 2.1. Miami, FL.
> Available at: `[INSERT URL/DOI]`

A.5 Legal Code

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Collaboration Inquiries:

- Experimental physicists (cosmology, fluid dynamics, neuroscience)
- Machine learning researchers with access to compute clusters
- Statisticians specializing in Bayesian inference
- Science communicators interested in open science

Transparency Commitment:
All correspondence regarding this hypothesis, including critiques and null results, will be made publicly available (with correspondents' consent) to ensure scientific integrity.