Intermediate-Evidence Substitution: A Benchmark Design Methodology for Isolating Numerical Derivation from Protocol Execution in Deterministic Climate Verification

Aaditya Anand Thokal
Universal College of Engineering, Mumbai
[aaditya.thokal24@gmail.com]

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Abstract

We introduce **Intermediate-Evidence Substitution (IES)**, a benchmark design methodology that changes evidence granularity while preserving task semantics: decisive aggregate statistics in benchmark evidence are replaced with the raw intermediate values from which they are derived, while task labels, decision protocols, thresholds, and evaluation criteria remain unchanged. IES functions as a diagnostic probe — any change in model accuracy between the original and transformed evidence reveals how model performance depends on information representation, whether that change is a decrease, an increase, or neither. We instantiate IES on **ClimateTwinBench**, a 240-question deterministic hypothesis-verification benchmark built over India Meteorological Department (IMD) gridded climate data, spanning six verification categories. Comparing the original evidence design (V1) to its IES-transformed counterpart (V2), we observe statistically significant accuracy changes for Claude Sonnet 4.6 (100.00% $\rightarrow$ 96.25%, McNemar $p = 0.008$, $\chi^2 = 7.111$) and Gemini 3.5 (32.50% $\rightarrow$ 45.42%, $p = 0.008$, $\chi^2 = 7.087$), while the change for DeepSeek Chat is not statistically significant ($p = 0.248$). ChatGPT improves markedly (+25.83 pp, $p \approx 4.8 \times 10^{-11}$); all such outcomes — in either direction — are informative empirical results of the diagnostic. To separate numerical derivation from protocol execution, we conduct a structured derivation evaluation in which five models explicitly output predicted intermediate metrics, followed by oracle protocol recovery and cascade analysis distinguishing absorbed from propagated derivation errors. Claude Sonnet 4.6, Claude Opus 4.6, and Gemini 3.5 achieve 100.00% oracle-recovered protocol accuracy; DeepSeek Chat achieves 99.58%, with its single propagated failure attributable to connected-component counting in the Spatial Coherence category. GPT-OSS-120B exhibits failures in both metric derivation (4.17%) and oracle-recovered protocol accuracy (42.92%), preventing the clean separation between error sources that characterizes the frontier models. For the evaluated frontier models on ClimateTwinBench, numerical derivation — not protocol execution — is the dominant source of residual error, a finding that has direct implications for where benchmark evaluation effort should be directed.

1 Introduction

Evaluating model capability on structured numerical verification tasks requires knowing whether a model's accuracy reflects the capability the task nominally tests. Many such benchmarks present evidence that is already condensed into decisive aggregate statistics — a minimum, a count, a mean — that directly resolve the task's decision protocol. When the evidence itself encodes the answer at that level of granularity, a model that performs well may be doing threshold comparison rather than the numerical derivation that the aggregate represents. This ambiguity cannot be resolved by inspecting accuracy alone: high accuracy under one evidence format leaves open whether performance would be maintained, degraded, or even improved under a different but semantically equivalent format (Geirhos et al., 2020; Gardner et al., 2020).

This paper does not propose a reasoning framework or evaluate climate knowledge. Instead, we propose **Intermediate-Evidence Substitution (IES)**, a benchmark design methodology that functions as a diagnostic probe by changing evidence granularity while preserving task semantics. IES replaces decisive aggregate statistics with the intermediate observations from which those aggregates are derived, while holding task labels, decision thresholds, protocols, and evaluation criteria fixed. Because the task does not change — only the information representation of the evidence does — any accuracy change between versions reveals how measured performance depends on evidence granularity for a given model. Such a change may be a decrease (if the model relied on the aggregate), an increase (if the aggregate was confusing or the structured intermediate evidence provides implicit scaffolding), or absent (if the model is equally capable under both representations). Each outcome is an informative empirical finding, not a contradiction.

We instantiate IES on ClimateTwinBench, a 240-question deterministic hypothesis-verification benchmark constructed over IMD gridded climate observations, and combine it with three connected analyses. First, we compare model accuracy on V1 (original) and V2 (IES-transformed) evidence using paired McNemar tests. Second, a structured derivation evaluation separates metric-derivation accuracy from oracle-recovered protocol accuracy by requiring models to explicitly output predicted intermediate metric values. Third, a cascade analysis classifies each derivation error as absorbed (the oracle still recovers the correct decision from the wrong metric) or propagated (the wrong metric leads to the wrong decision), revealing the relationship between derivation quality and decision accuracy at question level.

Our contributions are: (1) **Intermediate-Evidence Substitution (IES)**, a benchmark *design* methodology that changes evidence granularity while preserving task semantics (§4); (2) **ClimateTwinBench**, a 240-question deterministic verification benchmark instantiating IES across six IMD climate categories (§3); (3) a **Structured Derivation Evaluation**, an *evaluation* methodology that separately measures metric-derivation accuracy and oracle-recovered protocol accuracy (§5–§6); and (4) a **Cascade Analysis**, a *diagnostic* methodology that classifies each derivation error as absorbed or propagated, including a threshold-margin analysis for DeepSeek Chat (§7.3, Appendix F). These are three methodologically independent contributions: IES operates at benchmark construction time; the structured derivation evaluation is an evaluation protocol applied to an IES-transformed benchmark; cascade analysis is an error-diagnosis step applied to the structured derivation results.

2 Related Work

Shortcut learning and benchmark artifacts. A substantial body of work has shown that benchmark accuracy can reflect exploitation of dataset artifacts rather than the intended capability, motivating adversarial filtering, contrast sets, and counterfactual evaluation (Geirhos et al., 2020; McCoy et al., 2019; Gardner et al., 2020). IES extends this concern to a specific, previously under-examined shortcut type: aggregate statistics computed in advance and embedded directly in numerical evidence, allowing threshold comparison to substitute for derivation.

Structured and numerical verification benchmarks. Tasks requiring models to verify claims against structured numerical evidence — financial tables, scientific datasets, tabular reasoning — have grown as a distinct evaluation category (Chen et al., 2021; Zhu et al., 2021; Dua et al., 2019). Such benchmarks typically present evidence as a fixed table or value set from which a claim must be checked; few explicitly study how the granularity of presented evidence (final aggregate vs. raw intermediate observations) affects measured accuracy independent of the underlying decision task. Fact-verification benchmarks such as FEVER (Thorne et al., 2018) similarly evaluate claim verification against evidence, but over textual rather than numerical sources.

Climate and scientific NLP benchmarks. Climate-focused NLP evaluation has largely emphasized retrieval, classification, and claim detection over textual or report-derived climate content (Webersinke et al., 2021; Stammbach et al., 2023). ClimateTwinBench differs in evaluating deterministic numerical verification over gridded observational data rather than textual climate claims, and is not designed to test climate domain knowledge — no category requires knowledge external to the supplied numerical evidence.

3 ClimateTwinBench

ClimateTwinBench is a 240-question deterministic hypothesis-verification benchmark built over IMD gridded climate observations spanning 4,964 land grid cells. Each question presents a region, a time window, and a climate hypothesis, and asks the model to classify the hypothesis as `SUPPORTED`, `REFUTED`, or `INSUFFICIENT` according to a

Category	Derivation primitive
Persistent Regional Anomaly	Min.-over-years
Localized Intensification	Grid averaging
Wet Anomaly Consistency	Fraction / division
Compound State Transition	Subtraction
Spatial Coherence	Connected-component count
Reliability-Aware Claim	Logical thresholding

Table 1: Six verification categories, 40 questions each (N=240 total). Full category descriptions in Appendix A.

fixed, publicly specified decision protocol with numerical thresholds.

The benchmark spans six verification categories, each evaluating a distinct numerical derivation primitive, with 40 questions per category (Table 1). No category requires climate domain expertise beyond interpreting the supplied numerical evidence under the stated protocol; the benchmark evaluates structured numerical verification, not climate knowledge.

Benchmark construction and class balance. Hypotheses are generated algorithmically using a deterministic seeded generator (seed 20260626; `src/hypothesis_benchmark_generator_v2.py`). Regions, time windows, and threshold parameters are sampled programmatically; no individual hypotheses were hand-authored. A `balanced_select()` procedure enforces near-uniform class balance: SUPPORTED (78, 32.5%), REFUTED (79, 32.9%), INSUFFICIENT (83, 34.6%), with approximately 13/13/14 balance per category. The benchmark is fully reproducible from the released code.

Connection to climate-analysis tasks. The six primitives correspond to concrete monitoring computations: minimum-over-years selection (persistent drought/heat assessment); connected-component counting (extreme-event spatial footprint delineation); fraction computation (threshold-exceedance frequency); subtraction across periods (compound-event attribution); and completeness thresholding (quality-controlled observational monitoring). No climate domain expertise is required; the derivation primitives are the unit of evaluation.

V1 vs. V2 evidence design. The benchmark exists in two evidence configurations sharing identical questions, labels, thresholds, and decision protocols. **V1** evidence includes decisive aggregate statistics computed in advance — for example, the minimum yearly mean absolute anomaly across the evaluation window — directly alongside the protocol's thresholds; a model can in principle answer correctly by comparing the supplied aggregate to the threshold without performing any derivation. **V2** evidence applies IES: the decisive aggregate is removed and replaced with the year-by-year intermediate values from which it would be computed (e.g., the per-year mean absolute anomaly for each of three years). The model must derive the relevant aggregate — here, the minimum across years — before the decision protocol can be applied. The label, protocol, and thresholds are unchanged between V1 and V2; only the observable evidence differs in granularity. A worked example is given in Appendix B.

4 Intermediate-Evidence Substitution

Definition. Intermediate-Evidence Substitution (IES) is a benchmark design methodology that replaces decisive aggregate statistics appearing in benchmark evidence with the raw intermediate values required to derive those statistics, while preserving: task labels, decision protocols, numerical thresholds, and evaluation criteria. Only the observable evidence changes; ground truth is identical before and after substitution.

IES as a diagnostic probe. Because IES changes evidence granularity without changing what the task evaluates, a comparison of model accuracy under original and transformed evidence reveals how measured performance depends on the information representation used to present that evidence. The direction of the change is not predicted by IES and is not, in itself, a criterion for whether IES "worked": a performance decrease indicates that the model's accuracy under the original evidence was partly supported by the aggregate's presence; a performance increase indicates that the model performed better with structured intermediate evidence (possibly because the aggregate format was ambiguous or the intermediate values provided implicit structure); no significant change indicates that the model's measured performance is stable across both representations. All three outcomes are empirically informative. IES is therefore most precisely described as a diagnostic probe for the representation-sensitivity of benchmark accuracy, not primarily as a shortcut-removal mechanism.

What IES changes and what it does not. IES changes the computation required to produce a cor-

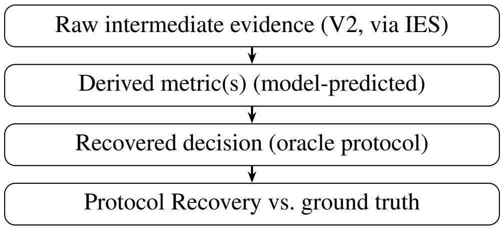

Figure 1: Structured derivation evaluation pipeline. IES determines the evidence granularity shown to the model (top); the model derives intermediate metrics; the oracle protocol applies the fixed decision procedure to those predicted metrics; Protocol Recovery compares the resulting decision against ground truth (§5.3–§5.4).

rect answer. It does not change which answer is correct, how that answer is scored, or what the task is nominally evaluating. Any accuracy difference between versions is attributable, by construction, to the change in evidence granularity — though the specific mechanism by which that granularity change affects a particular model's accuracy remains an empirical question to be investigated separately for each model (see §6 and §7.4).

Scope. IES operates entirely at benchmark construction time. We do not claim that IES eliminates all possible shortcuts from V2 evidence — only that it removes the decisive-aggregate shortcut present in V1. Additionally, V2 evidence differs from V1 not only in the derivation it requires but also in how information is presented: year-by-year values have different formatting, salience, and temporal structure than pre-computed aggregates, and our experiments cannot fully disentangle the effect of the derivation requirement from this change in information presentation (see Limitations, §9). Establishing IES as a general-purpose methodology beyond ClimateTwinBench is future work (§8).

Figure 1 summarizes the structured derivation pipeline used to separate derivation accuracy from protocol-execution accuracy.

5 Experimental Design

5.1 Evaluated Models and Reproducibility

Table 2 lists the models evaluated and the evaluations each participated in. **Claude Sonnet 4.6**, **Gemini 3.5**, and **DeepSeek Chat** were evaluated on both the V1/V2 multiple-choice task and the structured derivation task. **Claude Opus 4.6** and **GPT-OSS-120B** were evaluated on the structured derivation task only, the latter as a lower-performing comparison model. **ChatGPT** was evaluated on the V1/V2 multiple-choice task only; no version-specific identifier beyond "ChatGPT" is available in our evaluation records. ChatGPT was not included in the structured derivation evaluation because the structured JSON output format required by that evaluation could not be reliably obtained at scale from the ChatGPT interface used during evaluation; the single re-query mechanism used for other models was insufficient to produce consistently parseable structured outputs. This is acknowledged as a limitation (§9). **GPT-OSS-120B** is a 120B-parameter open-weights language model evaluated as a lower-performing comparison baseline; it is included to establish discriminative range in the structured derivation evaluation, not as a primary subject of analysis. Throughout the paper, each model is identified by its full name on first mention per section and abbreviated thereafter (Claude, Claude Opus, Gemini, DeepSeek, GPT-OSS).

Model	MCQ	Derivation
Claude Sonnet 4.6	✓	✓
Claude Opus 4.6		✓
Gemini 3.5	✓	✓
DeepSeek Chat	✓	✓
GPT-OSS-120B		✓
ChatGPT	✓	

Table 2: Evaluated models and evaluation participation.

All models were evaluated through their respective standard chat/API interfaces, using provider default decoding settings; no explicit temperature, top-p, or other sampling parameters were imposed or tuned per model or task. Each question was presented in a single-turn prompt containing the evidence, protocol description, and required output format. Outputs were parsed automatically by a schema-validating parser (§5.3); parses that failed were re-queried exactly once with an explicit format reminder, with no further retries. This re-query mechanism fired for only a small minority of GPT-OSS-120B responses and never for any frontier model (Claude Sonnet 4.6, Claude Opus 4.6, Gemini 3.5, DeepSeek Chat); no frontier-model conclusion in this paper depends on it. Full prompt templates are in Appendix B. Evaluation scripts, the benchmark JSON, the oracle implementation, and per-question model outputs are released in the project repository at `https://github.com/aadityat23/ClimateTwinIndia`.

5.2 V1/V2 Multiple-Choice Evaluation

Each model is independently evaluated on all 240 questions in both the V1 and V2 evidence configurations, using the same question set, protocol, and answer options across versions. Per-question correctness is recorded, enabling a paired (within-subject) comparison between V1 and V2 for each model. We test the significance of the V1→V2 accuracy change using McNemar's test with continuity correction (McNemar, 1947), applied to the 2×2 table of (V1-correct, V2-correct) outcomes for each model over the $N = 240$ paired questions, since the same questions are answered under both conditions. We note that Claude Sonnet 4.6 ($\chi^2 = 7.111$, $p = 0.0077$) and Gemini 3.5 ($\chi^2 = 7.087$, $p = 0.0078$) round to the same reported $p = 0.008$ from different transition counts (9 vs. 0 and 48 vs. 79); this is coincidental rounding, not a duplicated value (exact χ^2 given for independent verification).

5.3 Structured Derivation Evaluation

To separate numerical derivation from protocol execution directly, we conduct a structured evaluation on all 240 V2 questions for five models (Claude Sonnet 4.6, Claude Opus 4.6, Gemini 3.5, DeepSeek Chat, GPT-OSS-120B). Each model is presented with the year-by-year intermediate evidence for its question — the same intermediate values used in the V2 multiple-choice condition — and is required to output, in a structured format, (a) its derived value for each metric needed by the protocol (one to three metrics depending on category), and (b) its decision (`SUPPORTED`/`REFUTED`/`INSUFFICIENT`). Outputs are parsed with a schema-validating parser; malformed outputs that could not be parsed into the required fields were re-queried once with a clarifying format reminder before being recorded (this occurred for a small minority of GPT-OSS-120B responses and did not affect any frontier-model result reported in §6).

We then compute two independent quantities for each question:

- **Metric accuracy**: whether the model's predicted metric value(s) match the ground-truth metric value(s) within a numerical tolerance of $\mathrm{atol} = 10^{-4}$, matching the floating-point precision of the underlying IMD-derived data.
- **Protocol Recovery**: whether applying the fixed, deterministic decision protocol to the *model's predicted metric values* (not the model's stated decision) yields the ground-truth label. This oracle re-application isolates whether protocol execution would succeed *given the model's own derived numbers*, independent of any error in how the model verbalized its final decision.

This design does not supply the model with correct intermediate metrics; it requires the model to derive them, and measures derivation accuracy and oracle-recovered decision accuracy separately. We refer to this throughout as the *structured derivation evaluation*, distinct from an experiment in which correct metrics are supplied directly.

Oracle validation. The oracle protocol (`classify_with_thresholds()`) is the same deterministic function used to assign ground-truth labels during benchmark construction. Because labels are produced by applying this function to ground-truth metrics, Protocol Recovery of 100% for a model with zero metric errors is guaranteed by construction. The function has no learned parameters or stochastic components; its correctness is verified by a round-trip check confirming that it recovers ground-truth labels from ground-truth metrics for all 240 questions.

Three related quantities. **Metric accuracy** measures whether the model's *derived value* matches ground truth, independent of its final decision. **Protocol Recovery** measures whether the oracle protocol, applied to that *derived value*, yields the correct decision — well-defined even when the derived value is wrong. **Decision accuracy** (Appendix D) is synonymous with Protocol Recovery at category granularity. A model can thus show low metric accuracy alongside high Protocol Recovery if its errors fall on the correct side of every threshold (*absorbed*, §5.4) — the pattern reported for Claude Sonnet 4.6 and DeepSeek Chat in §6.

5.4 Cascade Analysis

For every question where a model's predicted metric value differs from the ground-truth metric value (a *metric error*), we classify the error as **absorbed** if the oracle decision computed from the model's incorrect predicted metric still matches the ground-truth decision label (typically because the error does not cross a decision threshold), or **propagated** if the oracle decision differs from the ground-truth

Model	V1	V2	Δ	χ^2	p
Claude Sonnet 4.6	100.00	96.25	−3.75	7.111	0.008
DeepSeek Chat	100.00	98.75	−1.25	1.333	0.248
Gemini 3.5	32.50	45.42	+12.92	7.087	0.008
ChatGPT	64.17	90.00	+25.83	43.267	<0.001

Table 3: Overall MCQ accuracy (%) by evidence version, with McNemar χ^2 (continuity-corrected) and p-value ($N = 240$ paired questions). Claude Sonnet 4.6 and Gemini 3.5 round to the same reported $p = 0.008$ from distinct χ^2 values (see §5.2); ChatGPT's exact $p \approx 4.8 \times 10^{-11}$.

Model	C→C	C→W	W→C	W→W
Claude Sonnet 4.6	231	9	0	0
DeepSeek Chat	237	3	0	0
Gemini 3.5	30	48	79	83
ChatGPT	142	12	74	12

Table 4: V1→V2 transition counts (C=Correct, W=Wrong).

Model	PR	MA	Err	Abs	Prop
Claude Sonnet 4.6	100.00	99.58	1	1	0
Claude Opus 4.6	100.00	100.00	0	0	0
Gemini 3.5	100.00	100.00	0	0	0
DeepSeek Chat	99.58	94.17	14	13	1
GPT-OSS-120B	42.92	4.17	230	93	137

Table 5: Structured derivation evaluation ($N = 240$ each). PR = Protocol Recovery (%), MA = Metric Accuracy (%), Err = metric errors, Abs = absorbed, Prop = propagated.

Model	Err	Abs. Rate	Prop. Rate
Claude Sonnet 4.6	1	100.00%	0.00%
Claude Opus 4.6	0	—	—
Gemini 3.5	0	—	—
DeepSeek Chat	14	92.86%	7.14%
GPT-OSS-120B	230	40.43%	59.57%

Table 6: Cascade analysis: disposition of metric errors.

label. The absorption rate (absorbed / total metric errors) quantifies how much of a model's derivation inaccuracy is consequential for the final verification decision, as opposed to falling within the protocol's effective tolerance.

6 Results

This section reports observations only; interpretation is deferred to §7.

6.1 V1 vs. V2 Multiple-Choice Accuracy

Table 3 reports overall accuracy and the paired McNemar test for each model evaluated on the multiple-choice task. Table 4 reports the underlying transition counts.

Category-level V1/V2 accuracy for Claude Sonnet 4.6 and DeepSeek Chat is given in Appendix C. All nine of Claude Sonnet 4.6's Correct→Wrong transitions (Table 4) occur in the Compound State Transition category (V2 accuracy: 77.50%); all other categories remain at 100.00% under V2.

6.2 Structured Derivation Evaluation

Table 5 reports the structured derivation evaluation across all five participating models. Per-category metric and decision accuracy is given in Appendix D.

6.3 Cascade Analysis

Table 6 reports absorption and propagation rates among metric errors. DeepSeek Chat's single propagated failure is question HYP-186 (Spatial Coherence Verification), where the model's predicted connected-component count crosses a decision threshold relative to the ground-truth count (full case detail in Appendix E).

7 Analysis

7.1 Derivation vs. Protocol Execution for Frontier Models

Across the four frontier models in the structured derivation setting (Claude Sonnet 4.6, Claude Opus 4.6, Gemini 3.5, DeepSeek Chat), Protocol Recovery is at or near ceiling (99.58–100.00%, Table 5). For Claude Opus 4.6 and Gemini 3.5, zero metric errors occur, so Protocol Recovery trivially reaches 100.00%. For Claude Sonnet 4.6 and DeepSeek Chat, metric errors do occur (1 and 14, respectively), yet Protocol Recovery remains near-ceiling because the large majority of those errors are absorbed (100.00% and 92.86%, Table 6). The co-occurrence of non-trivial metric error counts with near-ceiling Protocol Recovery indicates that, for these models, protocol execution given a derived metric is not the primary source of residual error; the derivation step is. IES makes this diagnostic separation possible: without the structured derivation evaluation, high overall accuracy would mask where residual errors originate.

7.2 GPT-OSS-120B: Failures in Both Error Sources

GPT-OSS-120B does not permit the same separation. Its metric accuracy is 4.17% and absorption rate 40.43%, meaning most derivation errors propagate into decision errors. Even among correctly derived questions, overall Protocol Recovery (42.92%) remains far below any frontier model, indicating that protocol execution itself contributes errors independently of derivation. GPT-OSS-120B thus exhibits substantial failures in both derivation accuracy and oracle-recovered decision accuracy, and these two sources cannot be cleanly disentangled. This establishes that the benchmark evaluation is not trivially easy and that the frontier-model pattern reflects a genuine capability difference.

7.3 DeepSeek Chat: Spatial Coherence and Threshold-Margin Analysis

DeepSeek Chat's 14 metric errors concentrate in Spatial Coherence (11 of 14; 72.50% category metric accuracy vs. $\geq$92.50% elsewhere). Spatial Coherence is the only category whose derivation primitive requires reasoning over two-dimensional spatial connectivity: the model must identify which active grid cells share edges and group them into connected regions to produce a component count. This differs structurally from all other categories, whose derivation primitives are scalar reductions (minimum, average, fraction, subtraction) over independent per-year or per-cell values. We note this structural distinction as an observation; our data do not establish why spatial-connectivity counting generates more errors for DeepSeek Chat than the other primitives do.

Despite 11 spatial metric errors, 10 are absorbed. A threshold-margin analysis (Appendix F) reveals that absorption is primarily a function of threshold geometry rather than error magnitude: all 10 absorbed errors have predicted and ground-truth component counts on the same side of the protocol's decision threshold, so the oracle recovers the correct decision regardless of how large the count error is. The single propagated failure (HYP-186) is the only case where GT (4.0) and predicted (2.0) straddle the threshold (2.5), placing them on opposite sides of the decision boundary. The three persistent regional anomaly errors are similarly absorbed: HYP-001's large error (GT 0.7789, Pred 1.1589) is absorbed because both values exceed the support threshold (0.7763), with a margin of 0.0026.

7.4 Model-Specific Responses to Evidence Granularity

IES reveals three distinct response patterns across models, each empirically informative.

Accuracy decrease (Claude Sonnet 4.6). Claude's -3.75 pp drop ($p = 0.008$) originates entirely in the Compound State Transition category (77.50% V2 accuracy; all other categories remain 100.00%). All nine V1-Correct$\rightarrow$V2-Wrong transitions occur there, suggesting that for this model, V1's pre-computed aggregate supported correct compound-subtraction answers that V2's intermediate evidence does not.

Accuracy increase (Gemini 3.5, ChatGPT). Gemini improves +12.92 pp ($p = 0.008$; 79 Wrong$\rightarrow$Correct vs. 48 Correct$\rightarrow$Wrong) and ChatGPT improves +25.83 pp ($p \approx 4.8 \times 10^{-11}$; 74 Wrong$\rightarrow$Correct vs. 12 Correct$\rightarrow$Wrong). Both directions are legitimate IES outcomes: for these models, V2 evidence granularity is associated with higher accuracy than V1. One candidate hypothesis is that year-by-year intermediate values provide implicit temporal structure that assists protocol application for these models, while the pre-computed aggregate was ambiguous or less usable in V1. We label this as a hypothesis only — our experimental design cannot confirm it — and neither model was included in the structured derivation evaluation, so no cascade analysis is available to investigate further.

No significant change (DeepSeek Chat). DeepSeek Chat's -1.25 pp change ($p = 0.248$) is not statistically significant, indicating stable decision-level accuracy across evidence versions. Derivation errors visible in the structured evaluation (§7.3) are largely absorbed and do not surface in the MCQ accuracy signal.

8 Discussion

The combined analyses support a specific, bounded conclusion: for Claude Sonnet 4.6, Claude Opus 4.6, Gemini 3.5, and DeepSeek Chat on ClimateTwinBench's deterministic protocols, oracle-recovered protocol accuracy is near-ceiling once a model has derived its intermediate metrics. Residual error, where it exists, concentrates in the derivation step. This finding does not depend on frontier models failing outright: it is revealed by the structured derivation evaluation and cascade analysis, which separate where errors originate in a way that aggregate accuracy cannot.

From measurement to diagnosis. Most benchmarks answer "right or wrong?"; the IES framework combined with cascade analysis answers "which stage fails, and does that failure change the final decision?" For the four evaluated frontier models on ClimateTwinBench's deterministic verification protocols, the diagnosis is: protocol execution is not the dominant source of residual error; numerical derivation — specifically spatial-connectivity counting and, to a lesser extent, temporal minimum selection — accounts for the dominant share of residual error on this benchmark. The benchmark's value is not that frontier models score below 100%, but that it reveals *why* they score what they do, at the granularity needed to redirect evaluation effort effectively.

What IES reveals about evidence representation. V1/V2 accuracy comparisons demonstrate that performance on identical tasks is sensitive to evidence granularity, and that this sensitivity differs across models in direction and magnitude. Each direction of change (decrease, increase, no change) is an informative empirical outcome of the diagnostic, not a contradiction. Benchmark designers should not treat evidence representation as a neutral presentational choice; IES provides a systematic way to probe its effect on measured accuracy without modifying the evaluation task itself.

Applicability beyond ClimateTwinBench. Applying IES to other benchmark families where decisive aggregates are common — financial, medical, remote-sensing verification — is a future methodological direction. Whether the cascade-absorption pattern observed here would replicate in other domains is an empirical question, not an assumption.

9 Limitations

- **V2 differs in derivation requirements and information presentation.** Year-by-year values present the same data as V1 aggregates with different formatting, salience, and temporal structure. Our experiments cannot disentangle the effect of requiring derivation from this change in information presentation. Accuracy improvements for ChatGPT and Gemini 3.5 may reflect information-presentation effects; this is acknowledged as an explicit scope limitation.
- **Mechanisms for ChatGPT/Gemini improvements are unresolved.** The candidate hypotheses in §7.4 are labeled as hypotheses; neither is supported by controlled evidence from the current design.
- **IES targets one specific shortcut.** Removing decisive aggregates does not eliminate all possible shortcuts from V2 evidence.
- **ChatGPT excluded from structured derivation evaluation.** Cascade analysis and metric-accuracy decomposition are unavailable for ChatGPT.
- **Domain and protocol specificity.** All conclusions are specific to ClimateTwinBench's six categories and protocols; generalization is future work.
- **Not a climate-knowledge evaluation.** All categories are answerable from the supplied numerical evidence alone.
- **Metric tolerance.** Metric accuracy uses $\mathrm{atol} = 10^{-4}$ matching IMD data precision. Supplementary statistics are in Appendix G.

10 Conclusion

We introduced Intermediate-Evidence Substitution (IES), a benchmark design methodology that changes evidence granularity while preserving task semantics, functioning as a diagnostic probe for how model accuracy depends on information representation. Applied to ClimateTwinBench, a 240-question deterministic climate verification benchmark, IES produces accuracy changes in both directions across models — a decrease for Claude Sonnet 4.6, increases for Gemini 3.5 and ChatGPT, and no significant change for DeepSeek Chat — with each outcome informative about the model's relationship to evidence representation. A structured derivation evaluation with cascade analysis further shows that oracle-recovered protocol accuracy is near-ceiling for four evaluated frontier models once intermediate metrics are derived, while derivation errors — particularly in spatial-connectivity counting — dominate residual error. For GPT-OSS-120B, failures in both derivation and protocol execution prevent this clean separation. A threshold-margin analysis of DeepSeek Chat's absorbed errors reveals that absorption is primarily determined by protocol-threshold geometry rather than error magnitude. These results support IES as a diagnostic methodology for separating where model accuracy originates on ClimateTwinBench, and motivate its application to other structured verification benchmarks where pre-computed decisive aggregates appear alongside decision protocols; cross-domain validation remains future work.

Ethics Statement

ClimateTwinBench is constructed entirely from publicly available IMD gridded climate observations and contains no personal, sensitive, or human-subject data. All models evaluated in this work were accessed through their standard public interfaces under their respective terms of service. We report all results, including empirical outcomes in both directions of the IES diagnostic (accuracy decreases and increases; see §7.4), without omission.

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A Benchmark Category Details

- **Persistent Regional Anomaly Verification**: requires identifying whether a region's anomaly remains above/below a threshold across *all* years in the window, via minimum-over-years selection.
- **Localized Intensification Verification**: requires averaging anomaly values over a spatial sub-grid to determine localized intensification relative to a threshold.
- **Wet Anomaly Consistency Verification**: requires computing the fraction of cells exceeding a percentile threshold and comparing it against a minimum-fraction criterion.
- **Compound State Transition Verification**: requires subtracting metrics between two time periods to determine whether a qualifying state transition occurred.
- **Spatial Coherence Verification**: requires constructing a binary active-cell mask and counting connected components (4-connectivity) to determine spatial coherence of the anomaly pattern.
- **Reliability-Aware Claim Verification**: requires joint thresholding over a magnitude metric and a data-completeness metric, with an explicit `INSUFFICIENT` outcome when completeness is too low.

B Structured Derivation Prompt Format

Models in the structured derivation evaluation receive, for each question, the year-by-year intermediate evidence used in the V2 multiple-choice condition (e.g., per-year mean absolute anomaly, per-year fraction of cells above a percentile threshold, per-year completeness), along with the category's decision protocol and thresholds. Models output a structured (JSON-like) record containing (a) their derived value for each required metric (one to three, depending on category) and (b) a final decision among `SUPPORTED`, `REFUTED`, `INSUFFICIENT`. No ground-truth metric values are supplied at any point.

Worked example (Persistent Regional Anomaly, HYP-001). The model receives three yearly mean absolute anomaly values (2021: 1.1589, 2022: 0.7789, 2023: 1.1242) and is asked to derive `min_yearly_mean_abs_anomaly`. Ground truth: $\min(1.1589, 0.7789, 1.1242) = 0.7789$, which under the category threshold (0.7763) yields `SUPPORTED`.

Output parsing. Outputs are parsed with a schema-validating parser. Outputs failing schema validation are re-queried once with a format reminder; a second failure is recorded as an error. This re-query mechanism was triggered only for a small minority of GPT-OSS-120B responses and was never invoked for any frontier model. Evaluation code is available in the project repository under `experiments/experiment_05_derivation/`.

C Category-Level V1/V2 MCQ Accuracy

Category	Cl.V1	Cl.V2	DS.V1	DS.V2
Persistent Regional Anomaly	100.00	100.00	100.00	100.00
Localized Intensification	100.00	100.00	100.00	97.50
Wet Anomaly Consistency	100.00	100.00	100.00	100.00
Compound State Transition	100.00	77.50	100.00	100.00
Spatial Coherence	100.00	100.00	100.00	100.00
Reliability-Aware Claim	100.00	100.00	100.00	95.00

Table 7: Category-level V1/V2 accuracy (%) for Claude Sonnet 4.6 (Cl.) and DeepSeek Chat (DS.).

D Category-Level Structured Derivation Results

E Propagated Failure Cases

GPT-OSS-120B's 137 propagated failures span all six categories and are concentrated in Localized Intensification, Wet Anomaly Consistency, Compound State Transition, Spatial Coherence, and Reliability-Aware Claim Verification. The full per-question listing is available in the project repository under the `experiments/` → `experiment_05_derivation/` → `results/` directory.

F Threshold-Margin Analysis: DeepSeek Chat Absorbed Errors

Table 10 reports the threshold-margin analysis for all 14 DeepSeek Chat metric errors. For each error, we identify the nearest protocol decision threshold and determine whether the ground-truth (GT) and predicted metric fall on the same or opposite sides. Errors where GT and predicted are on the same side are absorbed; the single error where they straddle the threshold (HYP-186) is propagated.

G Supplementary Metric-Level Statistics

Category	Claude / Cl. Opus		Gemini / DeepSeek		GPT-OSS	
	MA	DA	MA	DA	MA	DA
Compound State Transition	100.0 / 100.0	100.0 / 100.0	100.0 / 100.0	100.0 / 100.0	0.0	35.0
Localized Intensification	100.0 / 100.0	100.0 / 100.0	100.0 / 100.0	100.0 / 100.0	0.0	32.5
Persistent Regional Anomaly	100.0 / 100.0	100.0 / 100.0	100.0 / 92.5	100.0 / 100.0	0.0	90.0
Reliability-Aware Claim	100.0 / 100.0	100.0 / 100.0	100.0 / 100.0	100.0 / 100.0	0.0	32.5
Spatial Coherence	97.5 / 100.0	100.0 / 100.0	100.0 / 72.5	100.0 / 97.5	25.0	32.5
Wet Anomaly Consistency	100.0 / 100.0	100.0 / 100.0	100.0 / 100.0	100.0 / 100.0	0.0	35.0

Table 8: Per-category Metric Accuracy (MA, %) and oracle Decision Accuracy (DA, %) in the structured derivation evaluation. Claude/Cl. Opus and Gemini/DeepSeek columns show paired values; $N = 40$ per category per model. GPT-OSS MA and DA share the same column since Claude Opus and Gemini are not shown separately in that slot.

Model	Question	GT	Recovered
DeepSeek Chat	HYP-186 (Spatial Coherence)	REFUTED	INSUFFICIENT

Table 9: DeepSeek Chat's sole propagated failure. Root cause: connected-component count predicted as 2 (GT: 4); the 2.5 decision threshold is straddled.

ID	GT M1	Pred M1	Threshold	Margin	Status
Persistent Regional Anomaly (3 errors)					
HYP-001	0.7789	1.1589	0.7763	0.0026	Absorbed
HYP-002	1.6805	1.6805	1.0000	0.6805	Absorbed
HYP-003	0.9982	0.9982	1.0000	0.0018	Absorbed
Spatial Coherence (11 errors)					
HYP-185	0.0	4.0	0.5	0.50	Absorbed
HYP-186	4.0	2.0	2.5	1.50	**Propagated**
HYP-187	2.0	2.0	2.5	0.50	Absorbed
HYP-188	2.0	5.0	2.5	0.50	Absorbed
HYP-189	5.0	2.0	2.5	2.50	Absorbed
HYP-190	2.0	2.0	2.5	0.50	Absorbed
HYP-193	2.0	1.0	2.5	0.50	Absorbed
HYP-194	1.0	2.0	0.81	0.19	Absorbed
HYP-197	2.0	5.0	2.5	0.50	Absorbed
HYP-198	5.0	3.0	2.5	2.50	Absorbed
HYP-199	3.0	1.0	2.5	0.50	Absorbed

Table 10: Threshold-margin analysis for all 14 DeepSeek Chat metric errors (Metric 1 shown). "Margin" is the distance of the GT metric from the nearest protocol threshold. All absorbed errors have GT and predicted metric on the same threshold side. HYP-186 (propagated, bold) is the only case where GT (4.0) and predicted (2.0) straddle the threshold (2.5). For HYP-001, the model reports a per-year value rather than the minimum-over-years, but this value still exceeds the support threshold (margin = 0.0026), yielding absorption.

Model	Slot	N	MAE	Pearson r	EM (%)
Claude	1	240	0.0042	0.9997	98.75
Claude	2	240	<0.001	≈1.000	92.92
Claude	3	160	0.0000	1.0000	100.00
DeepSeek	1	239	0.1378	0.9792	78.24
DeepSeek	2	239	0.0628	0.9900	89.54
DeepSeek	3	160	0.0813	0.8726	95.00
GPT-OSS	1	240	0.9941	0.1203	19.58
GPT-OSS	2	240	0.9158	0.1361	19.58
GPT-OSS	3	160	0.4668	0.3854	48.75

Table 11: Per-metric-slot MAE, Pearson correlation, and exact-match rate. Slot 3 covers only the four categories with three required metrics ($N = 160$). DeepSeek Slots 1–2: $N = 239$ because one question's predicted value was non-numeric and excluded from continuous-error statistics only; the question is retained and counted as a metric error in the primary exact-match accuracy reported in Table 5 and Appendix D ($N = 240$). Per-category exact-match (Appendix D) is the primary metric-accuracy statistic; MAE is not comparable across categories with different metric scales.