CMB Evidence for Pre-Metric Physics: Operational Advantage from Extending Metric Physics

A morphology-sensitive analysis of Planck PR3 lensing using topology-based controls

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https://github.com/gradient-pulse/phi-mesh/blob/main/README.md

Abstract

We report an operational result from a morphology-sensitive analysis of Planck PR3 CMB lensing data using a control framework that compares observed reconstructions against (i) Gaussian synthetic controls matched to the (dat-mf) power spectrum and (ii) ΛCDM reconstruction controls. The analysis focuses on topology-derived observables and mean-field-aware diagnostics across $l_{max} \in \{128, 192, 256, 320\}$. The key empirical finding is a strong and persistent separation between the observed cohort and the Gaussian control cohort in the morphology-sensitive diagnostics *D1_L2* and *Z_mf*, while the observed cohort remains close to the ΛCDM reconstruction cohort on the same diagnostics. This separation remains stable after expanding the Gaussian cohort to $n = 40$ per l_{max} and applying cohort-hygiene filtering by Gaussian seed bands. By contrast, the auxiliary v1 metrics (energy ratio and peak shift) behave as secondary qualifiers: they help characterize morphological regime and stability, but they do not carry the primary separation signal. In this pipeline, the dominant discriminative signal is therefore morphological/topological rather than a simple amplitude or peak-location effect. We interpret this as evidence for an operational advantage in extending standard metric-only analysis with a morphology-sensitive ('pre-metric') descriptive layer. The result does not replace metric physics. Instead, it supports an extended framework in which metric observables and morphology-sensitive diagnostics are treated as complementary layers, improving discrimination between structured cosmological reconstructions and Gaussianized controls.

I. Introduction

Cosmological inference is built on a powerful metric framework: fields are reconstructed, expanded in harmonic space, and compared through statistics defined on amplitudes, spectra, and correlations. This approach has been extraordinarily successful. At the same time, many practical analyses remain sensitive to a methodological choice that is usually implicit: *which observables are treated as primary carriers of structure.* In most standard pipelines, morphology is either compressed into secondary summaries or treated as a visualization layer rather than a first-class diagnostic.

This paper reports an operational result from a morphology-sensitive analysis of Planck PR3 CMB lensing reconstruction data. The aim is not to replace metric physics, nor to challenge established cosmological reconstruction methods on their own terms. The aim is narrower and more practical: to test whether adding a morphology/topology-sensitive diagnostic layer improves discrimination between (i) observed reconstructed lensing fields, (ii) Gaussian synthetic controls matched to the *(dat–mf)* power spectrum, and (iii) ΛCDM reconstruction controls.

The central finding is that two morphology-sensitive diagnostics, denoted *D1_L2* and *Z_mf*, produce strong and persistent separation between the observed cohort and the Gaussian control cohort across an l_{max} sweep, while the observed cohort remains comparatively close to the ΛCDM reconstruction cohort on the same diagnostics. This separation remains stable after expanding the Gaussian cohort and applying cohort hygiene filtering by Gaussian seed bands. In contrast, auxiliary *v1* metrics (energy ratio and peak shift) behave as useful secondary qualifiers of regime and stability but do not carry the primary separation signal.

The scientific significance of this result is operational rather than metaphysical. It suggests that a metric-only analysis may leave discriminative structure underutilized when the target distinction is morphological organization rather than spectral consistency alone. In that sense, the present work supports extending standard metric analysis with a complementary *pre-metric layer* of morphology-sensitive observables. "Pre-metric" here does **not** mean anti-metric or non-physical; it refers to observables that are sensitive to the organization and coherence of structures before those structures are fully compressed into conventional metric summaries.

This framing is motivated by the Recursive Gradient Physics (RGPx) research program, which treats structured morphology as an informative layer of physical organization rather than as a residual artifact of metric description. However, the contribution of this paper is intentionally model-agnostic at the empirical level: the reported result stands as a control-based discrimination outcome independent of whether one adopts the broader RGPx interpretation. The paper therefore emphasizes reproducible pipeline design, explicit controls, cohort hygiene, and conservative interpretation.

The remainder of the paper is organized as follows. Section 2 describes the datasets, control cohorts, and morphology-sensitive observables. Section 3 presents the analysis pipeline and control construction procedure used for the cohort comparisons. Section 4 reports the empirical results across $l_{max} \in \{128, 192, 256, 320\}$, including the expanded Gaussian control cohort and hygiene-filtered decision summaries. Section 5 discusses interpretation, methodological implications, and limitations of the present result, including what remains to be tested in future control and replication work. Section 6 concludes with the paper's main claim and the proposed role of morphology-sensitive observables as a complement to standard metric analysis.

II. Data, Control Cohorts, and Analysis Pipeline

This section defines the data inputs, control cohorts, morphology-sensitive observables, and the analysis pipeline used to compare the observed Planck PR3 lensing reconstruction against Gaussian and ΛCDM-based controls. The emphasis is on reproducibility, explicit control design, and cohort hygiene rather than on model-dependent interpretation.

A. Data Source and Observed Cohort

The observed cohort is derived from the Planck PR3 CMB lensing harmonic reconstruction ϕ_{lm}, using the publicly released MV reconstruction and its associated mean-field correction. The analysis is performed in a mean-field-aware form by working with the reconstructed field and explicitly tracking the effect of mean-field subtraction in the control design.

For each analysis run, the observed pipeline is evaluated at fixed settings of:

- $l_{max} \in \{128, 192, 256, 320\}$
- fixed map-space resolution ($nside$)
- fixed threshold grid ($\nu_{min}, \nu_{max}, n_\nu$)
- fixed surrogate count for internal topology statistics

These settings are held constant across observed and control cohorts to ensure comparability.

B. Control Cohorts

Two control cohorts are used.

1. Gaussian synthetic controls (power-matched)

The first control cohort consists of Gaussian synthetic ϕ_{lm} realizations generated to match the angular power spectrum of the mean-field-corrected observed reconstruction, i.e. the *(dat-mf)* spectrum.
Operationally:

1. Read Planck PR3 harmonic coefficients ϕ_{lm}^{dat} and ϕ_{lm}^{mf}.
2. Compute the cleaned harmonic field:
   $\phi_{lm}^{\text{clean}} = \phi_{lm}^{\text{dat}} - \phi_{lm}^{\text{mf}}$
3. Estimate C_l from ϕ_{lm}^{clean}.
4. Generate Gaussian synthetic harmonics $\phi_{lm}^{(G)}$ from that C_l.
5. Set the Gaussian-control mean field to zero for the synthetic control run.

This yields a null cohort that preserves metric power-spectrum content while removing higher-order/non-Gaussian morphological organization. In other words, it is a deliberately strong control for testing whether the observed discrimination signal is spectral-only or morphology-sensitive.

2. ΛCDM reconstruction controls

The second control cohort consists of ΛCDM reconstruction controls produced through the same topology pipeline and summarized with the same diagnostics. These runs serve as a structured cosmological reference cohort rather than a Gaussianized null.

The practical role of this second cohort is important: if the observed cohort separates strongly from Gaussian controls but remains comparatively close to ΛCDM reconstructions, the signal is more consistent with structured morphology than with a generic amplitude or noise effect.

C. Morphology-Sensitive and Auxiliary Observables

The pipeline computes a small set of summary diagnostics per run. These are then aggregated by cohort and l_{max}.

1. Primary morphology-sensitive diagnostics

The primary separation signal in this study is carried by two morphology-sensitive diagnostics:

- **D1_L2** — an L_2-distance summary of morphology/topology response curves across threshold, quantifying how strongly the reconstructed field's excursion-set structure departs from the Gaussian-null expectation over the full threshold sweep.
- **Z_mf** — a mean-field-aware standardized morphology score, measuring the magnitude of the observed morphology signal relative to the surrogate spread after mean-field correction (i.e., a morphology significance-style diagnostic, not a power-spectrum amplitude statistic).

These diagnostics are derived from topology/morphology summaries of the reconstructed field and are treated as first-class observables in the cohort comparison. They are designed to be sensitive to structure in the field configuration (shape/connectivity/threshold evolution), rather than only to two-point spectral content.

Empirically, these two diagnostics provide the strongest and most persistent separation between the observed cohort and the Gaussian synthetic cohort across the tested l_{max} values, while the observed cohort remains comparatively close to the ΛCDM cohort on the same diagnostics. This is the core operational result reported in this paper.

2. Auxiliary v1 qualifiers

Two additional *v1* diagnostics are tracked as secondary qualifiers:

- *v1_energy_ratio*
- *v1_peak_shift*

These metrics help characterize regime and stability (e.g., relative redistribution or peak-location behavior), but they do not carry the primary observed-vs-Gaussian separation signal. They are therefore used as contextual qualifiers rather than headline discriminators. This distinction is important for interpretation: the dominant signal in this pipeline is morphological/topological rather than a simple amplitude or peak-location effect.

D. Cohort Construction, Archiving, and Hygiene

Each run is archived with a manifest containing run metadata (including l_{max} seeds, and control type), and post-processed into cohort-level tables. This design supports traceability and reduces ambiguity when cohorts are expanded over time.

A key practical issue encountered during cohort growth is **seed-band** mixing (older and newer Gaussian seed ranges coexisting in the same aggregated table). While not invalid, mixed cohorts are harder to explain and audit. To address this, the analysis includes a cohort hygiene step in which the Gaussian cohort can be filtered to a specific seed band before aggregation (e.g., $gauss\_seed \in [910, 949]$). This produces cleaner cohort summaries without altering the observed or ΛCDM cohorts.

In the present analysis, this hygiene approach was retained while the Gaussian cohort was expanded to $n = 40\ per$ $l_{\max}$ and the primary morphology-sensitive separation remained stable.

E. Analysis Pipeline and Reproducibility

The workflow is implemented as a staged pipeline in the repository:

1. **Control generation / run execution**
   - observed runs
   - Gaussian power-matched control runs
   - ΛCDM reconstruction control runs
2. **Post-processing**
   Per-run JSON outputs are reduced into cohort tables (including morphology and *v1* summaries).
3. **Analysis aggregation**
   Cohort tables are compared across l_{max}, with optional deduplication and Gaussian seed-band filtering.
4. **Decision block generation**
   A compact "decision block" summary is produced (including a transposed markdown version for readability), showing observed values alongside Gaussian and ΛCDM cohort means and standard deviations.

This staged design is deliberate. It separates raw run production from aggregation and interpretation, making it straightforward to re-run only the affected stage when cohort composition changes (e.g., adding Gaussian seeds or applying hygiene filters).

F. Scope of the Present Result

The pipeline is designed to answer a narrow empirical question:

> Does adding morphology-sensitive observables improve discrimination between observed Planck PR3 lensing reconstructions and matched Gaussian controls, relative to metric-only matching?

This section does not claim a new cosmological model. It defines a reproducible comparison framework and the observables used within it. Interpretation of the resulting separation—and its relation to an extended pre-metric layer—follows in later sections.

III. Results: Cohort Separation Across lmax and Stability Under Gaussian Cohort Expansion

This section reports the cohort comparison results for the morphology-sensitive and auxiliary diagnostics across $l_{max} \in \{128, 192, 256, 320\}$, using the observed Planck PR3 lensing cohort, the Gaussian synthetic control cohort (power-matched to the (dat-mf) spectrum), and the ΛCDM reconstruction control cohort.

The primary operational question is whether the observed cohort remains distinguishable from the Gaussian cohort when the Gaussian controls preserve the same two-point spectral content, and whether this distinction remains stable under cohort expansion and hygiene filtering.

A. Decision-block summary (expanded Gaussian cohort, $n = 40\ per\ \mathrm{l_{max}}$)

After expanding the Gaussian control cohort to 40 runs per l_{max} and re-running post-processing and analysis aggregation, the decision block remains qualitatively stable and becomes statistically cleaner due to tighter cohort estimates.

The headline result is unchanged:

- **Observed versus Gaussian separation is large and persistent** in the primary morphology-sensitive diagnostics (**D1_L2** and **Z_mf**) across all tested l_{max} values.
- **Observed versus ΛCDM remains comparatively close** on those same diagnostics.
- The auxiliary ***v1*** metrics remain informative but secondary: they help characterize regime and stability, but they do not carry the dominant separation signal.

This directly supports the claim that the strongest discrimination in this pipeline is not explained by metric power-spectrum matching alone.

B. Primary morphology-sensitive diagnostics

1. D1_L2 (morphology-curve distance)

Across all tested l_{max}, the observed cohort values of **D1_L2** remain far above the Gaussian control means:

- The Gaussian cohort ($n = 40\ per\ l_{max}$) stays clustered at relatively low **D1_L2** values.
- The observed cohort remains strongly separated from that Gaussian band.
- The ΛCDM cohort sits much closer to the observed cohort than the Gaussian cohort does.

This pattern is operationally important because the Gaussian controls are intentionally power-matched. In other words, they preserve the relevant two-point spectral content but do not reproduce the observed morphology-sensitive distance behavior.

That is exactly the expected signature if the dominant discriminative structure lives in field organization (*shape/connectivity/threshold evolution*) rather than in spectrum alone.

2. Z_mf (mean-field-aware morphology score)

The same qualitative pattern appears in **Z_mf**, and in practice it is even more visually striking:

- The observed cohort shows very large Z_mf values across the full l_{max} sweep.
- The Gaussian cohort remains low, with means near order-unity and moderate spread.
- The ΛCDM reconstruction cohort remains much closer to the observed cohort than the Gaussian cohort does.

This is a key robustness point: the separation is not isolated to one morphology-sensitive statistic. It appears in *two independent, mean-field-aware topology/morphology summaries,* both pointing in the same direction.

C. Auxiliary v1 qualifiers (context, not headline separation)

The auxiliary *v1* diagnostics behave differently from the primary morphology-sensitive observables:

- **v1_energy_ratio** shows broadly comparable behavior across cohorts, with relatively small Gaussian spread and values near unity.
- **v1_peak_shift** varies across l_{max} and cohorts, but does not produce the same strong, persistent observed-vs-Gaussian separation seen in *D1_L2* and *Z_mf*.

This contrast matters for interpretation. It shows that the result is not simply "everything separates from everything." Instead, the separation is **selective** and strongest in the morphology-sensitive diagnostics, which is exactly what one would expect if the underlying discriminative signal is morphological/topological.

D. Stability under cohort hygiene and seed-band filtering

A practical issue encountered during cohort growth was the coexistence of older and newer Gaussian seed ranges in the aggregated Gaussian tables. This was not a validity problem, but it reduced explainability and made cohort provenance less transparent.

To address this, a cohort hygiene step was introduced in the analysis workflow, allowing Gaussian controls to be filtered to a defined seed band prior to aggregation (e.g., a contiguous seed interval). The key result is that:

- *The observed-vs-Gaussian separation in D1_L2 and Z_mf remains stable after hygiene filtering*, and
- *The qualitative ranking of cohorts is unchanged* (Observed ≈ ΛCDM, both far from Gaussian on the primary diagnostics).

This is important because it reduces the likelihood that the reported separation is an artifact of mixed cohort composition or legacy-run contamination.

E. Operational interpretation of the result

Taken together, the expanded-cohort and hygiene-filtered results support a narrow but strong operational conclusion:

> A metric-only match (here, matching the Gaussian synthetic controls to the (dat-mf) power spectrum) is not sufficient to reproduce the morphology-sensitive structure captured by *D1_L2* and *Z_mf* in the observed Planck PR3 lensing reconstruction.

Equivalently, adding a morphology-sensitive diagnostic layer improves discrimination between:

1. the observed reconstructed lensing field, and
2. a deliberately strong Gaussianized null that preserves two-point spectral content.

Because the observed cohort remains comparatively close to the ΛCDM reconstruction cohort on the same morphology-sensitive diagnostics, the signal is more consistent with structured cosmological morphology than with a generic amplitude/noise mismatch.

F. What this section does and does not establish

These results establish a reproducible, control-based discrimination outcome. They do **not** by themselves establish a new cosmological model, nor do they claim that metric observables are inadequate. What they do show is that, for this pipeline and this comparison task, a morphology-sensitive layer carries substantial discriminative information that may be underutilized in metric-only summaries. This is the sense in which the present results support an **operational advantage** from extending metric physics with a complementary pre-metric layer of morphology-sensitive observables.

Table 1 summarizes the decision-block (transposed) comparison after expanding the Gaussian control cohort to $n = 40\ per\ \mathrm{l_{max}}$ and applying cohort hygiene filtering by Gaussian seed band.

Metric	Cohort	128	192	256	320
N	n_obs	2	2	2	1
N	n_gauss	40	40	40	40
N	n_lcdm	3	3	3	3
D1_L2	Observed	99.563	144.045	198.299	267.087
D1_L2	Gaussian control mean±std)	19.4978 ± 13.0667	16.835 ± 6.65602	18.4079 ± 6.05348	22.8245 ± 5.18926
D1_L2	ΛCDM reconstruction (mean±std)	107.001 ± 10.3608	159.707 ± 14.7568	218.178 ± 31.2522	288.032 ± 48.1411
Z_mf	Observed	64.3459	121.294	207.018	326.747
Z_mf	Gaussian control mean±std)	1.59943 ± 1.09038	1.16205 ± 0.61057	1.16844 ± 0.813328	1.37375 ± 1.22663
Z_mf	ΛCDM reconstruction (mean±std)	88.4766 ± 52.849	146.403 ± 85.4543	223.098 ± 117.299	329.574 ± 151.822
v1_energy_ratio	Observed	1.03795	0.971484	0.936089	0.90861
v1_energy_ratio	Gaussian control mean±std)	1.00262 ± 0.0106996	1.00153 ± 0.00569863	0.999364 ± 0.00443109	0.99999 ± 0.00300281
v1_energy_ratio	ΛCDM reconstruction (mean±std)	1.02088 ± 0.115509	0.964893 ± 0.0769973	0.931001 ± 0.0549648	0.905413 ± 0.0393735
v1_peak_shift	Observed	0.1	0.3	0.2	-0.7
v1_peak_shift	Gaussian control mean±std)	-0.02 ± 0.132433	0.0125 ± 0.0882523	-0.005 ± 0.0932325	0.0125 ± 0.0852974
v1_peak_shift	ΛCDM reconstruction (mean±std)	0.166667 ± 0.057735	0.166667 ± 0.11547	0.166667 ± 0.057735	-0.2 ± 0.43589

Table 1. Cohort comparison across $l_{max} \in \{128, 192, 256, 320\}$r the MF(V0,V1) pipeline. The observed Planck PR3 lensing reconstruction is compared against a Gaussian synthetic control cohort (power-matched to the *(dat – mf)* spectrum; $\mathrm{n} = 40\ per\ \mathrm{l_{max}}$ and a ΛCDM reconstruction control cohort (n=3). The strongest and most persistent separation appears in the morphology-sensitive diagnostics *D1_L2* and *Z_mf*, while *v1* metrics act as secondary qualifiers.

The table makes the operational pattern explicit: the observed cohort remains far from the Gaussian synthetic controls in *D1_L2* and *Z_mf*, while staying comparatively close to the ΛCDM reconstruction cohort on those same diagnostics. Higher values of *D1_L2* and *Z_mf* in the observed cohort relative to the Gaussian synthetic cohort indicate stronger non-Gaussian morphological organization in the reconstructed field, beyond what is preserved by power-spectrum matching alone.

IV. Results: Cohort separation in morphology-sensitive observables

The cohort comparison yields a clear and stable empirical pattern across the tested multipole cutoffs $l_{max} \in \{128, 192, 256, 320\}$. The primary morphology-sensitive diagnostics, D1_L2 and Z_mf, show a strong separation between the observed Planck PR3 lensing reconstructions and the Gaussian synthetic control cohort, while the observed cohort remains comparatively close to the ΛCDM reconstruction cohort on the same diagnostics.

This pattern persists after expanding the Gaussian synthetic control cohort to $n = 40\ per\ l_{max}$ with cohort hygiene filtering by Gaussian seed band). The expanded cohort reduces the likelihood that the observed separation is an artifact of small-sample fluctuation in the Gaussian control distribution. In particular, the observed values of *D1_L2* and *Z_mf* remain far outside the Gaussian cohort means (with large practical effect size), whereas they remain within the broad range spanned by the ΛCDM reconstruction controls.

By contrast, the auxiliary *v1* diagnostics (*v1_energy_ratio* and *v1_peak_shift*) behave as secondary qualifiers rather than primary separators. They provide useful information about morphology regime and stability, but they do not carry the dominant discrimination signal. In the present pipeline, the principal separation is therefore not driven by a simple amplitude-only effect or by peak-location shift alone; instead, it is concentrated in topology/morphology-sensitive structure captured by *D1_L2* and *Z_mf*.

Table 1 summarizes the decision block in transposed form for direct cross-l_{max} comparison. The table makes three points operationally visible: (i) the observed cohort is consistently separated from the Gaussian synthetic controls in the primary morphology-sensitive diagnostics, (ii) the observed cohort remains comparatively aligned with the ΛCDM reconstruction cohort, and (iii) the auxiliary v1 metrics provide contextual support but do not dominate the cohort decision.

Taken together, these results support the central claim of this paper: in this CMB lensing setting, extending metric analysis with a ‘pre-metric,’ morphology-sensitive observable layer provides operationally useful discrimination that remains underutilized in metric-only comparison frameworks.

In this paper, ‘pre-metric’ refers to morphology-sensitive structure in the field representation that is not captured by the metric-only comparison layer.

V. Discussion and Interpretation

The main result of this study is operational rather than ontological. Within the tested CMB lensing workflow, the strongest cohort separation appears in morphology-sensitive observables—especially D1_L2 and Z_mf—while the *v1* descriptors (*v1_energy_ratio*, *v1_peak_shift*) serve primarily as contextual qualifiers. In practical terms, this means that the most discriminative structure in the present pipeline is carried by organization-level properties of the reconstructed field, not by scalar summaries alone.

This is why a coherence-based interpretation is natural here, in a narrow operational sense. The term *coherence* is used to label sensitivity to the internal organization of the field as expressed in morphology/topology-aware observables. It does **not** imply that a unique physical mechanism has been established by this analysis alone. Rather, it identifies the level at which the separation becomes visible.

A useful way to phrase the present finding is therefore:

- **Metric-only summaries remain necessary**, but
- **they may leave discriminative structure underutilized** in this setting, and
- **morphology-sensitive observables recover part of that structure**.

This motivates the language of an *extended metric* analysis layer: the standard metric framework is retained, but supplemented with observables that are sensitive to field organization and morphology. In that sense, the present results are consistent with—though do not by themselves prove—the usefulness of a 'pre-metric' descriptive layer for certain classes of cosmological inference.

The selectivity of the effect also matters. If all observables separated cohorts equally, the result could be explained as a generic amplitude or scaling artifact. Instead, the separation is strongest in specific morphology-sensitive channels, which supports the interpretation that the pipeline is detecting structured differences in the reconstructed field rather than a trivial global shift.

Several limitations remain. The observed cohort is small, the LCDM reconstruction cohort is limited, and this paper does not yet establish a generative physical model for the morphology-sensitive differences. The result should therefore be read as an evidence-based methodological claim: **certain observables provide operational advantage in cohort discrimination, and those observables are morphology-sensitive**.

This framing is *intentionally conservative*. It is designed to support replication, extension, and falsification. Future work should test whether the same pattern holds under broader null families, alternative reconstructions, and additional morphology-sensitive diagnostics.

In the broader RGPx program, such organization-level sensitivity would be described in terms of coherence structure; in the present paper, however, we restrict ourselves to the operational claim that morphology-sensitive observables provide additional discriminatory power in a CMB lensing cohort comparison.

VI. Conclusion

This paper tested whether adding morphology-sensitive observables to a standard CMB lensing analysis pipeline improves cohort discrimination in a controlled comparison setting. The result is affirmative in operational terms. Across the analyzed l_{max} values, the strongest separation between observed, Gaussian-control, and LCDM-reconstruction cohorts appears in the morphology-sensitive observables D1_L2 and Z_mf. By contrast, the v1-derived quantities (v1_energy_ratio, v1_peak_shift) are informative but less discriminative in this dataset, functioning primarily as contextual descriptors.

The central contribution is therefore methodological: **extending a metric analysis layer with morphology-sensitive observables can recover discriminative structure that may otherwise remain underutilized**. This is what is meant here by *operational advantage*. The claim is not that a new fundamental theory is established, but that the tested observational cut reveals useful structure that standard summaries alone do not fully capture.

The present results also support a cautious conceptual distinction between:

- a **metric comparison layer** (standard scalar and reconstruction-based summaries), and
- an **extended layer** that includes morphology-sensitive descriptors of field organization.

In that restricted sense, the findings are consistent with the utility of a 'pre-metric' descriptive layer, understood here as an analysis layer that is sensitive to organization and morphology prior to any stronger ontological interpretation. At the same time, the study has clear limitations: the observed and LCDM cohorts are small, the current work is tied to a specific pipeline and dataset, and no unique physical mechanism is inferred from the present evidence alone.

The appropriate next step is not stronger rhetoric, but broader testing: additional null families, larger control cohorts, alternative reconstructions, and independent replication of the same morphology-sensitive separation pattern. If that pattern persists, the implication is significant. It would suggest that part of the informative structure in cosmological fields is carried not only by amplitude-like summaries, but by organization-level morphology that deserves first-class treatment in analysis pipelines.

The practical lesson is straightforward: when the question is discrimination, morphology may not be an accessory to metric analysis—it may be one of its most informative extensions.

References

Reproducibility note:
All workflow files, control manifests, postprocessing outputs, and analysis decision blocks used in this study are archived in the phi-mesh repository under experiments/rgpx_proof_proto/cmb_phase_dagger/.

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