

Precipitation Anomalies and Changes in Private Credit across Asia-Pacific Economies

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Abstract

Weather shocks can increase financing needs while simultaneously weakening income, collateral, investment, and repayment capacity, leaving their net effect on aggregate credit ambiguous. This paper examines whether annual precipitation anomalies are associated with subsequent changes in domestic credit to the private sector across Asia-Pacific economies. We combine GPCC Precipitation Analysis Monthly v2025 with World Development Indicators, UN M49, and fixed Natural Earth boundaries. The resulting unbalanced panel contains 950 economy-year observations for 49 economies over 2000-2024. Exposure is an annual dryness anomaly relative to each economy's 1991-2020 mean precipitation, and the outcome is the change in private credit as a share of GDP from year t to $t+1$. Two-way fixed-effects estimates with economy-clustered standard errors are negative but imprecise. In the controlled specification, a 10-percentage-point increase in dryness is associated with a 0.233-percentage-point lower subsequent credit-to-GDP change (95% CI: -0.548 to 0.082). The point estimate remains negative under extended controls, an alternative exposure scale, economy-specific trends, and leave-one-economy-out checks, although inference is sensitive to the covariance estimator. Because the primary confidence interval includes zero and the outcome is an aggregate credit-to-GDP measure, the evidence supports a bounded country-level association rather than a causal or bank-supply interpretation. The study provides a reproducible public-data benchmark for aggregate weather-credit relationships in the region.

Keywords

Precipitation Anomalies; Private Credit; Climate Finance; Asia-Pacific; Public Data; Panel Fixed Effects

JEL codes: G21; O16; Q54; C23

1. Introduction

Adverse weather can push credit in opposite directions. Lower income, weaker collateral, postponed investment, and greater uncertainty may reduce borrowing or

tighten lending conditions. The aggregate credit response is therefore not signed a priori, even when the underlying weather shock is clearly adverse (Hong, Karolyi, and Scheinkman 2020; Campiglio et al. 2018).

Economy-wide private credit is broader than a loan price or approval decision. Credit-to-GDP can move with borrowing, repayments, valuation, reporting coverage, and nominal GDP, so a dry-year change may reflect demand, underwriting, investment, recovery finance, or denominator effects. Country data capture the net outcome rather than a single mechanism.

Micro studies identify those margins: banks reallocate lending after disasters, borrowers can face tighter access, and recent China evidence links climate or flood exposure to bank lending, bank risk, and personal credit (Berg and Schrader 2012; Cortés and Strahan 2017; Ivanov, Macchiavelli, and Santos 2022; Li and Wu 2023; Zhang and Ming 2025; Chen et al. 2025). Whether these effects aggregate regionally remains open.

We examine that aggregate relationship across Asia-Pacific economies using public data. GPCC supplies monthly precipitation and WDI supplies private credit and macro controls. The sample has 49 economies and 950 economy-year observations for 2000-2024. Exposure is the annual precipitation shortfall from each economy's 1991-2020 mean; the outcome is the t -to- $t+1$ change in private credit as a share of GDP.

The empirical design uses economy and exposure-year fixed effects, with GDP growth and CPI inflation in the controlled specification and standard errors clustered by economy. A 10-percentage-point increase in the dryness anomaly is associated with a 0.233-percentage-point lower subsequent credit-to-GDP change, with a 95% confidence interval from -0.548 to 0.082. The sign remains negative across the pre-specified sensitivity analyses, whereas statistical precision changes with the covariance estimator.

The contribution is a reproducible regional benchmark. It tests whether annual precipitation anomalies covary with subsequent economy-wide credit-to-GDP changes after economy and year effects, documents the full public-data construction, and keeps interpretation at the country level. The coefficient is an average within-economy association, not a bank-, borrower-, industry-, or locality-level effect.

Section 2 develops the measurement and credit-adjustment arguments and positions the study relative to the closest evidence. Section 3 describes the data and variables, Section 4 presents the empirical design, and Section 5 reports the estimates and sensitivity checks.

2. Related Literature and Conceptual Motivation

2.1. Measuring precipitation as economic exposure

Weather measurement depends on spatial and temporal aggregation. National averages can hide subnational rainfall relationships, and macro estimates are sensitive to exposure construction (Damania, Desbureaux, and Zaveri 2020; Kotz, Levermann, and Wenz 2022; Kahn et al. 2021).

Accordingly, the exposure is read narrowly. An annual precipitation anomaly is neither long-run climate change nor hydrological drought, and identical shortfalls may have different effects across economies with different infrastructure, irrigation, storage, and sectoral composition.

The annual frequency matches the financial outcome and provides a complete exposure window before the $t+1$ endpoint of the credit change. The regressor should therefore be read literally as a country-average annual precipitation anomaly relative to a fixed historical mean.

2.2. Weather Shocks and Credit Adjustment

Weather can expand credit through recovery spending, working-capital needs, consumption smoothing, and lender reallocation (Cortés and Strahan 2017; Ivanov, Macchiavelli, and Santos 2022; Celil, Oh, and Selvam 2022; Berg and Schrader 2012). It can also contract credit when damage and income losses weaken repayment capacity, collateral, or bank balance sheets and alter underwriting or portfolios (Klomp 2014; Albuquerque and Rajhi 2019; Bos, Li, and Sanders 2022; Noth and Schüwer 2023).

These channels need not map directly into aggregate credit. Credit-to-GDP also moves with nominal GDP, so loan pricing, access, bank stability, borrower demand, and aggregate credit are related but distinct outcomes.

2.3. Asia-Pacific evidence and empirical positioning

Asia-Pacific evidence increasingly links climate exposure to financial outcomes, but at different units. Zhang and Ming (2025) study bank risk and Chen et al. (2025) personal credit after floods; such studies observe institutional margins that a country panel cannot.

Mohamed et al. (2026) provide the closest country-level comparator for private-sector credit. The present design differs in region, precipitation construction, timing, fixed effects, and its use of the next-year change in credit-to-GDP rather than the level.

The trade-off is scale: bank and borrower data measure mechanisms more directly, whereas public country panels offer broad coverage and reproducibility. The approaches are therefore complementary.

2.4. Conceptual Framework and Empirical Expectation

We impose no directional hypothesis. Dryness may weaken production, income, collateral, investment, and lender risk tolerance while increasing liquidity or

recovery needs. Figure 1 summarizes these competing channels and the role of time-varying conditions, measurement, reporting, and the GDP denominator. The model estimates only the reduced-form country-level association between year- t precipitation anomalies and the subsequent credit change; Figure 1's intermediate links are conceptual and are not separately identified.

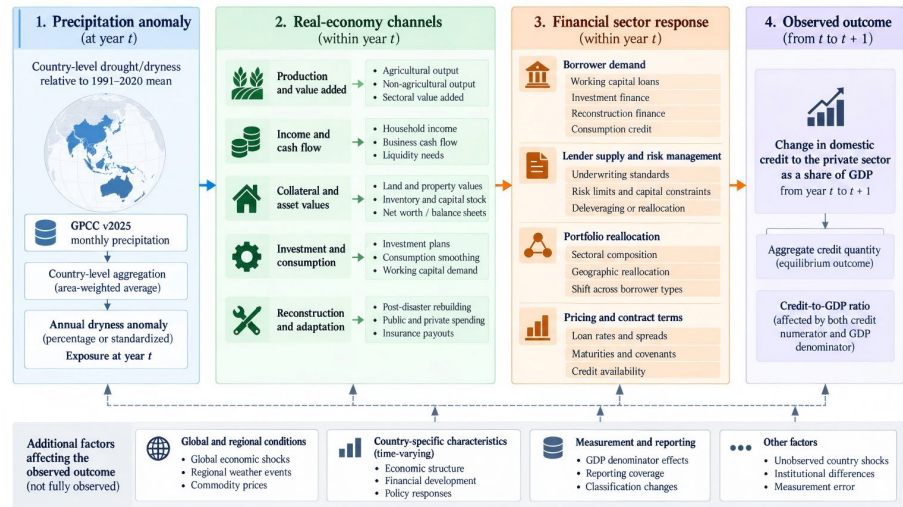


Figure 1: Conceptual transmission channels and the empirical identification boundary.

Notes: The figure summarizes possible real-economy and financial channels from the precipitation-based annual dryness anomaly to the observed credit-to-GDP change. The empirical design estimates only the final country-level association, not the intermediate mechanisms.

3. Data and Measurement

3.1. Geography and public sources

The candidate universe begins with UN M49 records for Asia and Oceania (United Nations Statistics Division 2026). World Bank aggregate regions are removed, and economy identifiers are matched to Natural Earth Admin-0 version 5.1.1 polygons (Natural Earth 2022). The pre-specified sample rule requires at least five GPCC grid-cell centers within the fixed polygon to avoid highly unstable spatial averages for very small land areas.

Monthly precipitation comes from GPCC Precipitation Analysis Monthly v2025 at 0.25-degree resolution (Rustemeier et al. 2025). Credit and macroeconomic variables come from the World Development Indicators (WDI) (World Bank 2026), frozen on 25 July 2026. Missing WDI observations remain missing; they are not interpolated or replaced with zero.

Source provenance was checked before constructing the analysis panel. GPCC archives were matched to DWD-published MD5 checksums, and frozen inputs were recorded with SHA-256 hashes. The geographic crosswalk retains the UN, World Bank, and Natural Earth identifiers used for included and excluded economies. Supplementary Section S2 reports the full source-integrity and reacquisition record.

3.2. Precipitation anomaly

For economy i , GPCC cell centers are assigned once to the fixed country polygon. Monthly precipitation is the cosine-latitude-weighted average across assigned cells, and all 12 months are required to construct annual precipitation, P_{it} . Let $\bar{P}_{i,1991:2020}$ denote the economy's mean annual precipitation over 1991-2020. The primary exposure is

$$Dry_{it} = -100 \frac{P_{it} - \bar{P}_{i,1991:2020}}{\bar{P}_{i,1991:2020}}. \quad (1)$$

Positive values indicate drier-than-normal years. Thus, $Dry_{it} = 10$ means annual precipitation was 10% below the economy's 1991-2020 mean. The pre-specified alternative scales the negative annual deviation by the economy's 1991-2020 standard deviation rather than by its mean.

Cosine-latitude weighting adjusts for the smaller surface area represented by regular longitude-latitude cells at higher latitudes. The resulting exposure is land-area weighted, not population or output weighted. A sparsely populated interior therefore contributes to the country mean, while a dense economic region receives no extra weight. The fixed 1991-2020 baseline keeps the physical reference constant across analysis years.

A pre-results version of the exposure averaged standardized calendar-month anomalies. It failed the pre-specified concentration gate because near-zero historical standard deviations in arid dry-season months generated mechanical outliers. The construct was stopped before any financial regression, retained in the audit trail, and replaced by the already registered annual percentage anomaly before the v2 analysis was frozen. Supplementary Section S3 documents the diagnostic and amendment.

3.3. Outcome, controls, and sample

The financial outcome uses WDI indicator FS.AST.PRVT.GD.ZS, domestic credit to the private sector as a percentage of GDP. The WDI definition covers claims by monetary authorities, deposit-taking banks, and other financial corporations where available. In some economies it can also include claims on public enterprises. The dependent variable is

$$\Delta Credit_{i,t+1} = Credit_{i,t+1} - Credit_{it}. \quad (2)$$

measured in percentage points of GDP. Precipitation in year t is measured before the endpoint of the credit change in $t+1$, but that ordering alone does not establish causality.

Writing $Credit_{it} = C_{it}/Y_{it}$, where C denotes covered nominal claims and Y nominal GDP, makes the interpretation clear. The outcome can move through the credit numerator, the GDP denominator, valuation, classification, or reporting coverage. A negative value need not mean nominal credit fell, and a positive value need not

imply an expansion in bank credit supply. The analysis is retrospective and uses the WDI release available on the retrieval date rather than historical data vintages.

Core controls measured in year t are real GDP growth (NY.GDP.MKTP.KD.ZG) and CPI inflation (FP.CPI.TOTL.ZG). GDP growth and inflation enter the controlled specification because real activity and prices can covary with weather and nominal credit ratios. Trade and urbanization are added separately because their availability reduces the complete-case sample.

Economies must have at least two credit observations and at least five GPCC land cells to enter the structural reporting universe. The primary sample also requires the exposure, outcome, GDP growth, and inflation. It contains 49 economies and 950 economy-year observations over 2000-2024, or 77.6% of potential economy-years in the structurally eligible universe. Missing observations are not interpolated, extrapolated, or replaced with regional means.

Table 1: Descriptive statistics

Variable	N	Mean	Std. dev.	P25	Median	P75
Change in private credit (% GDP, pp)	950	1.221	6.217	-1.177	0.876	3.343
Annual dryness anomaly (%)	950	0.167	20.297	-9.842	0.132	10.013
Annual standardized dryness	950	-0.043	0.972	-0.655	0.009	0.656
GDP growth (%)	950	4.417	4.921	2.397	4.620	6.756
CPI inflation (%)	950	5.296	6.733	1.725	3.727	6.900
Trade (% GDP)	877	81.543	36.227	53.107	78.193	102.786
Urban population (%)	950	56.199	25.119	31.221	57.355	79.116

Notes: Statistics are calculated on the registered primary sample except trade, whose missing observations reduce Model 3. Percentage-point changes can be negative even when the credit level remains positive.

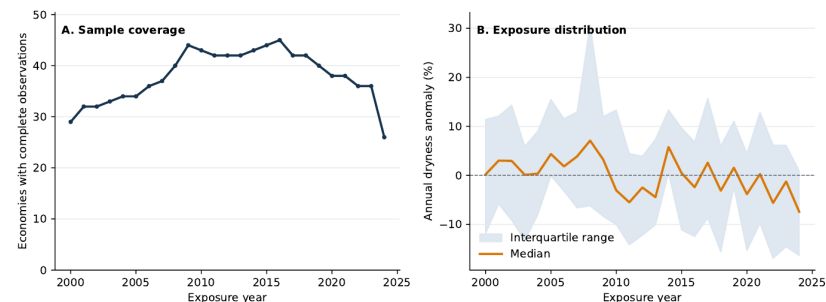


Figure 2: Sample coverage and the annual cross-economy exposure distribution. Panel A reports the number of complete primary observations in each exposure year. Panel B reports the median and interquartile range of the annual dryness anomaly. Positive values indicate drier conditions relative to each economy's 1991-2020 mean.

4. Empirical Strategy

The primary specification is

$$\Delta \text{Credit}_{i,t+1} = \beta \text{Dry}_{it} + \gamma' X_{it} + \alpha_i + \lambda_t + \varepsilon_{it}. \quad (3)$$

where α_i and λ_t are economy and exposure-year fixed effects. Model 1 includes the dryness anomaly and fixed effects only. Model 2, the primary controlled specification, adds GDP growth and inflation while preserving the Model 1 complete-case sample. Model 3 adds trade openness and urbanization, reducing the sample to 877 observations from 46 economies.

The coefficient β is identified from within-economy changes in dryness after common year shocks are removed. Economy fixed effects absorb time-invariant geography and persistent differences in institutions or financial depth. Year fixed effects absorb shocks common to all economies in an exposure year. Keeping the M1 and M2 samples identical separates covariate adjustment from changes in sample composition.

The coefficient is reported per one percentage point of the dryness anomaly and is rescaled by ten for interpretation. Standard errors are clustered by economy in the primary analysis. A separate dummy-variable OLS implementation reproduces the fixed-effects coefficient to numerical tolerance; Supplementary Section S4 reports that validation.

The pre-specified sensitivity analyses alter one feature at a time. They use the annual standardized exposure, add economy-specific linear trends, apply Driscoll-Kraay covariance with a Bartlett kernel and bandwidth three, and omit each economy in turn. Economy clustering remains the primary inference rule. The Driscoll-Kraay calculation assesses covariance sensitivity and does not replace that primary result. No unregistered lag, threshold, subgroup, or alternative financial outcome was searched.

The design is associational. Fixed effects address time-invariant economy differences and common year shocks, but time-varying confounding, measurement error, heterogeneous responses, and the numerator-denominator structure of the outcome remain possible.

5. Results

5.1. Main estimates

The main estimate is negative but imprecise (Table 2). Model 1 yields a dryness coefficient of -0.0238 with an economy-clustered standard error of 0.0166 ($p = 0.153$). Model 2 adds GDP growth and inflation on the same observations and gives -0.0233 ($SE = 0.0161$, $p = 0.147$), with a 95% confidence interval of [-0.0548, 0.0082]. The similarity of the three point estimates indicates that neither the core controls nor the extended specification materially changes the estimated direction in these samples.

At the 10-percentage-point scale, the Model 2 coefficient corresponds to a 0.233-percentage-point lower subsequent change in private credit as a share of GDP. The 95% confidence interval is [-0.548, 0.082]. The interval includes both a moderate negative association and a small positive one, so the primary analysis

does not reject zero. The descriptive distribution places this scale near the center of the observed exposure range: the dryness anomaly has a standard deviation of 20.297 percentage points and an interquartile range from -9.842 to 10.013 (Table 1).

Table 2: Precipitation anomalies and next-year changes in private credit

	M1	M2	M3
Dryness anomaly (%)	-0.0238	-0.0233	-0.0263
	(0.0166)	(0.0161)	(0.0190)
Core controls	No	Yes	Yes
Extended controls	No	No	Yes
Economy fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	950	950	877
Economies	49	49	46

Notes: The dependent variable is the change in domestic credit to the private sector as a share of GDP from t to $t+1$. Positive exposure values indicate drier years. M1 and M2 use the same primary sample. Core controls are GDP growth and CPI inflation; extended controls add trade and urbanization. Standard errors in parentheses are clustered by economy.

5.2. Pre-specified sensitivity checks

Across the pre-specified checks, point estimates remain negative while magnitude and precision vary (Table 3). Standardizing annual precipitation deviations by each economy's historical standard deviation gives -0.2782 (SE = 0.2241, $p = 0.215$). Because the exposure unit changes, this coefficient is not directly comparable in magnitude with the percentage-anomaly coefficient. Adding economy-specific linear trends yields -0.0176 (SE = 0.0176, $p = 0.318$), a smaller estimate with wider uncertainty relative to its magnitude.

Changing only the covariance estimator has a larger effect on precision. The Driscoll-Kraay calculation leaves the Model 2 coefficient unchanged at -0.0233 but reduces its standard error to 0.0066 ($p < 0.001$), producing a confidence interval below zero. Economy-clustered inference remains primary; the Driscoll-Kraay result is evidence that uncertainty is sensitive to the assumed error structure.

The 49 leave-one-economy-out estimates range from -0.0268 to -0.0072. Every estimate retains the negative sign, none has an economy-clustered p -value below 0.05, and omitting Qatar produces the estimate closest to zero. Figure 3 summarizes the same-scale main and sensitivity estimates. Taken together, the checks show a more stable direction of the point estimate than magnitude or inferential strength.

Table 3: Pre-specified sensitivity analyses

Check	Coefficient	Std. error	p-value	95% CI / range
Annual standardized exposure	-0.2782	0.2241	0.215	[-0.7180, 0.1617]
Economy-specific linear trends	-0.0176	0.0176	0.318	[-0.0520, 0.0169]
Driscoll-Kraay covariance	-0.0233	0.0066	<0.001	[-0.0363, -0.0103]
Leave one economy out	-	-	-	[-0.0268, -0.0072]

Notes: The annual standardized exposure is measured per one historical standard deviation and is not directly comparable in magnitude with the percentage-anomaly coefficient. Economy-clustered standard errors are used except for the Driscoll-Kraay row. The leave-one-economy-out interval is the range of point estimates, not a confidence interval.

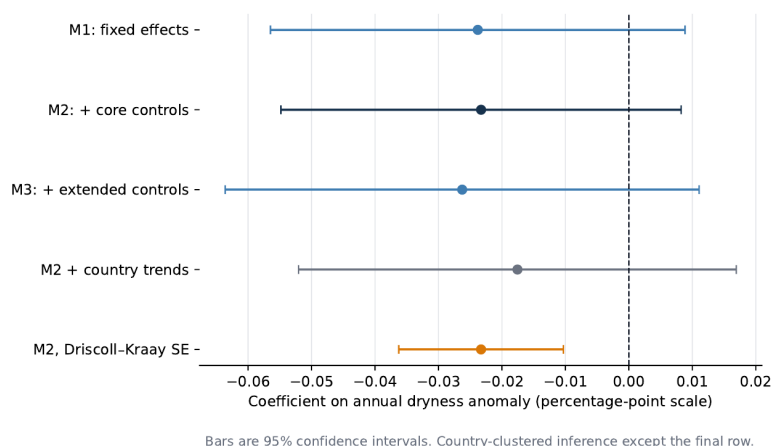


Figure 3: Coefficient estimates under the main and pre-specified same-scale specifications. Points are coefficients on the percentage dryness anomaly; bars are 95% confidence intervals. All rows use economy-clustered inference except the Driscoll-Kraay row.

6. Discussion

6.1. What the Aggregate Estimate Means

The central result is a repeated negative point estimate with limited primary precision: a 10-percentage-point dryness increase corresponds to -0.233 percentage points in the next credit-to-GDP change, with a 95% CI of [-0.548, 0.082].

That sign is economically plausible because dryness can weaken income, collateral, cash flow, investment, and lender risk tolerance (Do et al. 2021; Bos, Li, and Sanders 2022; Noth and Schüwer 2023). Yet the aggregate ratio cannot distinguish lower demand, tighter credit, denominator movements, or reporting changes.

Country estimates also need not match bank- or borrower-level effects. Relationship lending and recovery finance can sustain some credit while exposure tightens conditions elsewhere; the country coefficient records the net result after these responses and the GDP denominator interact.

6.2. Where the uncertainty comes from

Uncertainty is visible across checks: the primary interval crosses zero, trend controls shrink the estimate, and no leave-one-out regression is significant at 5% with economy clustering. Driscoll-Kraay instead yields much smaller uncertainty without changing the coefficient.

Because macro panels may share financial cycles, policy shifts, and regional shocks, economy-clustered inference remains primary and Driscoll-Kraay is treated as

covariance sensitivity. The defensible summary is therefore a negative point estimate whose precision depends on the error assumption.

The documented exposure amendment and reproducible data chain make the analysis traceable, but they do not convert an observational aggregate coefficient into a causal or mechanism estimate.

6.3. Measurement Limits and Next Research Steps

The exposure is coarse: a national annual anomaly can hide offsetting regional shocks and does not weight population, output, agriculture, or assets (Damania, Desbureaux, and Zaveri 2020). Alternative weights and compound exposures would answer different questions.

The outcome is also aggregated. A credit-to-GDP change combines covered claims, nominal GDP, valuation, classification, and reporting and therefore cannot isolate new lending, approvals, pricing, maturity, borrower type, nonperforming loans, or credit supply.

The design remains observational. The t -to- $t+1$ ordering does not create quasi-random exposure or reproduce lenders' historical information sets. Causal claims need exogenous variation; forecasting claims need historical vintages and genuine out-of-sample evaluation.

A common slope also averages heterogeneous climates, financial systems, income levels, and adaptation capacity. Future work should use more targeted exposure, disaggregated credit outcomes, and designs that identify specific behavioral margins rather than treat this coefficient as a regulatory parameter.

7. Conclusion

Using a reproducible public-data panel of 49 Asia-Pacific economies, this paper estimates the association between annual precipitation anomalies and subsequent changes in private credit as a share of GDP. The controlled point estimate is negative: a 10-percentage-point increase in the dryness anomaly is associated with a 0.233-percentage-point lower subsequent credit-to-GDP change. Its 95% confidence interval spans -0.548 to 0.082, and the primary economy-clustered analysis therefore does not reject zero. The sign remains negative across the pre-specified checks, whereas magnitude and statistical precision vary with trend controls, omitted economies, and the covariance estimator.

The contribution is a bounded aggregate benchmark. It shows the scale of the relationship that can be recovered from transparent regional public data while making clear what those data cannot resolve. Distinguishing borrower demand from lender supply, separating the credit numerator from the GDP denominator, and identifying causal responses will require more granular outcomes, more targeted exposure measures, and stronger research designs. Within those limits, the paper provides a reproducible starting point for comparing aggregate and institution-level

evidence on weather and credit.

Data and code availability

All empirical inputs are public. The release records the official source URLs, retrieval date, file sizes, DWD MD5 checks, SHA-256 hashes, geographic crosswalk, analysis sample, code, environment lock, tables, figures, and data dictionary. Raw GPCC files are reacquired from DWD rather than redistributed in the manuscript package. Natural Earth boundary data are public domain. The public release repository will be linked in the final submission after institutional review of the release package.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During preparation of this work, the author used OpenAI Codex to support public-source discovery, code development, data-quality auditing, reproducibility checks, visualization, and English-language drafting. The author specified the research decisions, reviewed the source material, verified the data and numerical outputs, edited the manuscript, and takes full responsibility for the content. The AI system is not an author.

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