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Data and code

The EUPPBench forecasts and observations are publicly available as described in reference [1] of the manuscript. Code and derived results will be released in a public GitHub repository upon acceptance.

Tail Skill and Ensemble-Configuration Sensitivity in Six-Hour Precipitation Postprocessing

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Abstract—Statistical postprocessing supports probabilistic precipitation forecasting. Comparing methods requires separating forecast performance from the effects of case selection, ensemble configuration, and scoring convention. We develop a paired diagnostic workflow that separates observation conditioning from aggregation, decomposes model and raw-ensemble responses to member reduction, and examines exceedance reliability. We apply it to semilocal censored shifted gamma regression (M2) on EUPPBench, using 1997–2016 training data and 2017–2018 forecasts at 116 European stations. At +24 h, the primary difference in threshold-weighted continuous ranked probability score between M2 and the adjusted raw ensemble is -0.002656 mm, with no statistically significant difference under paired bootstrap inference. The secondary full-distribution score improves by 5.91% against the same reference. Conditioning on observed active dates shifts the tail contrast by -0.005076 mm, compared with -0.000877 mm from subsequent equal-episode weighting. Reducing inputs to control plus ten members worsens the fixed model’s tail score, with the comparative shift changing sign between empirical and adjusted raw-ensemble scoring. Reliability analysis locates underprediction in the 0.4–0.8 probability bins despite lower mean Brier scores. The diagnostics also identify interannual instability and member-configuration sensitivity at +48 h, linking aggregate scores to distinct evaluation effects and calibration errors.

Index Terms—probabilistic precipitation, forecast evaluation, censored shifted gamma, ensemble postprocessing, threshold-weighted CRPS

I. INTRODUCTION

Statistical and machine learning postprocessing support probabilistic precipitation forecasting [1], [2]. These methods convert raw ensemble (RAW) forecasts into predictive distributions that describe both dry outcomes and rainfall amounts. Operational comparison depends on the evaluated cases, their aggregation, the input ensemble, and the scoring convention. Aggregate scores alone obscure the contribution of these choices and the location of calibration errors.

Existing scoring theory addresses distinct parts of this problem. Proper scoring rules evaluate predictive distributions by expected performance [3], and threshold-weighted continuous ranked probability scores (twCRPS) focus on a specified distributional region [4]. Selecting cases after observing extreme outcomes changes the evaluation target, as described by the forecaster’s dilemma [5]. Finite-member corrections address ensemble-score dependence on member count under their sampling assumptions [6]. Operational member roles and pairing [7], together with recent evidence on ensemble-size de-

pendence in neural postprocessing [8], motivate examining the model and RAW responses separately. A common diagnostic design can connect these evaluation choices to changes in the comparison.

We develop a paired diagnostic workflow for this purpose (Fig. 1). On EUPPBench [1], we evaluate a semilocal censored shifted gamma (CSG) regression, denoted M2, built on the distributional family of Scheuerer and Hamill [9]. A pooled regression and seasonal climatology provide complementary references. The workflow anchors the analysis in all-case scores, then examines observation conditioning and episode weights, decomposes the model and RAW responses to member configurations under two scoring conventions, and assesses exceedance reliability. Shared verification cases and paired resampling keep each diagnostic tied to a defined comparison.

The contribution is an integrated evaluation design and its empirical diagnosis of precipitation postprocessing. Separating case selection from aggregation locates the stronger tail contrast on observed active dates (Fig. 2). Component accounting identifies how predictor changes and RAW scoring jointly determine the response to member reduction (Fig. 3). Reliability analysis reveals underprediction in the 0.4–0.8 probability bins despite lower mean Brier scores (Fig. 4).

The EUPPBench data are publicly available [1]; code and derived results will be released in a public GitHub repository upon acceptance.

II. DATA AND EVALUATION DESIGN

A. Forecasts, observations, and temporal separation

We use European Centre for Medium-Range Weather Forecasts (ECMWF) forecasts and paired observations from EUPPBench [1]. The archive covers Austria, Belgium, France, Germany, and the Netherlands. Six of 122 stations lack training precipitation thresholds; the retained 116 stations contribute 84,111 valid station–date pairs per lead from 730 daily initializations in 2017–2018. Each lead has 569 missing pairs relative to a complete station–date panel. The target is six-hour precipitation ending at +24 or +48 h, covering +18–24 or +42–48 h. Verification dates extend to 1 or 2 January 2019, respectively.

The reforecasts have 11 members and 20 historical-year offsets for each of 209 reference initializations. Training uses actual valid years 1997–2016, with 463,537 and 463,536 valid station–dates at the two leads. Official valid-time coordinates

1 Shared evidence

2 Paired forecasts

3 Evaluation

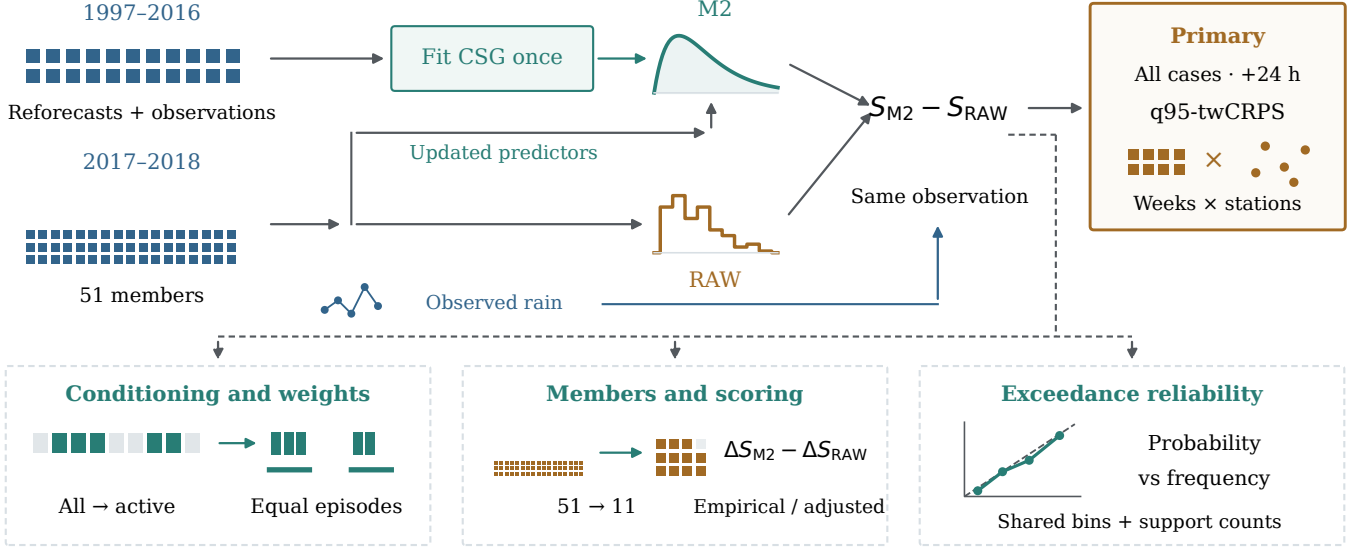


Fig. 1. Paired diagnostic workflow with illustrative glyphs. S denotes mean q95-twCRPS and ΔS its reduced-minus-full ensemble change. Training observations set q95 thresholds and normalization; verification observations supply the shared score targets and active-date labels. Fixed CSG parameters map updated ensemble predictors to M2 distributions. The solid path identifies primary all-case inference; dashed branches separate conditioning and weights, member responses under two scoring conventions, and reliability. Diagnostic temporal intervals hold the station panel fixed.

define the split; training and verification valid-time keys are disjoint. Historical valid years form five contiguous four-year cross-validation folds, with thresholds and normalization estimated on each fold’s training observations. The selected model is refitted to all eligible historical records. Control member 0 occurs in both the 11-member reforecasts and 51-member operational forecasts [1].

B. Quality control and tail definition

Amounts are converted from metres to millimetres. Forecast values in $(-0.1, 0)$ mm become zero; values at or below -0.1 mm are missing. Negative observations become zero, and observations are not interpolated. All methods use identical valid verification keys. Sensitivity refits treat negative Dutch observations as missing or remove Belgian reforecast observations above 100 mm, two at +24 h and three at +48 h.

At each station s and lead, u_s is the training-observation 95th percentile (q95), using the Hyndman–Fan type-8 quantile. Thresholds range from 0.1 to 9.5 mm, with medians 3.3 and 3.2 mm at +24 and +48 h. The model scale is $r_s = \max(u_s, 1 \text{ mm})$; one station per lead has $u_s < 1 \text{ mm}$. Events and tail scores use u_s itself, so the tail denotes station-relative high six-hour precipitation.

III. MODELS, SCORES, AND DIAGNOSTIC TARGETS

A. Semilocal CSG regression and pooling

Let Y be six-hour precipitation in millimetres. We model $Y^* = Y/r_s$ as $\max(0, X - \delta)$, where X is gamma with mean μ , variance v , shape $k = \mu^2/v$, and scale $\theta = v/\mu$. The semilocal model (M2) shares slopes across stations and uses country-specific intercepts. For ensemble mean m , sample

standard deviation s_e , and zero fraction p_0 , define $m^* = m/r_s$ and $s^* = s_e/r_s$. With softplus $h(x) = \log(1 + e^x)$ and annual phase $\omega = 2\pi \text{ dayofyear}/365.25$ from the valid date,

$$\mu = h(a_c + \beta_1 \sin \omega + \beta_2 \cos \omega + b_1 \log(1 + m^*) - b_2 p_0) + \epsilon, \quad (1)$$

$$v = h(g_0 + g_1 \log(1 + m^*) + g_2 \log(1 + s^*)) + \epsilon, \quad (2)$$

$$\delta = h(d_0) + \epsilon, \quad \epsilon = 10^{-6}. \quad (3)$$

Here c indexes countries; a_c is a country intercept; β_1, β_2 are seasonal coefficients; b_1, b_2 control mean and dry-fraction responses; g_0, g_1, g_2 determine variance; and d_0 determines the censoring shift. The small constant ϵ keeps parameters positive. Softplus transforms constrain b_1, b_2, g_1, g_2 to be positive. Five country intercepts and eight shared parameters give 13 free parameters.

The objective is mean normalized continuous ranked probability score (CRPS) plus $\lambda \text{mean}_c(a_c - \bar{a})^2$, where $\bar{a}$ averages the five country intercepts and λ controls their shrinkage. Historical cross-validation over $\{0, 0.01, 0.1, 1\}$ selects $\lambda = 0.1$ at both leads, choosing stronger shrinkage among losses within 0.1% of the minimum. This implementation combines the CSG family [9], station normalization, seasonal terms, and softplus links.

The nested pooled comparator (POOLED) constrains all country intercepts to one value, leaving nine free parameters. The country-deviation penalty then vanishes. Predictors, normalization, and the unpenalized objective are shared with M2. Both fits use fixed starting values and L-BFGS-B. Seasonal station climatology (CLIM) is the empirical distribution of eligible training observations within a circular ± 30 day-of-

year window. The raw ensemble (RAW) is evaluated using empirical and finite-member-adjusted scores.

The prespecified exploratory terrain extension (M3) adds two penalized interactions between $\log(1 + m^*)$ and standardized station altitude and signed station-minus-grid altitude difference. The two interaction coefficients are scaled together when needed to keep the total ensemble-mean slope positive across the 122 station locations. The same cross-validation rule selects $\lambda = 0.1$ and 0.01 at +24 and +48 h. M2 remains the primary evaluated model.

B. Scores and inferential hierarchy

For a predictive cumulative distribution function F , observation y , and threshold $u = u_s$, the q95-twCRPS is

$$\text{twCRPS}_u(F, y) = \int_u^\infty [F(z) - \mathbf{1}\{y \leq z\}]^2 dz, \quad (4)$$

where z is the integration variable and $\mathbf{1}$ is the indicator function. This equals CRPS after the transformation $x \mapsto \max(x, u)$. For M ensemble members x_i , set $z_i = \max(x_i, u)$ and $z_y = \max(y, u)$. The adjusted estimator is

$$\frac{1}{M} \sum_{i=1}^M |z_i - z_y| - \frac{1}{2M(M-1)} \sum_{i \neq j} |z_i - z_j|, \quad (5)$$

where i, j index members. The empirical version replaces $M(M-1)$ by M^2 . Adjustment follows transformation, including ties at u . Full-distribution CRPS uses untransformed amounts. Analytic CSG scores are evaluated in millimetres.

For event $o = \mathbf{1}\{y > u_s\}$ and forecast probability p , the Brier score is $(p - o)^2$. The adjusted RAW score subtracts $p(1 - p)/(M - 1)$. M2 and POOLED use $p = 1 - F(u_s)$ on the physical scale; RAW uses $p = M^{-1} \sum_i \mathbf{1}\{x_i > u_s\}$; CLIM uses the empirical exceedance frequency in its seasonal window.

The prespecified primary endpoint is the +24 h all-case station-date mean of M2 minus adjusted RAW twCRPS. Its primary 95% interval uses 5,000 paired bootstrap replicates of calendar weeks and stations resampled within countries. Dry dates remain included. Prespecified secondary and exploratory analyses include CRPS, Brier scores, +48 h, calendar-year and altitude strata, episode contrasts, equal-frequency reliability, M3, quality control, and unrestricted 11-member subsets. Pooling, expanded member designs, fixed-bin reliability, and aggregation diagnostics are post hoc; their settings were frozen before computation. All intervals are pointwise 95% intervals without multiplicity adjustment. Table I separates the evaluation targets and uncertainty units.

C. Conditioning, aggregation, and temporal uncertainty

A valid date is active when at least five stations exceed u_s . An episode is a maximal contiguous run of active dates, defined separately by lead. There are 221/220 active dates and 116/116 episodes at +24/+48 h, containing 25,444/25,328 valid station-dates. Labels remain fixed from the observed panel. These conditional summaries describe performance

TABLE I
EVALUATION TARGETS AND UNCERTAINTY UNITS

Target	Aggregation	Resampling unit
Primary all-case	Equal station-dates	Weeks and country-stratified stations
Temporal all-case	Equal station-dates	Fixed-panel date blocks
Active-day	Active station-dates	Fixed-panel date blocks
Episode-equal	Equal episode means	Whole episodes or fixed-weight date blocks
Member response	Mean of 100 subsets	Paired fixed-panel date blocks
Reliability	Frequency within bin	Paired fixed-panel date blocks

during observed high-precipitation activity [5]; all-case scores evaluate the original forecast target.

We separate the change from all cases to active station-dates from the subsequent change to equally weighted episode means. A station-date in episode e receives weight $1/n_e$, where n_e is that episode's original valid-pair count. The weighted ratio equals the average of episode means. The original episode-equal tail and Brier analysis resamples whole episodes without stratification. The additional whole-episode resampling is stratified by initialization-year quarter of the episode start; two/one episodes cross a quarter boundary at +24/+48 h.

Post hoc temporal intervals use 5,000 paired circular moving-block resamples within eight initialization-year quarters, with 7-day blocks and 3/14-day sensitivities. Daily score sums and valid counts are resampled jointly; ratio means retain station-date weighting under missingness. Episode weights and the station panel remain fixed. These intervals measure temporal variation on that panel, whereas primary inference also resamples stations.

The prespecified reliability analysis uses model-specific equal-frequency bins with adjacent sparse-bin merging. The post hoc diagnostic compares models on shared probability boundaries to resolve differences within the same probability ranges. It compares mean forecast probability with observed exceedance frequency in bins bounded by 0, 0.02, 0.05, 0.1, 0.2, 0.4, 0.6, 0.8, 1. Bins are left-closed and right-open, with 1 included in the last bin. Seven-day intervals for observed frequencies require at least 20 events and 20 distinct dates, a criterion fixed before computing the diagnostic.

D. Member-configuration score accounting

M2 parameters remain fixed while mean, sample SD (denominator $M - 1$), and zero fraction are recomputed for each member subset. Alongside the 100 prespecified unrestricted 11-member subsets, three post hoc designs each use 100 fixed subsets, comprising control plus 10 perturbed members, 11 perturbed members, and control plus five initial-perturbation pairs. The first matches the training ensemble's count and control-member role. ECMWF documents the pre-2019 initial pairs $(1, 2), \dots, (49, 50)$ [7]. Subsets remain constant across dates and methods. Each new design uses seed 20261020; temporal resampling uses that seed plus block length.

TABLE II
WHOLE-PANEL MEAN PROBABILISTIC SCORES

Lead (h)	Model	twCRPS (mm)	CRPS (mm)	Brier
24	CLIM	0.165483	0.460502	0.041872
24	RAW empirical	0.139855	0.338641	0.030935
24	RAW adjusted	0.138754	0.335289	0.030581
24	M2	0.136098	0.315476	0.029422
24	POOLED	0.136165	0.315862	0.029450
24	M3	0.136016	0.315128	0.029402
48	CLIM	0.167522	0.459773	0.042619
48	RAW empirical	0.145639	0.350847	0.033200
48	RAW adjusted	0.144174	0.346479	0.032736
48	M2	0.143561	0.338425	0.032259
48	POOLED	0.143639	0.338960	0.032295
48	M3	0.143156	0.337104	0.032187

RAW adjusted uses the conventional finite-member correction. RAW empirical and CLIM use empirical distributions; CSG scores are analytic. Lower scores are better.

Let S denote station–date mean q95-twCRPS in millimetres, $D = S_{M2} - S_{RAW}$, and subscripts sub/full denote one reduced subset/the full 51-member configuration. Then

$$D_{\text{sub}} - D_{\text{full}} = (S_{M2,\text{sub}} - S_{M2,\text{full}}) - (S_{RAW,\text{sub}} - S_{RAW,\text{full}}). \quad (6)$$

Reported shifts average this paired identity over 100 subsets; post hoc temporal intervals resample those subset-averaged daily quantities. Empirical scoring evaluates the issued discrete distribution. Under independent, identically distributed member sampling, adjusted scoring estimates the underlying-distribution score [6]. Member roles and pairing motivate reporting both conventions [7], [8].

IV. RESULTS

A. All-case scores and pooling

The primary +24 h M2 minus adjusted RAW q95-twCRPS difference is -0.002656 mm, with 95% interval [-0.005250, 0.000231], spanning zero. The corresponding +48 h interval also spans zero (Fig. 2). For the secondary full-distribution score, M2 reduces whole-panel mean CRPS by 5.91% relative to adjusted RAW at +24 h. CRPS difference intervals exclude zero in favor of M2 at both leads, while the Brier difference interval excludes zero at +24 h and includes zero at +48 h. M2’s clearest gain is in full-distribution accuracy.

Country-specific intercepts make a small contribution within the CSG family (Table II). POOLED minus M2 tail differences have 7-day intervals that include zero at both leads, while the CRPS differences favor M2 with intervals excluding zero. M3 lowers all three mean scores slightly at both leads; its week-and-station tail intervals narrowly include zero at both leads.

Quality-control refits preserve the direction and approximate magnitude of the all-case tail contrast. Treating negative Dutch observations as missing gives -0.002690 and -0.000531 mm at +24/+48 h; removing Belgian training observations above

TABLE III
PRESPECIFIED SECONDARY AND EXPLORATORY CHECKS

Check	+24 h	+48 h
Calendar 2017	-0.001165	0.000992
Calendar 2018	-0.004138	-0.002198
Altitude < 200 m	-0.001339	-0.000697
Altitude 200–499 m	-0.003184	0.001703
Altitude $\geq$ 500 m	-0.007863	-0.005637
Unrestricted subset reversals	0/100	99/100

First five rows are M2 minus adjusted RAW q95-twCRPS in mm. Altitude groups contain 69, 33, and 14 stations. Calendar-year rows use verification dates; the 1–2 January 2019 boundary dates are omitted from these rows. Reversals compare each 11-member subset with the full-ensemble sign.

100 mm gives -0.002654 and -0.000612 mm. Individual deletion of the two flagged Belgian observations at +24 h and three at +48 h likewise retains negative contrasts.

Table III separates temporal and terrain variation. The +24 h tail contrast remains negative in both calendar years and every unrestricted subset. At +48 h the yearly contrasts have opposite signs, and 99 of 100 unrestricted subsets reverse the full-ensemble sign, exceeding the prespecified 25% reversal threshold. These checks identify interannual instability and member-configuration sensitivity at this lead. The strongest negative tail contrasts occur in the highest altitude stratum, while the middle stratum changes direction between leads.

B. Observation conditioning and episode weights

Conditioning on active dates accounts for most of the +24 h change in the comparative tail score (Fig. 2). The conditioning step shifts the contrast by -0.005076 mm, whereas subsequent equal-episode weighting adds -0.000877 mm with an interval spanning zero. Comparative tail gains thus concentrate on observed high-activity dates, with little evidence of a further effect from reweighting episodes.

The conditioning-step intervals approach zero at every bootstrap block length. The 7- and 14-day intervals narrowly exclude zero, while the 3-day interval narrowly includes it. Both stratified and original unstratified whole-episode resampling support a negative +24 h episode-equal tail contrast. The original episode-equal Brier contrast also favors M2 at +24 h with an interval excluding zero. At +48 h, the active-day, episode-equal tail, and original episode-equal Brier intervals include zero.

Resampling stations as well as dates widens the +24 h all-case interval to include zero. On the fixed station panel, the temporal interval excludes zero (Fig. 2). The two intervals distinguish temporal variability at the observed sites from uncertainty that also reflects the station sample.

C. Configuration response and score convention

Reducing the input ensemble raises M2’s tail score at both leads (Fig. 3). For control plus 10 perturbed members, the M2 increase exceeds the adjusted RAW increase, worsening their comparative difference. Control plus five pairs has the smallest M2 increase among the three reduced designs. With fitted

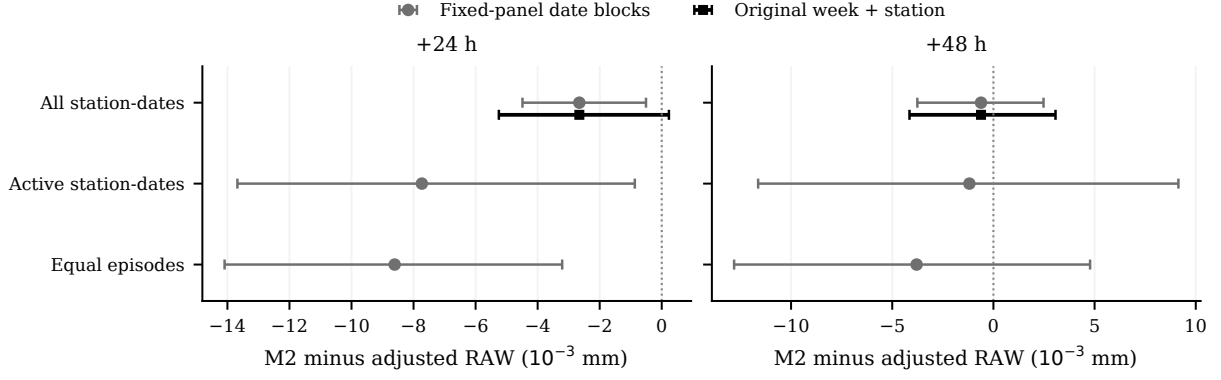


Fig. 2. Conditioning and aggregation effects on M2 minus adjusted RAW q95-twCRPS. Gray circles show 7-day fixed-panel temporal 95% intervals. Black squares show the original week-and-station 95% intervals for all cases; the +24 h black interval is primary. Active-day and episode-equal targets condition on observed high-precipitation activity. Axis units are 10^{-3} mm.

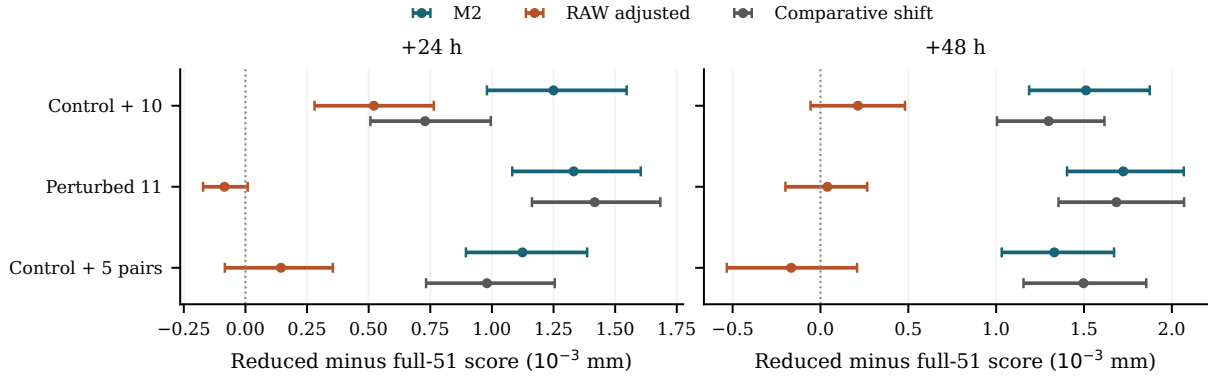


Fig. 3. Changes in mean q95-twCRPS from full 51-member inputs to reduced configurations. Each point averages 100 fixed subsets; bars are paired 7-day fixed-panel 95% intervals. The comparative shift equals the M2 shift minus the adjusted RAW shift. Axis units are 10^{-3} mm.

parameters held fixed, the control-plus-ten design matches the training ensemble's size and control role yet raises M2's tail score relative to the full ensemble. The prespecified unrestricted 11-member subsets show the same comparative deterioration, with 7-day shift intervals excluding zero at both leads.

Score convention determines the sign of the comparative shift for control plus 10 members. M2's score increase lies between the adjusted and empirical RAW increases, producing a positive shift under adjusted scoring and a negative shift under empirical scoring at both leads, each with an interval excluding zero. At +48 h the adjusted comparative shift is 0.001298 mm, with its interval excluding zero. The reduced-configuration M2 minus RAW difference is 0.000686 mm under adjusted scoring and -0.005937 mm under empirical scoring. Its point-estimate sign therefore reverses, while the adjusted interval includes zero and the empirical interval excludes zero. At +24 h both reduced-configuration point estimates favor M2. M2 uses the same score under both conventions, so the reference ensemble's correction drives this change in interpretation.

Control-member role affects the comparison even at fixed size. At +24 h, control plus ten members lowers the comparative score relative to eleven perturbed members under both conventions, with role-contrast intervals excluding zero. This effect acts mainly through RAW, whose adjusted score worsens, while the M2 role interval includes zero. At +48 h the adjusted role contrast also favors control plus ten members. The M2 score improves with an interval narrowly excluding zero; the adjusted RAW point estimate worsens with an interval including zero. Both point shifts lower the M2 minus RAW difference because the RAW shift is subtracted. Under empirical scoring, the +48 h role-contrast interval narrowly includes zero.

D. Exceedance reliability

The reliability curves in Fig. 4 locate opposing conditional errors within the average Brier results. In the supported 0.4–0.8 probability bins, M2 underpredicts observed q95 exceedance frequencies at both leads, while RAW overpredicts. At +48 h the 0.6–0.8 observed-frequency interval lies just above the mean forecast probability. POOLED closely follows M2, so country-specific intercepts have little effect on this pattern.

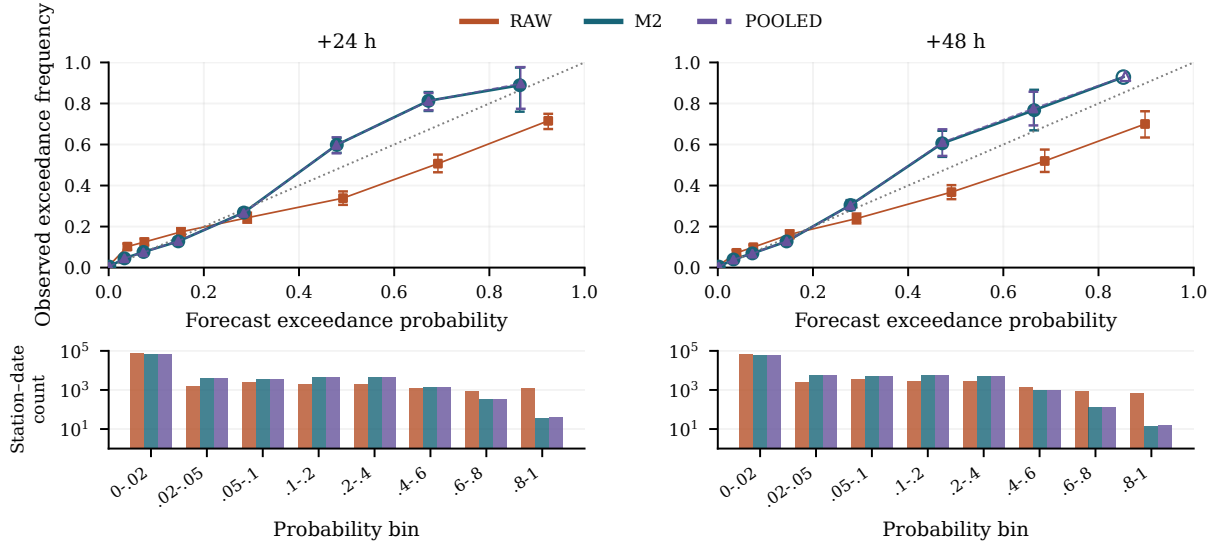


Fig. 4. Reliability of q95 exceedance probabilities. The diagonal marks agreement between forecast probabilities and observed frequencies. Error bars are 7-day fixed-panel 95% intervals for observed frequencies, shown for bins with at least 20 events on at least 20 dates; hollow markers denote bins below this criterion. Lower panels show bin counts for the same fixed probability boundaries, with colors following the model legend.

Lower mean Brier scores therefore coexist with calibration errors in higher-probability forecasts. The original equal-frequency scheme gives M2 top-bin forecast/observed means of 0.308/0.322 at +24 h and 0.277/0.305 at +48 h. The shared fixed bins resolve the higher-probability behavior within these broad top bins.

M2 issues probabilities of at least 0.8 on 36 and 14 station-dates at +24/+48 h, compared with 1174 and 670 for RAW. Its +48 h top bin has 13 events on 14 dates and falls below the interval-support criterion. Fig. 4 marks this sparse bin with hollow symbols.

V. CONCLUSION AND LIMITATION

The paired diagnostic workflow connects precipitation scores to case selection, ensemble configuration, scoring convention, and reliability. Its application on EUPPBench shows that M2 improves full-distribution CRPS while the primary tail interval spans zero. Observation conditioning accounts for most of the stronger +24 h tail contrast, and reduction to control plus ten members raises M2's tail score at both leads. The comparative shift changes sign between empirical and adjusted RAW scoring. The +48 h comparison is sensitive to year and member configuration. Reliability diagnostics identify underprediction in the 0.4–0.8 probability bins despite lower mean Brier scores. Future work will extend this five-country, 2017–2018 evaluation to additional regions and years, and test ensemble adaptation and targeted recalibration to improve higher-probability reliability.

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