

Preserving Probabilistic Meaning in Weather-to-Text Generation

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Abstract

Weather-to-text generation must preserve the event attached to a probability, not only its numerical value. We represent rainfall statements through event thresholds, boundary inclusion, probability levels and conditioning. A verifier bounds event probabilities under partially specified exact distributions and separately checks fidelity to operational reporting conventions. We evaluate eight model systems on Australian forecast inputs and controlled transformations, with number-copying, few-shot, post-editing, operator-plan and deterministic-template baselines. On a 2,304-case analytical challenge, source-blind extraction followed by verification gives 91.36% correct labels, compared with 30.43% for a text-only NLI baseline with different information access. Generation results expose a measurement problem: definitions can become certainty assertions, and unconditional statements can acquire conditions during extraction. Exact output comparisons also show that planning often reproduces the deterministic template, while post-editing can leave drafts unchanged. Under the residual-corrected estimator, 1,000 sampled analysis units retain a pooled few-shot advantage in preservation. A separate 223-target human study estimates that only 1.32–5.80% of extracted certainty assertions match a definite literal reading. These results support evaluating probability operators, source coverage and extraction validity together.

1 Introduction

A rainfall summary can reproduce every number and still change the forecast. Replacing *at least* with *up to* in a 25% probability of 8 mm, or adding *if it rains*, changes the event. Australian forecasts combine measurable-rain probabilities with displayed ranges whose positive endpoints carry reported exceedance probabilities [1, 2]. Faithful explanations must preserve events, thresholds, probabilities and conditions, distinguishing missing or suppressed amounts from zero.

We separate literal claim extraction from verification. For exact inputs, extracted event probabilities are bounded over all compatible distributions. For operational displays, verification checks reporting conventions without treating rounded amounts as exact. Contradictions, unsupported assertions, ambiguity and omissions distinguish accurate fragments from complete explanations.

Our contributions are an event-level representation and verifier; a paired eight-model study with deterministic controls and twelve analytical challenge families; and diagnoses of extraction errors and template reproduction. Frozen primary scores remain distinct from post-test sensitivities. Full-output human validation assesses generation preservation, while a targeted study independently assesses the validity of extracted certainty assertions.

2 Related Work

Rainfall interpretation and generation Weather NLG has long studied lexical choices that communicate numerical forecasts [3]. WeatherSyn uses multimodal instruction tuning for forecast reports [4], while Hierarchical AI-Meteorologist uses multiscale reasoning and keyword checks [5]. We isolate probability-event fidelity within this reporting task. Rainfall probabilities are often confused with the proportion of time or area affected [6]; stating the complementary chance of no rain can reduce interpretation errors [7]. These findings motivate source-hidden interpretation probes. Natural-language uncertainty explanations support decision-making [8], and compositional representations support controlled weather-related generation [9]. Numerical table-to-text reasoning [10], time-series understanding [11] and forecast-discussion grounding [12] concern numerical content. We test the event and condition attached to a probability, which can change even when every number is retained.

Factuality and uncertainty NLI evaluates data-to-text semantic accuracy [13]; EQUATE contrasts NLI models with symbolic quantity manipulation [14]. Our challenge includes claims left undetermined by partial probability constraints. FactReasoner estimates claim truth through probabilistic relations with retrieved evidence [15]; here, probabilities are themselves claim content and the forecast supplies the evidence. Graded entailment [16], probability-word reasoning [17], verbal likelihood calibration [18] and confidence-bearing climate synthesis [19] address related uncertainty judgments. Our verifier retains explicit event boundaries and conditioning.

Probabilistic reasoning Probabilistic logical entailment supports inference from incomplete numerical knowledge [20, 21]. Language-to-probabilistic-program approaches combine meaning construction and inference [22]. We use extracted event representations to separate exact distributional entailment from operational reporting fidelity.

3 Probability Meaning and Verification

Let $R \geq 0$ denote rainfall over a stated valid interval. A source packet identifies the place, interval and convention, together with event-probability atoms and display metadata. An exact atom constrains $P(E)$ for an event E with explicit endpoint closure. A reported atom records an operational product’s stated exceedance meaning. A display range and a missing field are separate objects; neither supplies an exact probability constraint by itself.

3.1 Bounds under partial information

For exact atoms, let $\mathcal{P}(S)$ be the set of probability distributions compatible with source S . For a generated event E , compute

$$\begin{aligned} L_S(E) &= \inf_{P \in \mathcal{P}(S)} P(E), \\ U_S(E) &= \sup_{P \in \mathcal{P}(S)} P(E). \end{aligned} \tag{1}$$

Source and query thresholds partition the nonnegative line into singleton thresholds and intervening open cells, including the final unbounded interval. Let x_j be cell j ’s probability mass and a_E its event-membership vector. Following probabilistic logical entailment [20], each bound minimizes or maximizes $a_E^\top x$ subject to

$$\ell_i \leq a_i^\top x \leq u_i, \quad x \geq 0, \quad \mathbf{1}^\top x = 1. \tag{2}$$

Every compatible distribution induces feasible cell masses; every feasible mass vector is realizable by placing each mass at a point in its cell. Thus the bounds are tight without continuity or parametric assumptions. Singleton cells retain mass at event boundaries.

An asserted probability interval is entailed when it contains the entire feasible range, contradicted when the ranges are disjoint, and underdetermined otherwise. An unqualified point claim in the third category is an unsupported assertion. Text that does not specify a unique event is recorded as ambiguous before verification. Inconsistent source constraints trigger a data error.

For example, exact constraints $P(R \geq a) = q_a$ and $P(R \geq b) = q_b$, with $a < b$, imply $P(a \leq R < b) = q_a - q_b$. The probability of the closed interval additionally depends on $P(R = b)$. Likewise, a statement conditioned on measurable rain is checked using $P(E \cap C)/P(C)$ rather than the unconditional probability. If $P(C)$ has upper bound zero, conditioning is undefined. Otherwise, the transformation $z = x/P(C)$ and $t = 1/P(C)$ of Charnes and Cooper [23] gives

$$\ell_i t \leq a_i^\top z \leq u_i t, \quad \mathbf{1}^\top z = t, \quad a_C^\top z = 1, \quad z \geq 0. \quad (3)$$

Optimizing $a_{E \cap C}^\top z$ gives the infimum and supremum over compatible distributions with $P(C) > 0$, allowing limits when an endpoint is not attained. The normalization above implies $t > 0$.

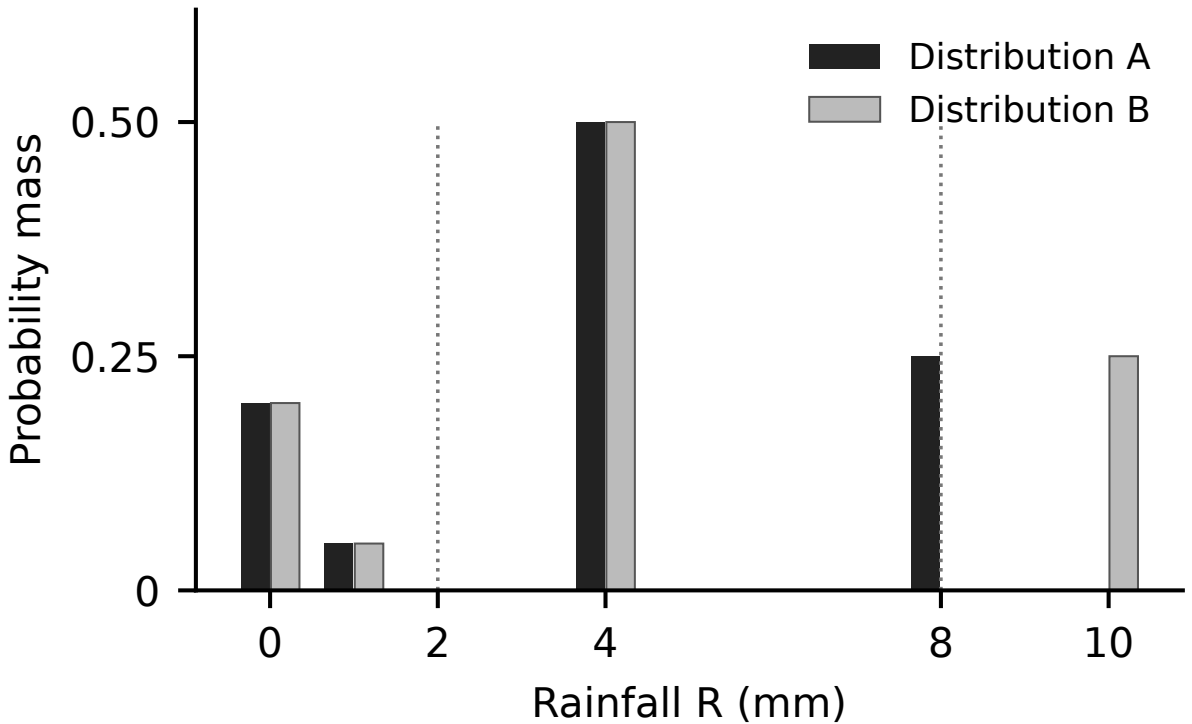


Figure 1: Two illustrative distributions satisfy $P(R \geq 0.2) = 0.80$, $P(R \geq 2) = 0.75$ and $P(R \geq 8) = 0.25$. Both assign probability 0.50 to $[2, 8)$, while their probabilities for $[2, 8]$ are 0.75 and 0.50. The source atoms leave the mass at 8 mm unidentified.

3.2 Reported forecasts

Operational displays are evaluated against their documented reporting semantics. Direct and equivalent paraphrases preserve the reported event, level and threshold. Event reversal, a substituted probability, added conditioning and certainty overstatement are recorded separately. New arithmetic claims require the information and precision needed to derive them. A phrase such as *possible rainfall of 2 to 8 mm* preserves a product range; it does not assert a guaranteed interval. We report coverage of the supplied probability atoms separately from errors and ambiguity.

Public descriptions use strict and inclusive variants of the 0.2 mm measurable-rain threshold. We accept and record both as operational reporting variants. Exact controlled packets specify one event closure, which verification retains.

Reported tail probabilities also impose an ordering: a more restrictive exceedance event cannot have a larger reported probability. We check this ordering using only explicitly supplied atoms. A suppressed zero endpoint contributes no fictitious probability constraint. These checks identify inconsistencies with the nominal reporting semantics; exact distributional entailment remains confined to the controlled inputs.

3.3 Generation regimes

All competing regimes receive the same facts and interpretation contract. Direct prompting supplies the contract alone; few-shot prompting adds synthetic examples; post-editing checks the corresponding few-shot draft. A number-copying ablation replaces numerical placeholders deterministically while leaving the surrounding probability language to the model.

In operator-plan generation, the model selects and orders verified fact realizations. A validator requires every supplied fact exactly once and checks each selected variant. Invalid plans use a fixed canonical realization, with fallback frequency reported as a system outcome. The deterministic explicit template uses the same fact inventory. This comparison measures the contribution and cost of model-based planning beyond a strong template. A separate terse product-style template provides a conventional display baseline.

3.4 Source-blind extraction

A fixed Qwen3-8B extractor sees numbered sentences from generated text without source values, generation regime or model identity. It returns evidence sentence IDs, events, probability levels, conditions and modality; IDs map directly to the original text. Verification then receives these extracted structures and the source. Canonicalization retains each independently valid claim and marks the exact evidence of a malformed claim as unresolved; it does not repair semantic fields. Every regime, including verified realizations, passes through this same extraction stage. Human validation measures field accuracy and missed claims, including substantive statements classified as explanatory text.

4 Forecast Inputs and Entailment Tests

4.1 Operational reporting

We captured seven public Bureau of Meteorology text-forecast products on 14 September 2026. The snapshot contains 4,788 location-day records for 684 places in 90 forecast districts. Of these records, 959 contain a possible-rainfall range. Although the snapshot covers many locations, it contains only 89 distinct combinations of rain probability and displayed amount endpoints. We therefore retain both geographic grouping and semantic-pattern identity in sampling and analysis.

Victoria supplies the development examples. The operational test frame contains 3,600 future location-days in the other state and territory products; current-day periods are excluded. We form strata by forecast district and semantic pattern, then sample one location-day uniformly in each stratum using a fixed seed. This yields 616 inputs across 81 districts and 79 patterns. Each representative receives an inverse inclusion weight equal to its stratum size. Table 1 distinguishes the number of inputs from the number of distinct probability patterns.

Table 1: Operational reporting sample. Inputs represent district–pattern strata; their weights cover 3,600 source location-days.

Operational case	Inputs	Patterns
Missing amount range	253	4
Zero lower display	260	35
Positive lower display	103	40
Total	616	79

The cited 2026 source documentation assigns reported exceedance probabilities of 75% and 25% to the positive lower and upper endpoints [1, 2]. A displayed zero lower endpoint does not supply a 75% atom at zero. We preserve this distinction in the input representation. Every positive-lower record in the snapshot satisfies the nominal rain-probability ordering, and every record with a range has at least a 25% reported chance of rain. These checks establish consistency of the encoded reporting convention; they do not measure forecast calibration against rainfall observations.

To assess sensitivity to the chosen location-day representative, we select 60 strata with at least three source records and retain two additional location-days per stratum. This gives 120 replication inputs, comprising 31 missing-range, 21 zero-lower and 8 positive-lower strata. Direct and few-shot generation use all these inputs. Their comparison measures variation within a semantic pattern when the place or date changes.

4.2 Exact controlled inputs

The controlled cohort contains 192 distinct sampled base parameter sets. Each specifies the probability of measurable rain and two positive exceedance endpoints, with explicit event closure and feasible probability ordering. Four transformations retain the draw identity: the original packet, a changed rain probability, a changed upper-endpoint probability, and removal of amount information. The resulting 768 packets use Australian place names with hypothetical forecasts and dates. Their probabilities are exact test constraints. Base parameter tuples exclude the development cases.

This cohort separates changes to probability levels, amounts and missing information from operational display conventions. It also tests probability levels beyond the current product’s 75/25 pairing. The four transformations share a statistical group, so they do not count as four independent draws.

4.3 Analytical entailment challenge

For each controlled base draw, we construct twelve premise–hypothesis pairs. Families test direct paraphrase, event reversal, added conditioning, half-open and closed intervals, an unreported threshold, a changed probability, a complement, a hard maximum, a strict threshold, an identified conditional interval and a conditioning event that can have zero probability. This produces 2,304 pairs with analytical labels specified from the construction. A separately implemented LP consistency check verifies the labels before model evaluation.

The distinction between the two interval families is structural. Exact upper-tail probabilities determine the mass in a half-open interval by subtraction, while a closed interval can include unidentified mass at its upper boundary. The final conditional family explicitly restricts its assertion to compatible distributions where the conditioning event has positive probability. For contradictory claims, we record the distance between the asserted probability and its feasible range. Family-specific results retain these margins rather than excluding difficult near-boundary cases.

5 Experimental Design

Models and execution Our local suite comprises revision-pinned Qwen2.5-7B-Instruct [24], Qwen3-8B [25], Phi-4-mini-instruct [26], and Qwen3.5-9B [27]. All use BF16 on one AMD Radeon AI PRO R9700, greedy decoding, batches of four, a 240-new-token cap and a 120-word paragraph instruction. Truncations, unresolved placeholders and invalid-plan fallbacks remain system outcomes. Local timing spans the batched generation call through device synchronization, amortized over the batch; loading, tokenization, decoding and verification are excluded. Post-edit cost includes the same-system few-shot draft; other model regimes use one generation pass. Templates make zero model calls, without measuring CPU rendering cost.

Additional systems GPT-5.6 Sol [28] and Qwen3.8-Max [29] use the local Codex CLI; DeepSeek-V4-Pro [30] and GLM-5.3 [31] use SiliconFlow. Sol requests low effort in all five regimes, Qwen3.8-Max requests **none**, DeepSeek disables thinking, and GLM-5.3 requests low effort. The provider documents high/max effort values and compatibility mapping for listed thinking models, without specifying GLM-5.3 handling [32]. Qwen3.8-Max development calls report zero reasoning tokens and no reasoning items; service responses do not independently confirm Qwen3.8-Max or GLM-5.3 effort. Each system targets the same 1,384 main inputs in five regimes and 120 replication inputs in direct and few-shot generation, yielding 7,160 outputs. Source packets, user prompts, examples, output resolution and same-system post-edit drafts match the local design. The design was frozen before formal generation. An execution constraint cancelled Sol medium (2,768 main outputs and 240 replications) after low-effort main generation but before scoring or held-out annotation. Its 68 development medium outputs from 34 packets remain excluded; formal results use low only.

API calls use temperature zero and a 240-visible-token cap; CLI clients retain the 120-word instruction but no independent token cap. Requested settings and actual usage are retained; CLI events do not reveal service revisions. Recovery reuses completed outputs under unchanged schedules. Sol’s timeout rose from 180 to 600 seconds. API/CLI wall times include client overhead and retries and are reported separately from local device timing; post-edit costs include drafts. Missing timing or termination records remain missing, without removing output weights.

Metrics Numerical fidelity compares required source values with generated numbers after decimal normalization and removal of the supplied place and date; the measurable-rain threshold is optional. Missing and introduced values are reported separately. An echo-exempt version ignores occurrences of exact numeric-bearing contract sentences and the convention identifier, without whitelisting their values. Both versions and echo frequency are retained. The dissociation rate counts numerical fidelity together with a verified operator error, unconditionally and among numerically faithful outputs, for both versions. Exact-source contradictions and operational reporting errors remain separate.

Coverage measures correctly expressed probability atoms; complete fact coverage also requires the range or its absence. Covered facts can coexist with unsupported additions. Screened preservation requires complete atom coverage, no adverse explicit probability or guarantee claim, and no unresolved numerical or certainty span. Explanatory clauses remain unresolved under whole-output certification. Strict certification and lenient treatment of unresolved material bound automatic preservation conditional on extraction validity. Schema failures remain in every denominator. Human review tests missed claims and other extraction errors outside these automatic bounds.

Inference comparison The analytical challenge compares source-blind extraction plus verification with pinned DeBERTa-v3-large trained on MNLI, FEVER, ANLI, LingNLI and WANLI [33]. Entailment, contradiction and neutral map to entailed, contradicted and underdetermined. We

report three-way accuracy by family; oracle typed claims isolate mathematical verification from text parsing.

Paired analysis Operational estimates use sampling weights and 10,000 district-cluster bootstrap replicates. Controlled resampling keeps the four transformations of each of 192 base-parameter groups together. The primary contrast is direct versus few-shot generation on screened preservation and operator errors. Secondary contrasts are number copying versus direct, planning versus few-shot, and post-editing versus few-shot. Effects are paired within model, cohort and source class, with simultaneous 98.33% intervals for the three secondary contrasts. Automatic ordering requires a positive interval for $L_A - U_B$ or a negative interval for $U_A - L_B$. Equal-weight pattern analysis checks concentration in repeated operational values. Clopper–Pearson reference intervals for any error within a controlled draw supplement degenerate zero-error bootstrap intervals. Inference budgets differ across model systems.

Human validation Both annotation roles completed 200 development/calibration outputs, excluded from held-out estimates. Held-out sampling uses 200 units per evaluation frame, stratified by model/regime, source and flagged or unresolved status. Model, method and machine labels are hidden, although style can provide cues. A stratified difference estimator combines automatic population predictions with weighted human–machine residuals; a human-only estimator provides a comparison. Intervals quantify annotation sampling within the observed frame. Deduplication, adjudication, reading probes and current completion status are specified in Section 6.4.

6 Results

6.1 Analytical challenge

On 2,304 controlled cases, extraction followed by verification classifies 2,105 correctly (91.36%), compared with 701 (30.43%) for generic NLI (Table 2). The systems have different information access: the verifier receives the structured source packet, whereas NLI receives premise and hypothesis text. NLI predicts only 17 neutral labels, all on entailed cases, and misses all 768 underdetermined cases. Constant entailed and underdetermined predictions achieve 41.67% and 33.33%, respectively.

The largest extraction failure concerns the word *below*: 189 of 192 outputs incorrectly close the upper endpoint, despite giving the correct complementary probability. Ten conditional-interval cases contain duplicate claims and trigger the frozen single-claim rule’s abstention. Collapsing identical claims after the frozen JSON parser makes those ten cases correct; all other predictions remain unchanged. The frozen parser retains the last duplicate probability key; 181 of 192 interval outputs contain such keys. Keeping the first value leaves individual claim semantics and verifier outputs unchanged, but prevents exact-object deduplication from resolving these ten abstentions. The strict single-claim rule remains primary.

A post-test reference audit corrected 37 floating-point endpoints to their displayed decimal values, retaining predictions, labels and closure. Unreported-threshold typed correctness changes from 155/192 to 192/192, and macro typed correctness from 89.76% to 91.36%; oracle agreement remains 2,304/2,304, a construction-consistency check.

Each family instantiates one wording on the same 192 parent draws. Family-level intervals concern variation in numerical inputs under that wording; the macro averages describe these twelve selected families.

Table 2: Correct three-way labels out of 192 cases per family. Extraction abstentions count as incorrect. The extraction system uses structured source information in addition to language parsing.

Family	NLI	Extract + verify
Direct paraphrase	192	192
Direction inversion	148	192
Added condition	0	192
Half-open interval	0	192
Closed boundary	0	192
Unreported threshold	0	192
Wrong probability	192	192
Complement (<i>below</i>)	169	3
Unsupported certainty	0	192
Strict threshold	0	192
Conditional interval	0	182
Possibly-zero condition	0	192

6.2 Primary generation contrast

Table 3 reports the frozen primary comparison between direct and few-shot generation for all eight models. Few-shot outputs have higher automatic screened-preservation scores in all sixteen model/source comparisons. The operational differences range from 0.81 to 99.28 percentage points in favour of few-shot, and the controlled differences from 3.26 to 96.09 points.

Table 3: Direct minus few-shot automatic screened preservation, in percentage points. 95% intervals resample 81 operational districts or 192 controlled source draws. Negative values favour few-shot. These frozen scores include extraction errors; human-corrected results appear separately.

Model	Operational difference [95% interval]	Controlled difference [95% interval]
Qwen2.5-7B	−36.03 [−44.76, −27.69]	−54.69 [−60.16, −49.09]
Qwen3-8B	−91.39 [−93.98, −88.73]	−74.35 [−78.12, −70.44]
Phi-4-mini	−90.83 [−93.64, −87.65]	−68.62 [−72.79, −64.19]
Qwen3.5-9B	−60.36 [−67.68, −53.69]	−68.10 [−70.05, −66.15]
GPT-5.6 Sol	−25.44 [−31.93, −19.16]	−24.22 [−27.48, −20.96]
DeepSeek-V4-Pro	−0.81 [−1.25, −0.43]	−3.26 [−4.95, −1.82]
GLM-5.3	−46.78 [−53.41, −39.93]	−21.61 [−24.61, −18.62]
Qwen3.8-Max	−99.28 [−100.00, −97.98]	−96.09 [−97.40, −94.66]

The automatic contrast combines changes in generated text with changes in what the extractor can interpret. Exact template matches and the extraction diagnoses below distinguish these effects. In particular, definitions and added conditions can reduce a direct output’s automatic score without establishing a generation error. Human validation and the fixed definition-screen sensitivity analysis therefore accompany interpretation of the primary comparison.

The three secondary comparisons show different patterns. Across the sixteen model/source conditions, the within-condition adjusted intervals for copy minus direct lie above zero in seven conditions and below zero in two. Planning minus few-shot has eight intervals above zero and none below; post-editing has one above and one below. The remaining intervals include zero. These counts describe automatic-score contrasts, and do not establish equivalence in conditions whose intervals include zero.

6.3 What the automatic scores measure

The frozen evaluator confounds some generation errors with errors in literal claim extraction. In the original four-model suite, a fixed post-test screen detects definitions represented as certainty of rain. It changes 306 of 31,408 analysis units. For Qwen3.5 direct generation on controlled inputs, the automatically flagged error rate falls from 24.22% to 10.29%, and the direct-versus-few-shot ordering becomes unresolved. Applying the same screen to Qwen3.8-Max changes 525 of 7,160 units; its operational direct error rate falls from 17.69% to 5.75%, but the upper identification bound remains 100%. Routing a definition to review does not certify the original text.

Other mechanisms escape this screen. All 114 flagged Sol controlled-direct contradictions arise from an added measurable-rain condition absent from the quoted statement. This also removes rain-probability coverage in all 114 cases, with 78 losing all operator coverage. GLM’s five flagged direct-output cases include denial and definition misreads, while one also contains a genuine zero-versus-positive endpoint mismatch. DeepSeek’s 28 controlled direct strict-certification failures contain unsupported event assertions; 25 use *being exceeded*, extracted with an open threshold. These diagnoses distinguish an error in the generated statement, its interpretation, and its measured coverage. The full analysis records retain counts, raw-text evidence, numerical checks and replication results.

Output identity explains a second part of the generation contrast. All 1,384 Qwen3.8-Max post-edits equal their few-shot drafts. DeepSeek revises 76 drafts and GLM one, while their operator-plan outputs exactly match the explicit template in 1,384 and 1,339 cases, respectively. Sol revises 989 drafts, and its exact template matches decrease from 1,246 few-shot outputs to 395 post-edits. These counts distinguish actual revision and alternative realisation from reproduction of a strong deterministic baseline. The human evaluation assesses semantic errors and omissions together with readability and text-only interpretation; its completed results follow.

6.4 Human validation

Sampling and adjudication An analysis unit is one model–regime–source–packet output within a generation cohort, or a deterministic–template output; repeated generations remain separate units. The local frame contains $4 \times 5 \times 1,384 + 2,768$ template units and 960 replication units (31,408 total); each additional frame contains $5 \times 1,384 + 240 = 7,160$. Five frozen frames each contribute 200 sampled analysis units: the four-model local suite and four additional systems. The frames have 79, 17, 19, 17 and 13 strata respectively (local, Sol, DeepSeek, GLM and Qwen3.8-Max): 145 in total, with 1–21 sampled units from strata of 1–768 units; singleton samples are census strata. The 1,000 units map to 982 frame-specific cases and 932 distinct text–source combinations, each annotated independently by two human roles and reviewed by a third expert. Identical text and source cards share one annotation while retaining original strata, inclusion probabilities and weights. The expert reviews literal spans, source support, statement roles and required-fact coverage. Overlapping spans cannot multiply the case-level Boolean error indicator. Role labels do not establish the same people’s participation across batches.

The completed local and Qwen3.8-Max batches contain 195 and 197 cases, with six shared combinations whose primary outcomes agree. A further 546 combinations complete the remaining frames; 24 earlier combinations supply 31 additional case aliases. For the earlier batch, *expected between* was adjudicated under an explicit convention: interval probability greater than 50%, with both amount endpoints included. This is an annotation convention, not a universal interpretation of English.

Reading and readability Text-only probes precede source display; subsequent claim and readability judgments use the source. Only a case’s original probe allocation authorizes its contribution. Previously reviewed combinations cannot supply new first-exposure observations.

Six such combinations received supplementary source-visible readability and completeness ratings. Exact-span agreement is descriptive, with unmatched spans retained separately. In the 546-combination batch, 1,109 uniquely matched spans have 98.56% label agreement ($\kappa = 0.33$, with skewed labels); 1,271 A spans and 1,640 B spans are unmatched. This conditional agreement does not measure agreement over the entire claim inventory.

Across 588 distinct original role-response records, mean source-visible readability is 4.84/5 and completeness 4.51/5 (both medians 5); these include 12 supplementary records. Among 283 reading responses eligible by recorded order and prior-exposure exclusions, 149 deny a guaranteed maximum, 37 affirm one and 97 report no range. For the event question, 175 choose *at least*, one *more than*, three unclear and 104 no stated probability. These unweighted response distributions describe interpretation, not accuracy or causal gains; shared origins are counted once.

Human-corrected finite-frame estimates Let m_i be the frozen automatic binary outcome, y_i the adjudicated outcome, w_i the source-population weight and $W = \sum_i w_i$. The correction combines whole-frame predictions with sampled residuals, as in prediction-powered mean estimation [34], using our stratified design. In stratum h , n_h of N_h units are sampled without replacement. With $z_i = w_i(y_i - m_i)$,

$$\hat{\theta} = \frac{\sum_i w_i m_i + \sum_h N_h \bar{z}_h}{W}, \quad (4)$$

$$\hat{V} = \frac{1}{W^2} \sum_h \frac{N_h^2 (1 - n_h/N_h) s_h^2(z)}{n_h}. \quad (5)$$

Census strata contribute zero variance; other strata contain at least two sampled units. Method contrasts use signed weights and the single-condition population-weight denominator. We estimate lower and upper human outcomes separately. Contrast bounds cross the positive method’s lower endpoint with the negative method’s upper endpoint, and vice versa. Their sampling intervals retain unresolved meaning as an identification interval. District/draw resampling and annotation sampling address different sources of uncertainty; neither expands the observed temporal coverage.

Approximate normal intervals use estimated within-stratum residual variance. Small samples, including several zero-variance non-census strata, can understate uncertainty; the human-only counterpart makes this estimator dependence visible.

Human-corrected generation results The supplementary equal-model summary of the primary contrast gives lower direct-generation preservation under residual correction (Table 4). The operational human-only interval includes zero, while the controlled interval excludes it; the operational conclusion therefore depends on the residual-corrected estimator. Individual-model corrected and human-only results are retained in the accompanying analysis. The corresponding corrected operator-error differences are 16.70 points operationally ($[-0.33, 33.73]$) and 10.17 on controlled inputs ($[-0.47, 20.80]$), leaving their direction unresolved.

Table 4: Equal-model direct minus few-shot screened preservation, in percentage points. Both estimators use the same eight-model finite frames; brackets are approximate 95% annotation-sampling intervals.

Source	Estimator	Difference [interval]
Operational	Residual-corrected	−32.58 [−45.32, −19.85]
Operational	Human-only	−21.47 [−63.22, 20.28]
Controlled	Residual-corrected	−23.99 [−40.27, −7.70]
Controlled	Human-only	−24.85 [−38.40, −11.30]

For the three secondary preservation comparisons, within-source family-adjusted intervals all include zero: planning minus few-shot is 6.38 points operationally and 7.45 on controlled inputs; post-editing minus few-shot is -0.27 and 1.25 points. This does not establish equivalence. The unbounded corrected preservation level for operational number-copying is 1.224 with interval $[0.400, 2.049]$, exposing high sampling variability. Estimates are not clipped or selected by favourable significance.

6.5 Human evaluation of extracted certainty

After full-output annotation, two roles assessed 223 targets sampled without replacement from a frozen inventory of 1,028 extracted certainty assertions in 1,024 contexts. The 31 strata cross model route, cohort, source type, automatic label, definition-screen status and full-output overlap. The allocation contains 100 local, 121 Qwen3.8-Max and two GLM-5.3 targets. Empty inventories for other systems do not imply that their outputs lack certainty assertions. Annotators interpret the highlighted text before this task reveals the source, then judge support for that saved interpretation. This ordering does not erase prior source exposure.

Of 223 targets, 181 have complete resolved A/B agreement; 42 require expert adjudication. Complete-record agreement is $181/214$ (84.58%) among records with resolved, mappable meanings and linked support; nine pairs have unresolved meaning. All responses remain in estimation. The expert resolves 30 referrals and leaves 12 unresolved. The expert return was supplied as a structured final-decision file rather than the planned browser history. Its shared per-stage timestamps do not establish an independent pre-peer stage. Under a documented intake amendment, we retain the original records, bind their identifiers and literal text to the frozen assignment, and use only source-assisted final decisions. We also report a sensitivity treating all 42 referrals as unresolved.

A match requires the extracted certainty event, boundary, polarity and condition to agree with a resolved literal interpretation. Unresolved meaning receives bounds $[0, 1]$; a mismatch receives $[0, 0]$. Joint validity additionally requires source support. With weights N_h/N , endpoint means use the stratified sample. For $H = \sum_{h:n_h < N_h} (N_h/N)^2/n_h$, a bounded-variable, without-replacement argument [35] gives $t = \sqrt{H \log(2/\alpha)/2}$. Each outcome separately has interval $[\max(0, \hat{L} - t), \min(1, \hat{U} + t)]$, conditional on fixed human judgments. This is sampling uncertainty, not annotator reliability.

The estimated literal-match bounds are 1.32–5.80%, and the match-plus-support bounds are 0.49–4.96%. Their respective 95% sampling intervals are 0–15.78% and 0–14.94%. Without the custom expert decisions, the identification bounds widen to 0.35–13.83% and 0–13.48%, with sampling upper limits 23.80% and 23.45%. Thus most assertions in this extraction-defined certainty inventory do not match a definite literal certainty reading. This result diagnoses extraction validity; it does not estimate missed-claim recall or the error rate of all generated outputs.

7 Discussion

7.1 Operators, coverage and extraction

Numerical agreement can coexist with reversed events, altered conditions, omissions and additions. Residual correction retains the pooled few-shot preservation advantage, while the operator-error contrast remains uncertain. The human-only operational interval also includes zero.

Source-blind extraction can turn definitions into occurrence claims. The certainty inventory diagnoses extracted fields without measuring missed claims. Operational fidelity differs from exact entailment because rounded displays cannot support arbitrary distributional inference. Annotation-sampling intervals condition on fixed expert decisions; the all-referrals-unresolved sensitivity retains the consequence of unavailable expert process history.

7.2 Added value beyond templates

All 1,384 DeepSeek operator-plan outputs and 1,339 GLM outputs equal the deterministic template; their post-editors revise only 76 drafts and one draft, respectively. Human-corrected secondary contrasts do not resolve planning or post-editing benefits. Readability alone cannot establish improved comprehension.

Limitations and availability Operational evidence covers one Australian product family at a 14 September 2026 snapshot; inference budgets differ across systems. Qwen3-8B is both extractor and generator, so extraction validity may vary by generator family. The certainty study covers the local suite, Qwen3.8-Max and GLM-5.3, using source-assisted expert finals with unverified pre-peer history. Code, controlled inputs, CPU replays and de-identified human-corrected analysis outputs are prepared for release; raw Bureau products and identifying human records remain private pending redistribution permissions.

8 Conclusion

Faithful generation preserves probability events, boundaries and conditions alongside source coverage. The eight-model study distinguishes generation errors from extraction errors and template reproduction. Residual-corrected human estimates support a pooled few-shot preservation advantage; the operational human-only interval remains inconclusive. Targeted interpretation reveals extensive certainty-extraction mismatch, separating generation quality from measurement error.

References

- [1] Bureau of Meteorology, *Bureau of Meteorology Text Forecasts User Guide*, 2026, version 2.1; updated 24 April 2026, accessed 14 September 2026. [Online]. Available: https://www.bom.gov.au/catalogue/Bureau_of_Meteorology_text_forecasts_user_guide.pdf
- [2] —, “Right as rain: How to interpret the daily rainfall forecast,” 2026, updated 21 May 2026; accessed 14 September 2026. [Online]. Available: <https://www.bom.gov.au/news-and-media/right-as-rain-how-to-interpret-the-daily-rainfall-forecast>
- [3] E. Reiter, S. Sripada, J. Hunter, J. Yu, and I. Davy, “Choosing words in computer-generated weather forecasts,” *Artificial Intelligence*, vol. 167, no. 1–2, pp. 137–169, 2005.
- [4] Z. Zheng, Y. Liu, N. Chen, J. Zheng, H. Cheng, and J. Li, “WeatherSyn: An instruction tuning MLLM for weather forecasting report generation,” 2026. [Online]. Available: <https://arxiv.org/abs/2605.07522>
- [5] D. Sukhorukov, A. Zakharov, N. Glazkov, K. Yanchanka, V. Kirilin, M. Dubovitsky, R. Sultimov, Y. Maksimov, and I. Makarov, “Hierarchical AI-meteorologist: LLM-agent system for multi-scale and explainable weather forecast reporting,” 2025. [Online]. Available: <https://arxiv.org/abs/2511.23387>
- [6] G. Gigerenzer, R. Hertwig, E. van den Broek, B. Fasolo, and K. V. Katsikopoulos, ““a 30% chance of rain tomorrow”: How does the public understand probabilistic weather forecasts?” *Risk Analysis*, vol. 25, no. 3, pp. 623–629, 2005.
- [7] S. Joslyn, L. Nadav-Greenberg, and R. M. Nichols, “Probability of precipitation: Assessment and enhancement of end-user understanding,” *Bulletin of the American Meteorological Society*, vol. 90, no. 2, pp. 185–194, 2009.

- [8] D. Gkatzia, O. Lemon, and V. Rieser, “Natural language generation enhances human decision-making with uncertain information,” in *Proc. ACL (Short Papers)*, 2016, pp. 264–268.
- [9] A. Balakrishnan, J. Rao, K. Upasani, M. White, and R. Subba, “Constrained decoding for neural NLG from compositional representations in task-oriented dialogue,” in *Proc. ACL*, 2019, pp. 831–844.
- [10] L. H. Suadaa, H. Kamigaito, K. Funakoshi, M. Okumura, and H. Takamura, “Towards table-to-text generation with numerical reasoning,” in *Proc. ACL (Long Papers)*, 2021, pp. 1451–1465.
- [11] M. Arai, T. Ishigaki, M. Kawarada, Y. Miyao, H. Takamura, and I. Kobayashi, “Evaluating LLMs’ ability to understand numerical time series for text generation,” in *Proc. INLG*, 2025, pp. 232–248. [Online]. Available: <https://aclanthology.org/2025.inlg-main.16/>
- [12] M. Singh, S. Luitel, P. Singh, M. Banga, N. Sudharsan, and J. Durkee, “AFDBench: A reasoning-first AI scientist for National Weather service forecast discussions,” 2026, version 1, preprint. [Online]. Available: <https://arxiv.org/abs/2608.24954>
- [13] O. Dušek and Z. Kasner, “Evaluating semantic accuracy of data-to-text generation with natural language inference,” in *Proc. INLG*, 2020, pp. 131–137.
- [14] A. Ravichander, A. Naik, C. Rose, and E. Hovy, “EQUATE: A benchmark evaluation framework for quantitative reasoning in natural language inference,” in *Proc. CoNLL*, 2019, pp. 349–361.
- [15] R. Marinescu, D. Bhattacharjya, J. Lee, T. T. Tchrakian, J. Carnerero-Cano, Y. Hou, E. M. Daly, and A. Pascale, “FactReasoner: A probabilistic approach to long-form factuality assessment for large language models,” in *Findings of EMNLP*, 2025, pp. 14 547–14 577.
- [16] T. Chen, Z. Jiang, A. Poliak, K. Sakaguchi, and B. Van Durme, “Uncertain natural language inference,” in *Proc. ACL*, 2020, pp. 8772–8779.
- [17] D. Sileo and M.-f. Moens, “Probing neural language models for understanding of words of estimative probability,” in *Proc. *SEM*, 2023, pp. 469–476.
- [18] D. Cerda-Mardini, S. Chandar, and S. Madathil, “Consistent but miscalibrated: Evaluating LLM limitations for risk communication in natural language,” 2026, version 2, preprint. [Online]. Available: <https://arxiv.org/abs/2607.03882>
- [19] Y. Lu, “Can reasoning LLMs synthesize complex climate statements?” in *Proc. ClimateNLP*, 2025, pp. 288–303.
- [20] N. J. Nilsson, “Probabilistic logic,” *Artificial Intelligence*, vol. 28, no. 1, pp. 71–87, 1986.
- [21] R. Fagin, J. Y. Halpern, and N. Megiddo, “A logic for reasoning about probabilities,” *Information and Computation*, vol. 87, no. 1–2, pp. 78–128, 1990.
- [22] L. Wong, G. Grand, A. K. Lew, N. D. Goodman, V. K. Mansinghka, J. Andreas, and J. B. Tenenbaum, “From word models to world models: Translating from natural language to the probabilistic language of thought,” 2023, version 2. [Online]. Available: <https://arxiv.org/abs/2306.12672>
- [23] A. Charnes and W. W. Cooper, “Programming with linear fractional functionals,” *Naval Research Logistics Quarterly*, vol. 9, no. 3–4, pp. 181–186, 1962.

- [24] Qwen Team, “Qwen2.5 technical report,” 2024. [Online]. Available: <https://arxiv.org/abs/2412.15115>
- [25] A. Yang, A. Li, B. Yang, B. Zhang, B. Hui, B. Zheng, B. Yu *et al.*, “Qwen3 technical report,” 2025. [Online]. Available: <https://arxiv.org/abs/2505.09388>
- [26] Microsoft, “Phi-4-Mini technical report: Compact yet powerful multimodal language models via mixture-of-loras,” 2025. [Online]. Available: <https://arxiv.org/abs/2503.01743>
- [27] Qwen Team, “Qwen3.5-9B model card,” 2026, accessed 14 September 2026. [Online]. Available: <https://huggingface.co/Qwen/Qwen3.5-9B>
- [28] OpenAI, “GPT-5.6 Sol model,” 2026. [Online]. Available: <https://developers.openai.com/api/docs/models/gpt-5.6-sol>
- [29] Alibaba Cloud, “Qwen3.8-Max model info,” 2026. [Online]. Available: <https://help.aliyun.com/en/model-studio/qwen3-8-max>
- [30] DeepSeek, “DeepSeek-V4-Pro model card,” 2026. [Online]. Available: <https://huggingface.co/deepseek-ai/DeepSeek-V4-Pro>
- [31] SiliconFlow, “Model catalogue,” 2026. [Online]. Available: <https://www.siliconflow.com/models>
- [32] —, “Chat completions API reference,” 2026. [Online]. Available: <https://docs.siliconflow.cn/docs/api/chat-completions-post>
- [33] M. Laurer, “DeBERTa-v3-large-mnli-fever-anli-ling-wanli model card,” 2022, accessed 14 September 2026. [Online]. Available: <https://huggingface.co/MoritzLaurer/DeBERTa-v3-large-mnli-fever-anli-ling-wanli>
- [34] A. N. Angelopoulos, S. Bates, C. Fannjiang, M. I. Jordan, and T. Zrnic, “Prediction-powered inference,” *Science*, vol. 382, no. 6671, pp. 669–674, 2023.
- [35] R. Bardenet and O.-A. Maillard, “Concentration inequalities for sampling without replacement,” *Bernoulli*, vol. 21, no. 3, pp. 1361–1385, 2015.