

ENSO and IOD Teleconnection with Sumbawa Rainfall: Seasonal Predictability Beyond Monthly Lag Structure

Romi Aprianto^{1*}, Akbar Tawaqqal², Syaharuddin³

¹Physics Education Study Program, University of Samawa, Sumbawa, West Nusa Tenggara 84315, Indonesia.

²Industrial Engineering Study Program, University of Mataram, Mataram, West Nusa Tenggara 83115, Indonesia.

³Mathematics Education Study Program, Muhammadiyah University of Mataram, Mataram 83225, West Nusa Tenggara, Indonesia.

*Corresponding author. Email: romi.aprianto@samawa-university.ac.id

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Abstract

Cross-correlation analysis is the standard tool for quantifying how the El Niño-Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD) influence Indonesian rainfall, and it routinely yields an "optimal time lag" offered as operational lead time. For Sumbawa Regency (West Nusa Tenggara) we show that this lag structure is an artefact. Using 44 years of NASA POWER precipitation (1982-2025; 528 months) with the SOI, Niño 3.4 and Dipole Mode Index from NOAA PSL, the conventional cross-correlation function returns significant coefficients at non-causal negative lags (rainfall leading the index), with the naive maximum for Niño 3.4 falling at a negative lag. After Box-Jenkins pre-whitening the structure collapses: only the concurrent SOI signal survives ($r = 0.239$), while the concurrent oceanic coefficients also fall to zero, so the reported "climate memory" is predictor persistence. Predictability exists at seasonal aggregation. Using June-August index means to forecast September-November (SON) rainfall across 43 years under leave-one-year-out cross-validation, a LASSO model attains an out-of-sample R^2 of 0.405 and an RMSE skill score of +0.247 against climatology, and predicts the wet-season onset month with a skill score of +0.219. Skill is carried almost entirely by the JJA-mean SOI; the IOD contributes nothing detectable here, and a random forest does not outperform linear regression. As a categorical warning for below-normal SON rainfall the forecast reaches a critical success index of 0.53 against chance 0.20. Usable lead time therefore comes from seasonal aggregation, not monthly lag structure, and reported optimal lags in the regional literature should be re-examined.

Keywords: Forecast verification; Pre-whitening; Southern Oscillation Index; Warning skill; Wet-season onset.

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Introduction

Sumbawa Regency, in West Nusa Tenggara, lies in one of the driest and most climatically exposed parts of the Indonesian Maritime Continent. Its rainfall is strongly monsoonal: most annual precipitation falls between December and March, while core dry-season totals can approach zero. The regional economy rests on rainfed dryland agriculture, so the timing of the wet-season onset, rather than

the annual total, most directly governs planting, water allocation and crop outcomes. A delayed or failed onset propagates within one season into water scarcity and food insecurity, and Nusa Tenggara in particular is projected to become drier and to experience longer dry spells under continued warming (Ghosh & Shepherd, 2023; Hariadi et al., 2024; Kurniadi et al., 2024).

Interannual rainfall variability here is dominated by two coupled ocean-atmosphere modes, ENSO and the IOD. The classification of Indonesian rainfall into monsoonal, equatorial and local regimes, with southern Indonesia in the monsoonal class (Aldrian & Susanto, 2003), is long established, as is the finding that ENSO modulates seasonal rainfall and extremes most strongly during the dry season and the dry-to-wet transition and only weakly during the peak wet season (As-syakur et al., 2014; Kurniadi et al., 2021; Marzuki et al., 2025; Supari et al., 2018). The two flavours of ENSO leave distinct rainfall signatures across Southeast Asia (Nguyen-Thanh et al., 2023), and the teleconnection propagates into hydrological regimes such as Java stream-flow (Nugroho et al., 2022). ENSO and IOD exert partially independent effects on Indonesian extremes (Kurniadi et al., 2021), their co-occurrence can delay onset and extend dry conditions for several months (Hidayat et al., 2025; Sulaiman et al., 2023), and the teleconnection is projected to intensify and shift eastward under warming (Chen et al., 2023; Chen et al., 2025). The background state is itself changing: the Pacific Walker circulation shows contested multi-decadal trends (Heede & Fedorov, 2023; Kosovelj & Zaplotnik, 2023; Watanabe et al., 2023) whose longer-term weakening is increasingly attributed to anthropogenic forcing (Watanabe et al., 2024; Wu et al., 2024), ENSO variability is projected to intensify (Cai et al., 2023), while IOD-related sea surface temperature variability is projected to increase this century (Wang et al., 2024a) before reversing to a reduction after 2100 (Wang et al., 2024c); the 2023 El Niño was a recent demonstration across the archipelago (Zehri et al., 2025). The existence and seasonality of this teleconnection are well established and are the point of departure for this study, not its result.

What remains unresolved, and what motivates this study, are three problems that sit between this established physical picture and its operational use at district scale.

First, a methodological problem. Much regional and district-scale work in Indonesia quantifies the teleconnection by applying a cross-correlation function (CCF) to deseasonalised monthly anomalies, reporting an "optimal lag" plus a tail of significant coefficients extending several months, interpreted as short-term climate memory (Wei & Yuan, 2024). This carries a well-known pitfall. The SOI, Niño 3.4 and Dipole Mode Index (DMI) are themselves strongly autocorrelated at monthly resolution (lag-1 typically 0.85-0.95). If a predictor X influences rainfall Y only concurrently, the expected cross-correlation at lag k is still approximately $\rho_X(k)$, the predictor's own autocorrelation. A slowly decaying tail of "significant" lagged correlations is therefore the null expectation, not evidence of atmospheric memory; without pre-whitening both the lag structure and its significance are inflated (Box et al., 2016; Bretherton et al., 1999; Ebisuzaki, 1997). To our knowledge no published assessment for the Lesser Sunda Islands has tested whether a reported lag structure survives this correction.

Second, and more consequentially, an inferential problem: the leap from correlation to operational lead time. Teleconnection coefficients in this literature typically fall in $|r| = 0.2-0.6$, that is 4-36% of explained variance, yet are routinely presented as justifying early warning and dynamic crop scheduling. Three distinctions are collapsed in that move. An in-sample correlation is not out-of-sample skill; predictive skill is meaningful only against a climatological baseline, since a model can correlate positively with observations yet perform worse than a forecast of the long-term mean; and skill on a continuous target is not

skill at issuing the categorical warning a decision-maker consumes. Warning metrics such as probability of detection (POD), false alarm ratio (FAR), critical success index (CSI) and Peirce skill score (PSS) can remain near zero where a continuous correlation is nominally significant. The caution is not new: the limited predictability of Indonesian wet-season rainfall was shown two decades ago (Haylock & McBride, 2001). Yet district-scale Indonesian studies almost never report climatology-referenced, out-of-sample skill, so the operational value of the teleconnection at this scale remains effectively unquantified.

Third, a specification problem. Work in the Lesser Sunda Islands has frequently examined ENSO in isolation, even though ENSO and IOD co-occur and their September-November impacts are partially collinear (Amirudin et al., 2020; Hidayat et al., 2025; Kurniadi et al., 2021; Wang et al., 2024b). Attributing rainfall variability to ENSO without partialling out the DMI risks double-counting a shared signal. Relatedly, claims that the teleconnection has "strengthened" in recent decades are common but seldom tested: comparing correlation coefficients between two epochs requires a formal test of the difference, and comparisons based on Niño 3.4 anomalies referenced to a long, fixed base period are additionally confounded by the secular warming trend in tropical Pacific Sea surface temperature.

This study addresses these three problems for Sumbawa Regency over 1982-2025 using entirely open data and a fully reproducible pipeline. Its objectives are: (i) to quantify the ENSO-IOD-rainfall association using both a naive CCF, for comparability with the existing literature, and a pre-whitened CCF with effective-degrees-of-freedom and phase-randomisation significance testing, and thereby to determine whether any true lagged signal survives; (ii) to isolate the

independent contributions of ENSO and IOD by partial correlation; (iii) to evaluate, strictly out of sample, whether June-August (JJA) mean values of the SOI, Niño 3.4 and DMI carry usable predictive skill for two decision-relevant targets: the September-November (SON) rainfall total and the wet-season onset month, each relative to a climatological baseline; and (iv) to translate that skill into categorical warning metrics for below-normal SON rainfall, and to test formally whether the teleconnection differs between 1982-2003 and 2004-2025.

Three falsifiable hypotheses follow. H1: after pre-whitening, significant cross-correlation is confined to lag 0, and the multi-month climate memory reported in the literature is an artefact of predictor persistence. H2: notwithstanding H1, seasonal aggregation (JJA predictors, SON target) yields genuine and non-trivial out-of-sample skill, because a three-month mean integrates the concurrent coupling and delivers a real operational lead time of one to three months. H3: continuous skill overstates warning skill: the critical success index for below-normal SON rainfall will be substantially lower than the correlation coefficient alone would suggest.

This work therefore contributes a decision-relevant quantification of how much lead information the teleconnection contains at district scale, rather than a new claim for the teleconnection itself, together with a transparent, executable pipeline that other Indonesian districts can reuse. This is consistent with a broader shift in the machine-learning weather and climate literature from accuracy metrics in isolation toward operational utility, interpretability and verification (Camps-Valls et al., 2025; Gibson et al., 2021; Materia et al., 2024; Price et al., 2025; Yang et al., 2024; Zhou & Zhang, 2023).

Materials and Methods

Study area

Sumbawa Regency (approximately 8.2–9.1°S, 116.7–118.4°E) occupies the western half of Sumbawa Island in West Nusa Tenggara Province. Analyses are anchored on a representative point at 8.50°S, 117.42°E, close to the regency capital Sumbawa Besar. The regency falls within the monsoonal rainfall regime of southern

Indonesia (Aldrian & Susanto, 2003), with a single pronounced wet season centred on December–February and a severe dry season from June to September. Agriculture is predominantly rainfed. The location of the regency and the analysis point is shown in Figure 1, and the complete analytical workflow in Figure 2.

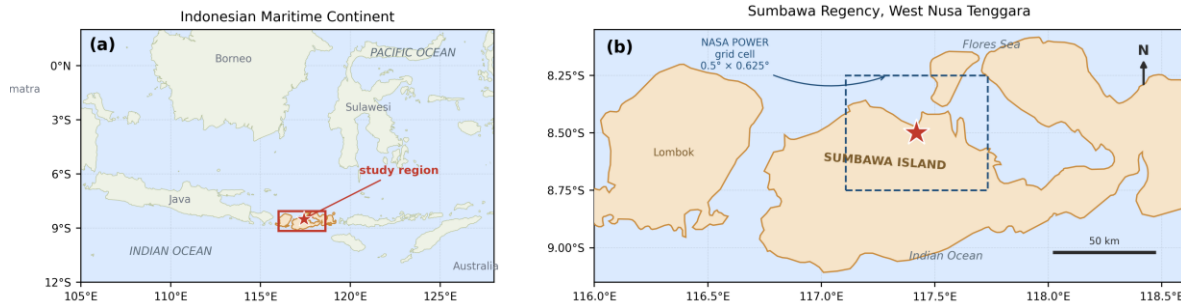


Figure 1. Study area. (a) Location of West Nusa Tenggara (orange) within the Indonesian Maritime Continent; the red box marks the extent of panel (b) and the star the analysis point. (b) Sumbawa Regency on Sumbawa Island, with the analysis point at 8.50°S, 117.42°E near Sumbawa Besar and the 0.5° × 0.625° NASA POWER grid cell from which precipitation is drawn. Coastlines are from Natural Earth (1:10 m).

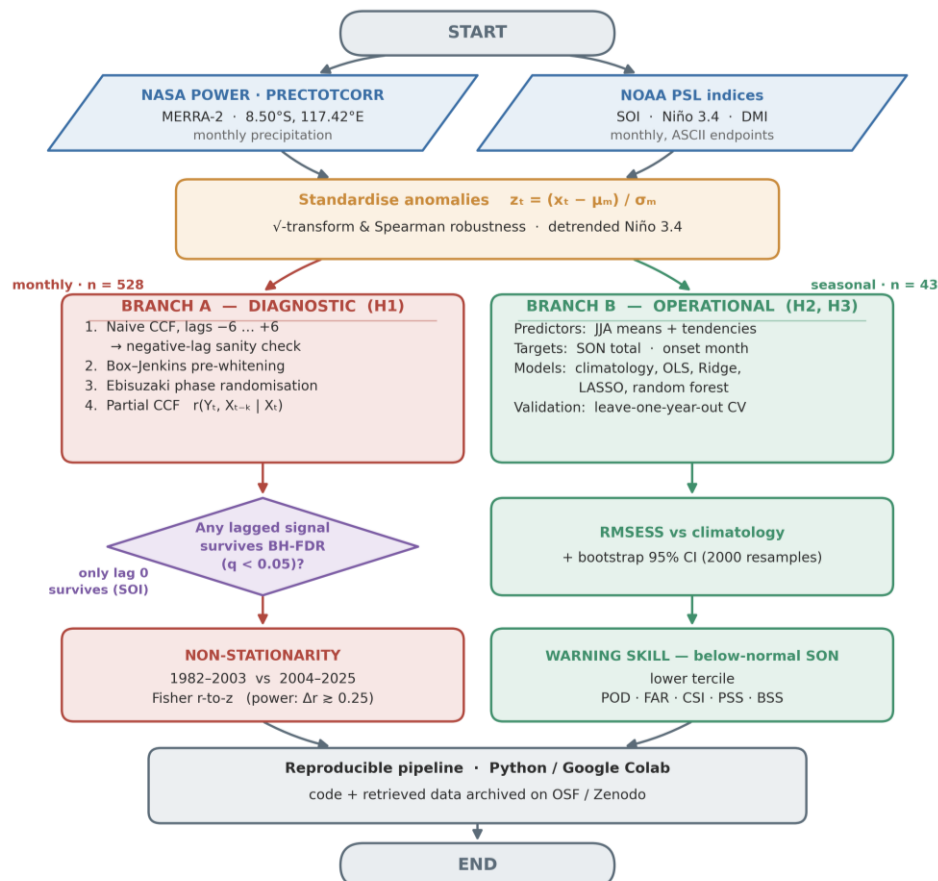


Figure 2. Analytical workflow. Branch A (red) is the diagnostic analysis at monthly resolution and tests hypothesis H1. Branch B (green) is the operational analysis at seasonal resolution, which uses one sample per year and is therefore structurally free of the autocorrelation artefact examined in Branch A; it tests H2 and H3.

Rainfall data

Monthly precipitation was obtained from the NASA Prediction of Worldwide Energy

Resources (POWER) project, parameter PRECTOTCORR (bias-corrected total precipitation), for January 1982 to December 2025, giving 528 monthly values spanning 44 complete calendar years, with no missing months. Data were retrieved on 14 July 2026 through the POWER REST API for the point (-8.50° , 117.42°); the same series is accessible through the nasapower client (Sparks, 2018). POWER meteorological parameters derive from NASA's MERRA-2 reanalysis (Gelaro et al., 2017) on a $0.5^\circ \times 0.625^\circ$ grid, with near-real-time values appended from GEOS-IT. POWER reports monthly precipitation as a mean daily flux (mm day^{-1}); values were multiplied by the number of days in each calendar month to obtain monthly totals.

Three limitations of this product are carried through to interpretation. First, POWER is a reanalysis, not a gauge record: over tropical basins it reproduces climatology and rain-day occurrence reasonably but underestimates totals and especially extremes (Madushan et al., 2025; Tan et al., 2023; Tayyeh et al., 2023), with skill uneven across variables and regions (Khalid et al., 2024); satellite products such as GSMaP show comparable difficulties over the Maritime Continent (Ramadhan et al., 2023), and POWER is nonetheless widely used as an operational input for data-driven rainfall models (Saleh et al., 2024). Second, the native cell is coarse relative to Sumbawa's topography and contains a substantial marine fraction, so the series is a grid-cell areal estimate, not a point observation, and orographic contrasts are unresolved. Third, NASA recommends ending climate analyses roughly two months behind real time because of the GEOS-IT append, so the series is truncated at December 2025; the retrieval date is reported above because POWER is periodically reprocessed.

Because the inferences concern the relative association between large-scale indices and local anomalies rather than absolute

magnitudes, these biases are unlikely to reverse the sign or seasonality of the teleconnection, though they place a ceiling on achievable skill; the skill reported in the subsection “Seasonal aggregation recovers genuine, cross-validated skill” should be read as an upper bound for a single grid cell. The POWER series is validated against the CHIRPS observational product in the subsection “Validation of the rainfall series and grid-cell representativeness”, which also shows the single grid cell to be representative of regional interannual variability; direct validation against multi-decadal BMKG gauge records, whose access requires an institutional data agreement, remains a next step before operational use (see the subsection “Limitations”).

Climate indices

Three monthly indices covering 1982–2025 were obtained from the NOAA Physical Sciences Laboratory (PSL) archive: the Southern Oscillation Index (SOI; standardised Tahiti minus Darwin sea-level pressure anomaly), the Niño 3.4 sea surface temperature series (5°N – 5°S , 170°W – 120°W), and the Dipole Mode Index (DMI), which represents the IOD as the difference in SST anomaly between the western and south-eastern tropical Indian Ocean. The DMI is a new predictor relative to earlier versions of this analysis and is included because ENSO and IOD forcing of southern Indonesian rainfall is partially independent (Hidayat et al., 2025; Kurniadi et al., 2021; Wang et al., 2024b). Satellite and reanalysis rainfall products have well-documented regional biases over Indonesia (As-syakur et al., 2013), reinforcing the need for the validation reported in the subsection “Validation of the rainfall series and grid-cell representativeness”. All files are distributed as fixed-width ASCII (one row per year, twelve monthly values, with a sentinel missing-value code) and are parsed programmatically at run time. Endpoints are listed in Table 1.

Two data notes are important for reproducibility. The PSL SOI series has a sample standard deviation of 1.61 over 1982-2025 and a range of -6.0 to +4.8, and is therefore not identical in scaling to the standardised SOI distributed by the NOAA Climate Prediction Center; because all series are subsequently standardised by calendar month (see the subsection “Anomaly construction and

transformation”), this leaves every correlation reported here unchanged, though the specific product must be stated. The PSL DMI is HadISST-based and terminates in April 2025, leaving eight missing months at the end of the record; this excludes 2025 from the seasonal analysis (see the subsection “Out-of-sample seasonal predictability experiment”) but does not affect the monthly diagnostics.

Table 1. Data sources and endpoints.

Variable	Product / index	Source endpoint	Notes
Precipitation (mm month ⁻¹)	NASA POWER PRECTOTCORR (MERRA-2 / GEOS-IT, bias-corrected)	power.larc.nasa.gov →/api/temporal/monthly/point (lat -8.50, lon 117.42)	Served in mm day ⁻¹ ; converted to monthly totals. 0.5° × 0.625° grid cell. Retrieved 14 Jul 2026.
SOI	Standardised Tahiti-Darwin SLP anomaly	psl.noaa.gov/data/correlation/soi.data	Positive = La Niña-like state. $\sigma = 1.61$ (not CPC scaling).
Niño 3.4 SST (°C)	ERSSTv5-based, 5°N-5°S / 170°W-120°W	psl.noaa.gov/data/correlation/nina34.data	Anomalies computed in-house; detrended variant used for the epoch comparison.
DMI - IOD (°C)	Dipole Mode Index (west minus south-east tropical Indian Ocean SST anomaly)	psl.noaa.gov/gcos/wgsp/Timeseries/Data/dmi.had.long.data	HadISST-based; ends April 2025 (8 missing months).
Precipitation - validation (mm day ⁻¹)	CHIRPS v2 (gauge-blended satellite; Funk et al., 2015)	developers.google.com/earth-engine/datasets/catalog/UCSB-CHG_CHIRPS_DAILY (via Google Earth Engine)	0.05° grid; independent observational reference used to validate POWER (see the subsection “Validation of the rainfall series and grid-cell representativeness”).
Precipitation - station (attempted)	NOAA ISD/GSOD daily, WMO 97260 (Sumbawa Besar)	ncei.noaa.gov/data/global-summary-of-the-day	Digitised record too incomplete over 1982-2025 (26.6% of days) for interannual validation (see the subsection “Validation of the rainfall series and grid-cell representativeness”).

Anomaly construction and transformation

For each variable, the monthly climatological mean μ_m and standard deviation σ_m ($m = 1 \dots 12$) were computed over the full 44-year record, and standardised anomalies were formed, following Wilks (2019), as

$$z_t = \frac{x_t - \mu_m}{\sigma_m} \quad (1)$$

Dividing by σ_m , rather than subtracting μ_m alone, is essential in a monsoonal regime. The interannual standard deviation of rainfall in January is one to two orders of magnitude larger than in August, so a mean-only anomaly series remains strongly heteroscedastic and allows a small number of wet-season months to dominate any pooled Pearson correlation. This is a material departure from the common

practice of subtracting the monthly mean only.

Because monthly rainfall in this regime is strongly right-skewed and contains near-zero values (Figure 6b), two robustness variants are carried through the entire analysis: rainfall is additionally analysed after a square-root transform, and Spearman's ρ is computed alongside Pearson's r wherever a correlation is quoted. Conclusions are reported only where they are stable across all three variants.

Cross-correlation: naive and pre-whitened

For comparability with the existing literature, the conventional cross-correlation function (Box et al., 2016) was computed for lags $k = -6$ to $+6$ months, where a positive lag denotes the index leading rainfall (Box et al., 2016):

$$r_{XY}(k) = \text{corr}(y_t, x_{t-k}) \quad (2)$$

Negative lags are included deliberately as a diagnostic rather than as a physical hypothesis. Since no mechanism allows rainfall over Sumbawa to force the Pacific or Indian Ocean basins, any apparent significance at negative lags is direct evidence that the significance test is contaminated by serial correlation.

The pre-whitened cross-correlation, our primary analysis, follows the Box-Jenkins procedure (Box et al., 2016), an ARIMA(p, d, q) model was fitted to each predictor series by minimising AICc; the fitted filter was then applied to both the predictor and the rainfall series, and the CCF was computed between the two residual series. Under the null hypothesis of no relationship, the pre-whitened cross-correlations are approximately mutually independent with standard error $1/\sqrt{n}$, so the conventional $\pm 1.96/\sqrt{n}$ significance bounds are valid, which is precisely what is not true of the naive CCF.

Two further significance procedures are reported alongside. An effective-sample-size correction (Bretherton et al., 1999) is applied to the naive coefficients,

$$N_{eff} = N \frac{1 - \rho_X(1)\rho_Y(1)}{1 + \rho_X(1)\rho_Y(1)} \quad (3)$$

which adjusts the degrees of freedom for the serial dependence of both series; and a nonparametric phase-randomisation test (Ebisuzaki, 1997) with 1000 surrogates is used to construct an empirical null distribution. Because phase randomisation preserves the power spectrum, and hence the autocorrelation function, of each series, it provides a significance test valid without any parametric model of the serial dependence. It should be noted, however, that this test establishes only that $r \neq 0$ in the presence of autocorrelation; it does not by itself distinguish a lag-0 signal from a lagged one.

A partial cross-correlation tests explicitly whether lagged predictors carry information beyond the concurrent one; the partial correlation $r(Y_t, X_{t-k} | X_t)$ was computed for $k = 1 \dots 6$. A lag is treated as genuine only if this partial correlation remains significant after correction for multiple comparisons. Together, pre-whitening and partial cross-correlation render hypothesis H1 falsifiable: a real lagged signal would survive both.

Separating the ENSO and IOD signals

Because the DMI and Niño 3.4 covary, particularly during SON, partial correlations $r(Y, \text{Niño3.4} | \text{DMI})$ and $r(Y, \text{DMI} | \text{Niño3.4})$ were computed so that each mode's independent contribution can be reported. Variance inflation factors (VIF) were computed for the multiple-predictor models described in the subsection "Out-of-sample seasonal predictability experiment"; all remained below 4 (maximum 3.53 for the JJA Niño 3.4 mean), and collinearity was in any case handled by regularisation.

Out-of-sample seasonal predictability experiment

This experiment is the operational core of the study, and it is constructed so as to be structurally immune to the autocorrelation artefact described in the subsection “Cross-correlation: naive and pre-whitened”, because it uses one sample per year, giving 43 effectively independent observations rather than 528 serially dependent ones. Predictors are issued at the end of August, giving a genuine operational lead time of one to three months: the June–August means of the SOI, the Niño 3.4 anomaly and the DMI, together with the within-season tendency (August minus June) of each index, which captures the developing rather than the mature phase of an event.

Two targets are used. T1 is the SON rainfall total (September + October + November, in mm), which conditions water availability at the start of the growing season. T2 is the wet-season onset month, defined at monthly resolution as the first month from September onward in which rainfall reaches at least 100 mm and the following month also reaches at least 100 mm; thresholds of 75 mm and 125 mm were tested as sensitivity variants.

Four models are compared. M0 is a climatological baseline that predicts the mean of the target, and every other model must beat it. M1 is a multiple linear regression on the JJA predictors. M2 is a regularised regression (ridge and LASSO), appropriate given $n = 43$ and collinear predictors. M3 is a nonlinear benchmark (random forest, 500 trees, minimum leaf size 3), included to test whether the ENSO–IOD–rainfall relationship is materially nonlinear at seasonal scale; the same predictor–target framing underlies CMIP-based assessments of Indonesian rainfall drivers (Kurniadi et al., 2023).

Validation uses leave-one-year-out cross-validation. All preprocessing, namely standardisation, feature selection and

hyperparameter choice, is performed inside each training fold, so that no information leaks from the held-out year, following recommended practice for climate-forecast verification (Risbey et al., 2022). Skill is reported as RMSE, MAE and out-of-sample R^2 , and, decisively, as the RMSE skill score relative to climatology (Wilks, 2019),

$$RMSESS = 1 - \frac{RMSE_{model}}{RMSE_{clim}} \quad (4)$$

A model that correlates positively with the observations but returns $RMSESS \leq 0$ has no operational value, and this quantity, not the correlation coefficient, is the figure on which the practical claims of this paper stand or fall. Ninety-five per cent confidence intervals for all skill scores are obtained by bootstrapping years (2000 resamples).

Warning skill

The continuous forecasts are converted into a categorical warning for below-normal SON rainfall, defined as the lower tercile of the observed distribution. From the 2×2 contingency table we compute POD, FAR, CSI and PSS, testing CSI against a permutation null (5000 permutations preserving the forecast rate). For probabilistic forecasts from a leave-one-year-out logistic regression on the same predictors, the Brier skill score is computed against a climatological base-rate forecast (Wilks, 2019). Continuous and categorical skill are reported separately, since a system can be accurate in the mean-square sense yet of little use for warning; this decision-threshold view follows recent guidance (Loveday et al., 2024; Necker et al., 2024).

Non-stationarity

The record is divided into two equal epochs, 1982–2003 and 2004–2025. Rather than compare correlations descriptively, differences are tested with Fisher's r -to- z transform. With roughly 264 months per epoch the design has about 80% power to

detect only $\Delta r \gtrsim 0.25$; smaller differences are not resolvable and will not be read as change. Anomalies are recomputed within each epoch and the linearly detrended Niño 3.4 series is used, so the comparison is not confounded by the secular warming of tropical Pacific SST.

Control of multiple comparisons

The diagnostic analysis involves 99 hypothesis tests across three predictors, thirteen lags and four testing procedures. Reporting an uncorrected maximum coefficient selected from such a family would materially overstate both its magnitude and its significance. All p-values in the Results are therefore adjusted using the Benjamini-Hochberg false discovery rate procedure at $q = 0.05$ (Benjamini & Hochberg, 1995), and both raw and adjusted values are archived with the code.

Software and reproducibility

All analyses were performed in Python 3.12 on Google Colab using pandas, NumPy, statsmodels (ARIMA, CCF), scikit-learn (regularised regression, ensemble models, cross-validation), SciPy and Matplotlib. The rainfall series and the climate indices are retrieved at run time directly from the NASA POWER REST API and the NOAA PSL ASCII endpoints, so no data files are redistributed and the analysis is exactly reproducible. The notebook, retrieved series, figure code and the full table of 99 tests are archived at <https://doi.org/10.5281/zenodo.21636374> (Aprianto et al., 2026a). The revised archive additionally includes the CHIRPS validation, inter-cell coherence and skill re-run code (see the subsection “Validation of the rainfall series and grid-cell representativeness”), the station-audit notebook, and all article figures, and is available as a new version at <https://doi.org/10.5281/zenodo.21636373> (Aprianto et al., 2026b). Hypotheses H1-H3, the model set, the validation scheme

and the skill metrics were specified before the analysis was run.

Results

Validation of the rainfall series and grid-cell representativeness

POWER was compared against CHIRPS v2 (0.05°, gauge-blended satellite; Funk et al., 2015), an observational product independent of the MERRA-2 lineage of POWER, over 1982-2025 at the analysis point. The two series share the monsoonal annual cycle with matched phase, both peaking in January and reaching their minimum in August; POWER is drier in the wettest months (January climatology 244.6 versus 362.5 mm) but nearly identical in the dry season (August 6.1 versus 8.2 mm). The distinction between magnitude and co-variation is explicit in the correlation structure: on raw monthly totals the products agree at $r = 0.899$, inflated by the shared seasonal cycle; on standardised monthly anomalies the agreement is $r = 0.721$, and for the interannual SON total the products correlate at $r = 0.889$ (Spearman 0.877; 95% CI 0.81-0.94) (Figure 4). The interannual variability ratio is $\alpha = 1.10$ (CI 0.93-1.28) and the mean ratio $\beta = 0.91$ (SON PBIAS -8.8%), giving KGE = 0.83 (CI 0.68-0.87). POWER therefore reproduces the interannual SON variability the seasonal analysis uses with high fidelity while underestimating totals modestly; because Pearson correlation is invariant to a linear magnitude bias, the teleconnection inferences are unaffected (Figure 3, Table 2). A direct comparison against the co-located station (WMO 97260, Sumbawa Besar/ WADS) was attempted through the NOAA ISD/GSOD archive, but the digitised daily record is too incomplete over 1982-2025 (26.6% of days present; only three SON seasons with fewer than four missing days) to support interannual validation. Direct validation against the multi-decadal BMKG gauge record, whose access requires an institutional data

agreement, remains the appropriate next step (see the subsection “Limitations”).

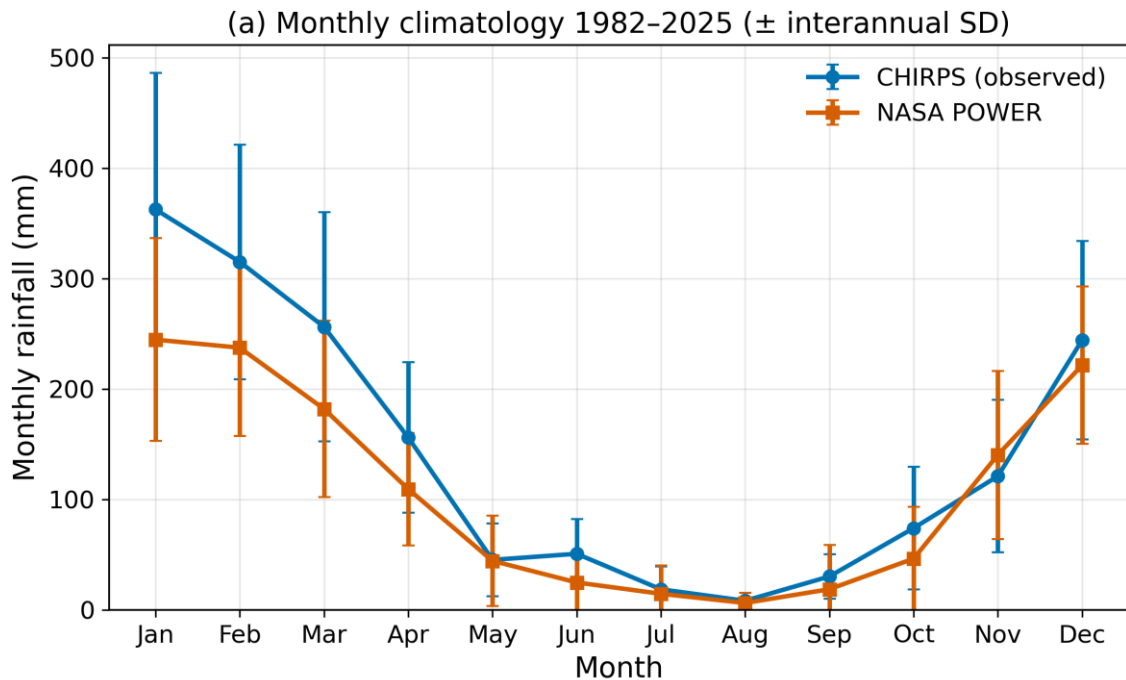


Figure 3. Monthly rainfall climatology at the analysis point, 1982–2025, for NASA POWER and CHIRPS; error bars show interannual standard deviation.

Table 2. Agreement between NASA POWER and CHIRPS rainfall at the analysis point, 1982–2025.

Metric	All months	SON
Pearson r (raw monthly)	0.899	-
Pearson r (standardised anomaly)	0.721	0.889
Spearman ρ (anomaly)	0.711	0.877
Variability ratio α	-	1.10
Mean ratio β	-	0.91
PBIAS	-	-8.8%
RMSE / MAE (mm)	-	63.8 / 53.0
KGE	-	0.83

To test whether the single cell represents the regency, the interannual SON anomaly of the analysis cell was correlated with the eight surrounding POWER cells spanning Sumbawa Regency. The mean SON total varies substantially across the block (166–261 mm), reflecting spatial heterogeneity in absolute rainfall associated with topography, elevation and coast; the interannual anomalies, however, are highly coherent (correlations 0.88–1.00, median 0.92; all eight ≥ 0.87). Interannual variability is thus spatially coherent across

the regency even where climatological totals differ with position (Haylock & McBride, 2001; Moron et al., 2009). The single cell is representative of the regional interannual variability the analysis uses; it is not claimed to resolve intra-regency contrasts in totals (Figure 5).

Finally, the leave-one-year-out SON experiment (see the subsection “Out-of-sample seasonal predictability experiment”) was repeated with CHIRPS as the rainfall target in place of POWER, using identical predictors and validation. The out-of-sample skill is essentially unchanged (LASSO out-of-sample $R^2 = 0.407$, RMSESS = +0.248, 95% CI +0.12 to +0.35), statistically indistinguishable from the POWER-based result reported in the subsection “Seasonal aggregation recovers genuine, cross-validated skill”. The seasonal predictability therefore does not depend on the reanalysis product; an independent, gauge-informed observational dataset yields the same skill.

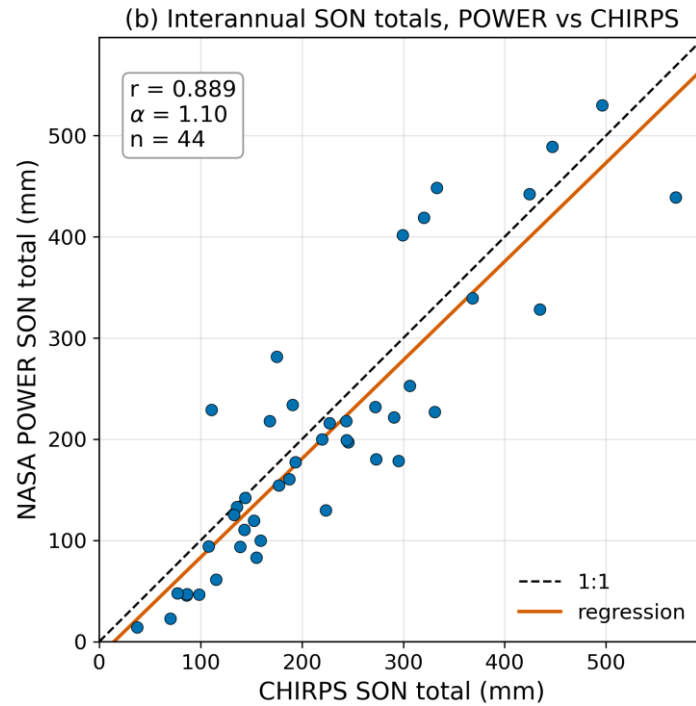


Figure 4. Interannual SON totals, NASA POWER versus CHIRPS ($n = 44$); dashed line 1:1, solid line least-squares fit. $r = 0.889$, $\alpha = 1.10$.

Analysis cell (centre, *): anomaly coherence 0.88–1.00 while totals vary 166–261 mm

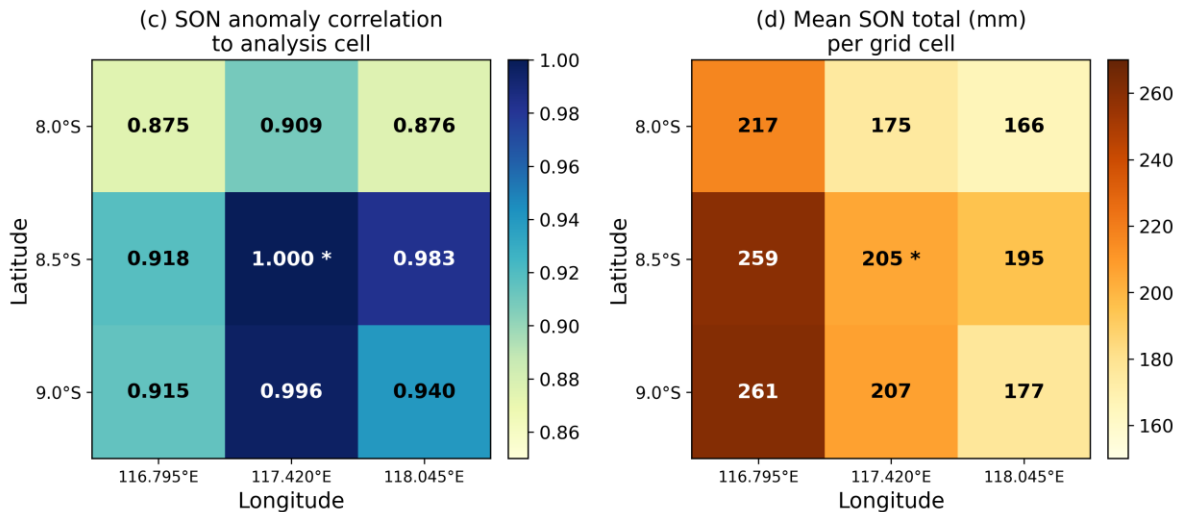


Figure 5. Representativeness of the analysis cell (centre, *): (a) correlation of interannual SON anomalies with the eight surrounding NASA POWER cells; (b) mean SON total per cell. Anomalies are coherent (0.88–1.00) while totals vary (166–261 mm).

Data characteristics and the autocorrelation problem

The NASA POWER series for the Sumbawa grid cell reproduces the expected monsoonal regime (Figure 6). Mean monthly rainfall over 1982–2025 is 107.5 mm with a standard deviation of 107.1 mm, and the climatology ranges from 244.6 mm in January to 6.1 mm in August; the wettest

month is January 1990 (428.4 mm) and the driest September 2007 (0.3 mm). The near-equality of mean and standard deviation and the pronounced right skew (median 77.3 mm against a mean of 107.5 mm) reflect the extreme intra-annual contrast and are why anomalies are standardised by month rather than merely centred.

The critical quantity for what follows is the lag-1 autocorrelation of each series (Table 3). The two oceanic indices are highly persistent (Niño 3.4 $\rho_1 = 0.952$, DMI 0.795), whereas the atmospheric SOI is markedly less so (0.665) and the rainfall anomaly series is almost serially

independent (0.132). The effective sample size for the Niño 3.4-rainfall pair is about 410 rather than 528, a reduction of only 22%: the effective-degrees-of-freedom correction alone, the most common remedy in the applied literature, is far too weak to remove the artefact demonstrated below.

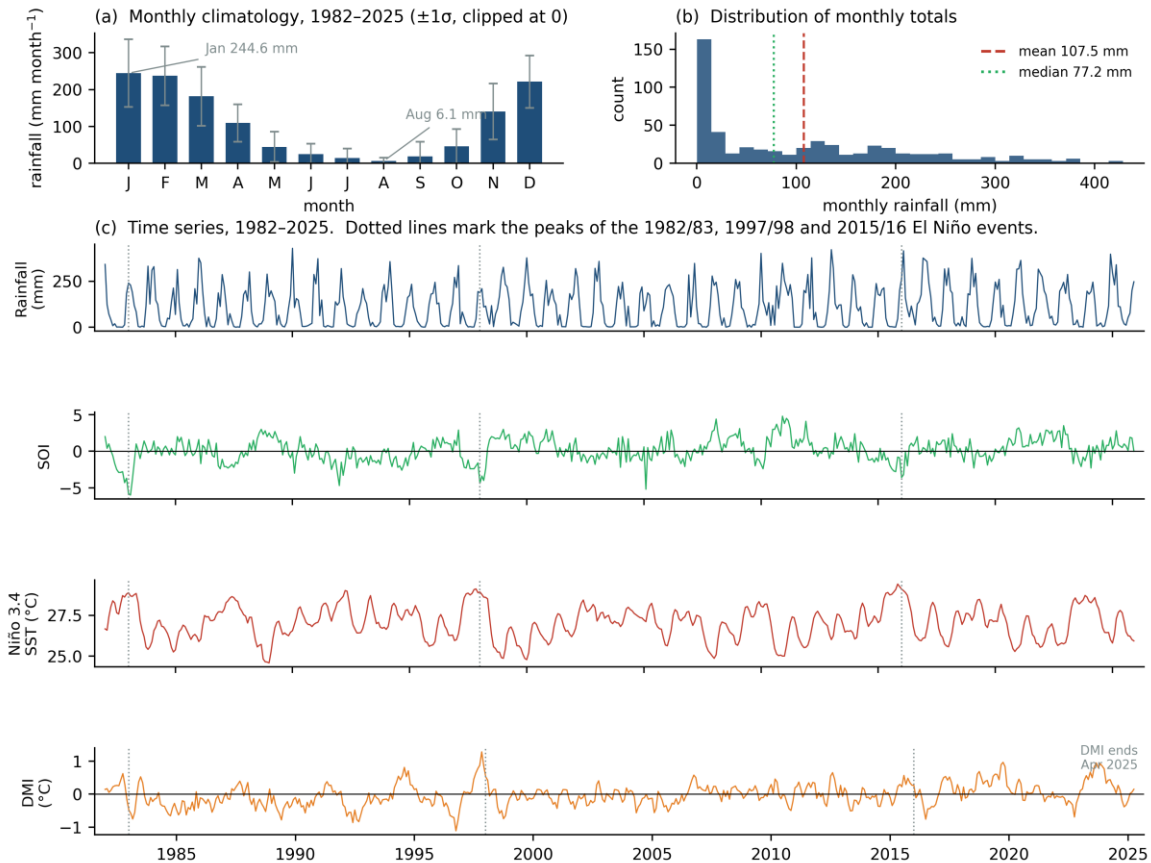


Figure 6. Characteristics of the analysed series. (a) Monthly rainfall climatology with interannual standard deviation, clipped at zero since negative rainfall is not admissible. (b) Distribution of monthly totals, showing the strong right skew that motivates the square-root and Spearman robustness checks. (c) Time series of rainfall, SOI, Niño 3.4 SST and the DMI, 1982–2025; dotted lines mark the peaks of the 1982/83, 1997/98 and 2015/16 El Niño events. The DMI record terminates in April 2025.

Table 3. Lag-1 autocorrelation of the standardised anomaly series.

Series	ρ_1	Character
Rainfall (NASA POWER)	0.132	Effectively serially independent
SOI	0.665	Atmospheric; retains month-to-month variability
Niño 3.4 SST	0.952	Oceanic; variance almost entirely low-frequency
DMI (IOD)	0.795	Oceanic; strongly persistent

The naive cross-correlation function fails a physical sanity check

Computed conventionally on standardised monthly anomalies, the CCF reproduces the pattern reported throughout the regional literature: a positive association with the SOI peaking at lag 0 ($r = 0.364$) and a

negative association with Niño 3.4, both decaying slowly and remaining nominally significant for several months. Had the analysis stopped there, we would have reported an SOI signal significant to lag 5 and a Niño 3.4 signal significant to lag 3, and interpreted the tail as short-term climate memory.

The lags below zero refute that interpretation. A negative lag places rainfall ahead of the index, which no mechanism permits: convection over Sumbawa cannot force central-Pacific Sea surface temperature two months later. Yet the naive CCF, even after the effective-sample-size correction and Benjamini-Hochberg adjustment, returns significant coefficients at every negative lag from -6 to -1 for both the SOI and Niño 3.4 (Figure 7, top row;

Table 4). For Niño 3.4 the naive maximum in the window falls not at lag 0 ($r = -0.241$) but at a non-causal negative lag (lag -2, $r = -0.249$), a value statistically indistinguishable from lag -1 ($r = -0.248$; difference 0.001), so no distinct two-month lead is implied; taken at face value the method would make Sumbawa rainfall the better predictor of the Pacific. The method, not the physics, is at fault.

Table 4. Naive cross-correlation coefficients with effective-sample-size correction. Asterisks denote significance after Benjamini-Hochberg FDR correction ($q < 0.05$).

Lag (months)	SOI	Niño 3.4	DMI	Interpretation
-6	0.177 *	-0.164 *	0.123 *	Non-causal (rainfall leads index)
-5	0.198 *	-0.205 *	0.069	Non-causal (rainfall leads index)
-4	0.236 *	-0.224 *	0.048	Non-causal (rainfall leads index)
-3	0.238 *	-0.238 *	-0.015	Non-causal (rainfall leads index)
-2	0.256 *	-0.249 *	-0.044	Non-causal (tied with lag -1)
-1	0.193 *	-0.248 *	-0.092	Non-causal (rainfall leads index)
0	0.364 *	-0.241 *	-0.139 *	Concurrent
1	0.266 *	-0.230 *	-0.148 *	Apparent lead
2	0.221 *	-0.193 *	-0.087	Apparent lead
3	0.217 *	-0.151 *	-0.040	Apparent lead
4	0.141 *	-0.112	0.005	-
5	0.118 *	-0.070	0.019	-
6	0.046	-0.013	0.062	-

The naive CCF (top) returns significant coefficients at non-causal negative lags, where rainfall would lead the index; the Niño 3.4 maximum falls at a negative lag. After Box-Jenkins pre-whitening (bottom), only the concurrent SOI signal remains.

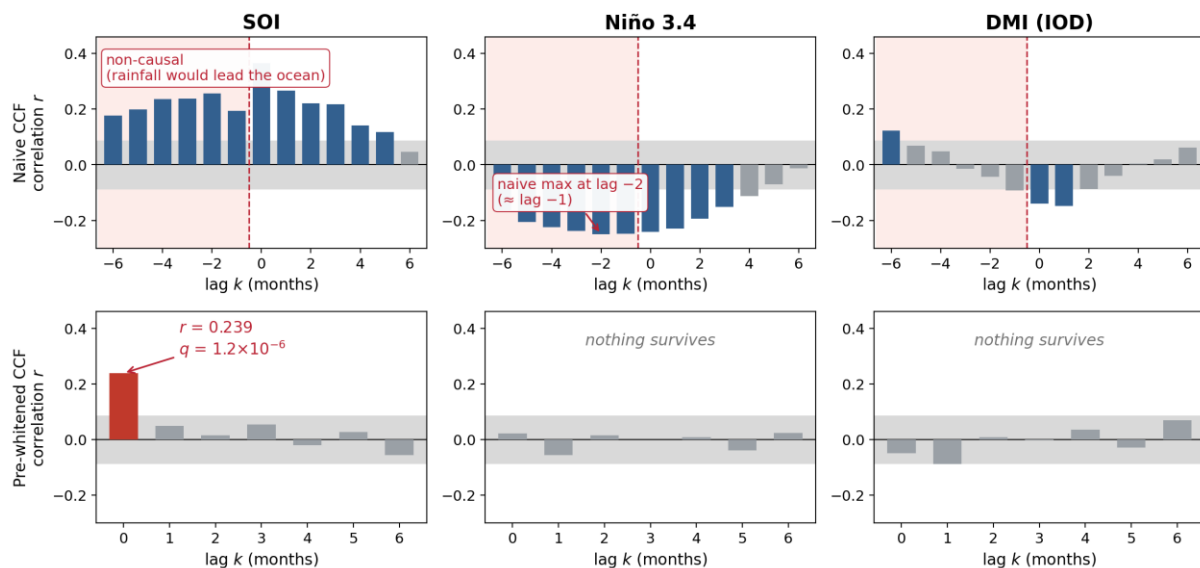


Figure 7. Naive (top) and pre-whitened (bottom) cross-correlation between the climate indices and Sumbawa rainfall anomalies, 1982-2025. Coloured bars are significant after BH-FDR correction; the shaded band is the $\pm 1.96/\sqrt{n}$ bound. The red panel at the left of each upper plot marks negative lags, at which significance would be non-causal (rainfall leading the index).

Figure 8 makes the mechanism explicit. If a predictor X influences rainfall Y only concurrently, the expected cross-correlation at lag k is nevertheless $r_0 \cdot \rho_X(k)$. Plotted against the observed CCF, this null accounts for the observed lagged correlations in full: for the SOI the two curves are almost indistinguishable, and for Niño 3.4 and the DMI the observed

correlations decay faster than the null, so at every lag the observed coefficient is equal to, or weaker than, what persistence alone would generate. At no lag, for any index, does the observed correlation exceed the concurrent-only expectation. The decaying tail of "significant" lagged coefficients is therefore what persistence produces in the absence of any lagged mechanism.

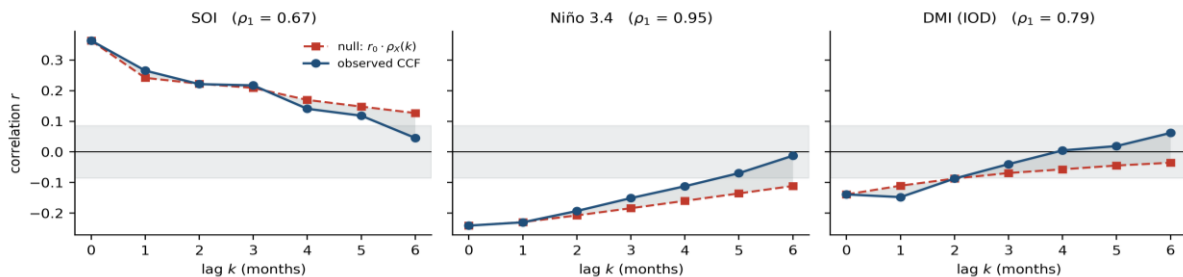


Figure 8. Observed lagged correlations (blue) against the concurrent-only null expectation $r_0 \cdot \rho_X(k)$ (red); the shaded area is the difference. At every lag and for every index the observed correlation is equal to, or weaker than, the null. No lagged coefficient exceeds what the predictor's own persistence alone would produce.

After pre-whitening, only the concurrent SOI signal survives

ARIMA models were fitted to each index and the same filter applied to the rainfall series, so that the cross-correlations of the residuals are approximately independent with standard error $1/\sqrt{n} = 0.043$ and a 95% bound of ± 0.085 . The result is unambiguous (Table 5, Figure 7 bottom row). Of the twenty-one pre-whitened coefficients tested, exactly one survives FDR correction: the SOI at lag 0, $r = 0.239$ ($q = 1.2 \times 10^{-6}$). Every coefficient at lags 1 through 6 falls inside the noise band for all three predictors.

Two features of this result stand out. First, the entire multi-month climate memory reported by the naive method disappears. Second, and this was not anticipated, the concurrent coefficients for Niño 3.4 ($r = 0.023$) and DMI ($r = -0.048$) also collapse to zero. At monthly resolution, once the shared low-frequency component is removed, the oceanic indices carry no information about Sumbawa rainfall anomalies at all. Only the SOI does. The physical reading of this asymmetry is developed in the Discussion, in the

subsection “Why the ocean indices carry no monthly signal”.

Table 5. Pre-whitened cross-correlation coefficients. Significance bound = ± 0.085 (95%).

Lag (months)	SOI	Niño 3.4	DMI
0	0.239 *	0.023	-0.048
1	0.050	-0.056	-0.087
2	0.015	0.016	0.009
3	0.055	0.000	-0.001
4	-0.020	0.008	0.035
5	0.028	-0.038	-0.028
6	-0.055	0.024	0.069

* $q = 1.2 \times 10^{-6}$ (BH-FDR). No other coefficient is significant.

The partial cross-correlation $r(Y_t, X_{t-k} | X_t)$ reaches the same conclusion: no lagged predictor is significant at lags 1-5 for any index. Two lag-6 coefficients are formally significant (Niño 3.4, $r = 0.114$, $q = 0.027$; DMI, $r = 0.104$, $q = 0.049$) but both carry the wrong sign (positive, where the mechanism requires a negative association) and a six-month lag is half the annual cycle; we read these as aliasing of the semi-annual harmonic, not teleconnection. Hypothesis H1 is accepted.

Seasonal aggregation recovers genuine, cross-validated skill

The seasonal experiment uses one sample per year and is therefore structurally free of the autocorrelation artefact. Over 43 independent years, the June-August mean SOI correlates with the SON rainfall total at $r = +0.643$ ($p < 0.0001$) and with the wet-season onset month at $r = -0.663$. The corresponding coefficients for the JJA Niño 3.4 mean are -0.563 and $+0.575$, and for the JJA DMI mean only -0.223 ($p = 0.15$) and $+0.295$ ($p = 0.054$).

Under leave-one-year-out cross-validation, a LASSO model achieves an out-of-sample R^2 of 0.405 for the SON total and an RMSE skill score of $+0.247$ against a climatological baseline, with a bootstrap 95% confidence interval of $[+0.109, +0.353]$ that excludes zero (Table 6, Figure 9). For the onset month the skill score is $+0.219$ with a confidence interval of $[+0.128, +0.338]$. Hypothesis H2 is accepted: a real operational lead time of one to three months exists.

Table 6. Out-of-sample skill (leave-one-year-out, 43 years). RMSESS is referenced to climatology; a value ≤ 0 indicates no operational value.

Model	r	R ² (oos)	RMSESS	95% CI	Skill?
Target T1: SON rainfall total (mm)					
M0 Climatology	-	-	0.000	-	-
M1 OLS	+0.607	0.345	+0.209	[+0.034, +0.347]	Yes
M2 Ridge	+0.615	0.378	+0.230	[+0.108, +0.326]	Yes
M2 LASSO	+0.638	0.405	+0.247	[+0.109, +0.353]	Yes
M3 Random forest	+0.502	0.235	+0.146	[-0.003, +0.282]	No
Target T2: wet-season onset month					
M0 Climatology	-	-	0.000	-	-
M1 OLS	+0.569	0.286	+0.175	[-0.035, +0.328]	No
M2 Ridge	+0.592	0.350	+0.212	[+0.090, +0.334]	Yes
M2 LASSO	+0.610	0.361	+0.219	[+0.128, +0.338]	Yes
M3 Random forest	+0.602	0.356	+0.216	[+0.092, +0.362]	Yes

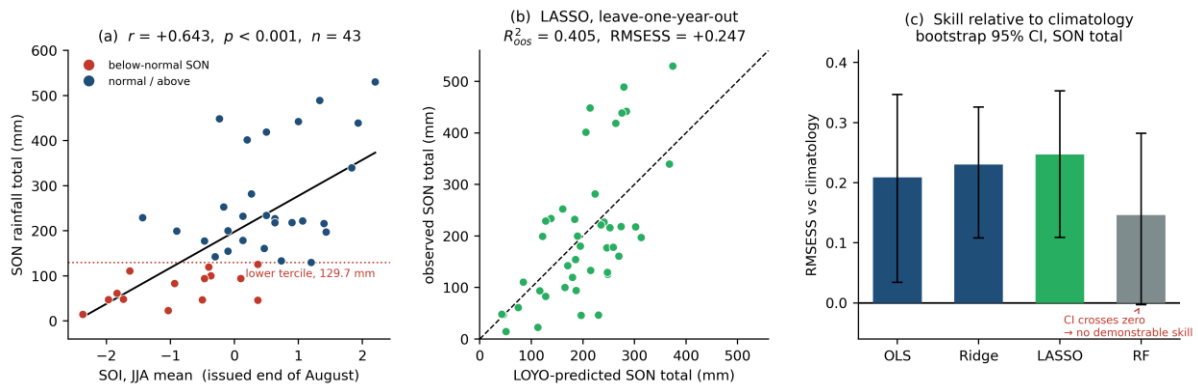


Figure 9. (a) JJA-mean SOI against SON rainfall total; red points fall in the lower tercile. (b) Observed versus leave-one-year-out predicted SON total (LASSO); the dashed line is the 1:1 reference. (c) Skill relative to climatology with bootstrap 95% confidence intervals. The vertical axis extends below zero so that the random-forest interval, whose lower bound is -0.003 , can be seen to cross it.

Two secondary results follow. First, the random forest does not outperform regularised linear regression on either target, and for the SON total its confidence interval includes zero. The seasonal ENSO-rainfall relationship in Sumbawa is, to the resolution of a 43-year record, linear; the

additional flexibility of a nonlinear learner buys nothing and costs variance.

Second, the model is radically parsimonious. LASSO eliminates the JJA Niño 3.4 mean, the JJA DMI mean and the DMI tendency entirely, retaining only the

JJA SOI (standardised coefficient +54.3 mm), the Niño 3.4 tendency (-28.5 mm) and the SOI tendency (+20.9 mm). A model using the JJA-mean SOI alone attains RMSESS = +0.218 for the SON total and +0.233 for the onset month, equal to, and for onset better than, the full six-predictor model. The operationally relevant information in this system is contained in a single number.

On the multicollinearity raised for the two ENSO indices: the JJA-mean SOI and Niño 3.4 are strongly anti-correlated ($r = -0.78$), which is exactly why a single joint regression would be unstable; nonetheless all variance inflation factors remain below 4 (maximum 3.53), and collinearity is handled by design through regularisation. That LASSO retains the SOI rather than Niño 3.4 is physical, not arbitrary: the SOI is an atmospheric index carrying sub-seasonal Walker-circulation variability whereas Niño 3.4 is a slowly varying oceanic index, and the two carry distinct information at monthly resolution.

Consistently, an SOI-only model matches the full six-predictor model (RMSESS +0.218 for the SON total, +0.233 for onset), confirming that the operational information resides in a single atmospheric index.

The forecast translates into usable, but incomplete, warning skill

Below-normal SON rainfall was defined as the lower tercile of the 1982-2024 distribution (129.7 mm; base rate 0.326) and the continuous forecasts were converted into categorical warnings. Contrary to hypothesis H3, warning skill does not collapse. The Ridge model attains a critical success index of 0.53 against a permutation-derived chance value of 0.20 ($p = 0.0002$), with a probability of detection of 0.57, a false alarm ratio of 0.11 and a Peirce skill score of +0.54 (Table 7, Figure 10). A probabilistic version of the forecast achieves a Brier skill score of +0.422 against a climatological forecast equal to the base rate. Hypothesis H3 is rejected.

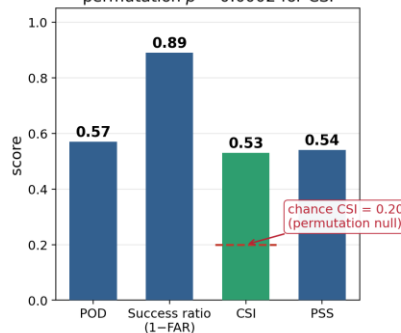
Table 7. Warning skill for below-normal SON rainfall (lower tercile, threshold 129.7 mm, base rate 0.326, $n = 43$).

Model	POD	FAR	CSI	PSS	Permutation p (CSI)
M1 OLS	0.57	0.27	0.47	+0.47	0.0030
M2 Ridge	0.57	0.11	0.53	+0.54	0.0002
M2 LASSO	0.57	0.20	0.50	+0.50	0.0014
M3 Random forest	0.64	0.25	0.53	+0.54	0.0006
Chance (permutation mean)	—	—	0.20	0.00	—

(a) Contingency table, Ridge (LOYO)

	Warned	Not warned
Below-normal SON observed	hits 8	misses 6
Normal / above observed	false alarms 1	correct neg. 28

(b) Warning skill, below-normal SON permutation $p = 0.0002$ for CSI



(c) Probabilistic forecast (LOYO) Brier skill score = +0.422

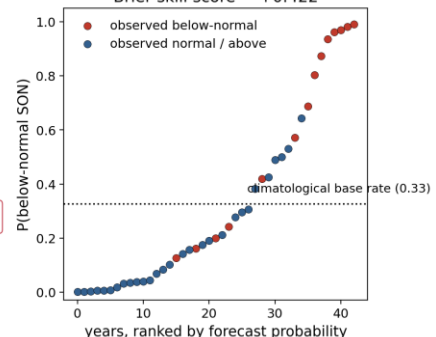


Figure 10. (a) Contingency table for the Ridge forecast under leave-one-year-out validation. (b) Warning scores; the success ratio is 1-FAR. The dashed reference marks the permutation-derived chance value of the CSI (0.20) and applies to the CSI bar only. (c) Leave-one-year-out probabilistic forecasts, ranked; red points are the observed below-normal seasons.

The operational reading is nevertheless sober. A probability of detection of 0.57 means that six of the fourteen below-normal seasons in the record would not have been warned. The system is decision-relevant, but it is not a safety net, and it should be communicated as a probabilistic shift in the odds rather than as a deterministic alert.

No detectable change between epochs

Correlations were recomputed for 1982-2003 and 2004-2025 using within-epoch anomalies and the detrended Niño 3.4 series. The concurrent SOI correlation moves from 0.328 to 0.368 and detrended Niño 3.4 from -0.229 to -0.256, but neither difference, nor any of ten others, is significant: all twelve Fisher r -to- z tests give $p \geq 0.199$. With about 264 months per epoch the design resolves only $\Delta r \gtrsim 0.25$, so this indicates absence of detectable change, not stability. These data give no evidence of intensification, and descriptive epoch comparisons of correlations should not be reported without a formal test of the difference.

Discussion

Why the ocean indices carry no monthly signal

After pre-whitening, the Niño 3.4 and DMI coefficients fall to zero even at lag 0 ($r = 0.023$ and $r = -0.048$), while the SOI keeps a clear concurrent signal ($r = 0.239$). This does not contradict the established physics; it locates where each index holds its variance. Niño 3.4 has a lag-1 autocorrelation of 0.952, so almost all of its variance sits at interannual and longer periods. Pre-whitening strips that component and leaves only month-to-month residuals in a slowly evolving sea surface temperature field, and those residuals have no physical route to change convection over Sumbawa inside the same month.

The SOI behaves differently because it measures the atmosphere rather than the ocean. As the standardised Tahiti-minus-Darwin pressure difference it carries real sub-seasonal variability (lag-1 autocorrelation 0.665) that tracks the instantaneous Walker circulation, and that variability couples to local convection within the month. The monthly rainfall-SST correlations reported across the region are therefore the monthly footprint of an interannual co-variation, not evidence of a month-scale ocean-to-rainfall mechanism. This is the sense in which "climate memory" applies here (Wei & Yuan, 2024): the memory sits in the ocean index, not in the local rainfall response, which also bears on which flavour of ENSO a predictor represents (Nguyen-Thanh et al., 2023).

Stated dynamically, the coupling is direct. During El Niño and negative-SOI conditions the ascending branch of the Walker circulation shifts east and subsidence strengthens over the Maritime Continent; low-level divergence weakens the convergence of water vapour over Sumbawa and suppresses deep convection, and rainfall drops. La Niña and positive-SOI conditions reverse the sign, strengthening convergence and convection. Because this bridge acts through the atmosphere within a single month, the index that retains a concurrent signal is the SOI, which measures the pressure gradient driving it, and not the oceanic indices, whose sub-monthly residuals carry no such information once pre-whitened (As-syakur et al., 2014; Chen et al., 2023; Supari et al., 2018).

One consequence is worth stating plainly. The Darwin pole of the SOI lies inside the Maritime Continent, so the lag-0 SOI-rainfall correlation reads more naturally as a concurrent diagnostic of one coupled state than as a signal travelling from the Pacific to Sumbawa in under a month. Calling it a fast teleconnection, as is common, attaches a causal story the data do not require.

Which lag results survive, and which do not

The negative-lag result is the most portable finding here, so it is worth being exact about what it shows. Cross-correlating a highly persistent index against a weakly autocorrelated local series always produces a decaying tail of nominally significant lagged coefficients (Table 4), and that tail imitates climate memory. Every significant coefficient at a negative lag is an artefact of serial correlation and predictor persistence, not a physical finding; we report these coefficients only to expose the failure of the naive test, and the concurrent-only null $\rho_X(k)$ reproduces them in full (Figure 8). The signal that survives is the concurrent SOI correlation alone ($r = 0.239$). The negative seasonal correlation between Niño 3.4 and SON rainfall ($r = -0.563$) is a real in-sample association, but we do not present it as predictive skill: the operational claims of this paper rest only on the cross-validated, climatology-referenced scores reported in the subsection “Seasonal aggregation recovers genuine, cross-validated skill”, never on a correlation coefficient.

The check that catches the artefact costs nothing. Compute the negative lags; if they are significant, the significance test is contaminated and the reported optimal lag cannot be trusted. Running this check, together with pre-whitening or an equivalent correction, before quoting a lag structure would alter the conclusions of several district-scale Indonesian teleconnection studies, and their published lags should be revisited on that basis.

The same logic reaches into data-driven modelling. Supplying a network with lagged copies of an index (SOI at $t-2$, SST at $t-3$) as separate predictors, as an earlier version of this work did, adds collinear and largely redundant features once the index is strongly autocorrelated, and the partial cross-correlations show those lags carry nothing beyond the concurrent value. The seasonal experiment agrees: the random

forest does not beat regularised linear regression, and LASSO keeps three of six predictors. Models that now reach real skill in ENSO and weather forecasting (Price et al., 2025; Zhou & Zhang, 2023) draw it from large, physically meaningful state vectors, and recent multivariate rainfall models improve on the same principle rather than on autocorrelated lags (El Hafyani et al., 2024; Fredyan & Kusuma, 2022; Wani et al., 2024).

The IOD leaves no footprint here

The DMI contributes nothing detectable to Sumbawa rainfall at either time scale (JJA DMI against the SON total, $r = -0.223$, $p = 0.15$; dropped by LASSO). This is a substantive result, not a null to be explained away. The contrast with Sumatra is instructive: there a positive IOD coinciding with El Niño can delay onset and extend the dry season by several months (Hidayat et al., 2025), and peatland groundwater has served as an IOD-sensitive alert variable in the western archipelago (Sulaiman et al., 2023). Sumbawa lies far from the eastern pole of the dipole in the south-eastern tropical Indian Ocean, and the IOD footprint over Indonesia weakens eastward from Sumatra (Amirudin et al., 2020; Hanifa & Wiratmo, 2024). For the Lesser Sunda Islands, the Pacific dominates, and reporting that the IOD adds nothing locally is more useful than carrying a predictor with no local information. The IOD is itself a partially predictable mode whose seasonal skill peaks in JJA-SON (Ling et al., 2022; Zhang et al., 2024), so its negligible local footprint reflects Sumbawa’s position rather than a limit on the mode’s own predictability.

What the skill means operationally for Sumbawa

The operational content is small and specific. The June-August mean SOI, one publicly available number, explains about 40% of the out-of-sample variance in SON rainfall and predicts the onset month with a

skill score near 0.22 against climatology. The same skill appears when CHIRPS replaces NASA POWER as the target (see the subsection “Validation of the rainfall series and grid-cell representativeness”), so the result is a property of the rainfall itself, not of the reanalysis. Issued at the end of August, the forecast gives one to three months of lead before the planting decision (Moron et al., 2009). For a rainfed economy, anticipating eight of the fourteen below-normal seasons in the record with one false alarm in twenty-nine normal seasons beats a fixed climatological calendar, and it stays inside the predictability limits established for Indonesian wet-season rainfall two decades ago (Haylock & McBride, 2001). Comparable seasonal-regression benchmarks confirm that skill varies by season and that simple regularised models remain competitive (Shravankumar et al., 2026).

The limits belong with the claim. Six of the fourteen below-normal seasons would have gone unwarned. The forecast supports shifting the odds, moving planting windows, staging water reserves and pre-positioning drought contingency, not triggering irreversible action, and it should be issued as a probability rather than a yes-or-no alert. We had expected warning skill to fall well short of the continuous accuracy (hypothesis H3), and it did not: the critical success index reaches 0.53 against a chance value of 0.20. Even so, the distance between a correlation of 0.64 and a detection rate of 0.57 is exactly where a forecast that looks strong can still fail the people relying on it, which is why we report the contingency table rather than the correlation alone.

Limitations

Four limitations bound these conclusions. First, the rainfall series is a NASA POWER reanalysis grid cell, not a gauge record. POWER reproduces tropical climatology and rain-day occurrence acceptably but

underestimates extremes (Madushan et al., 2025; Tan et al., 2023), and the $0.5^\circ \times 0.625^\circ$ cell contains a substantial marine fraction and does not resolve orographic contrast within the regency. The POWER series has now been validated against the CHIRPS observational product (see the subsection “Validation of the rainfall series and grid-cell representativeness”): the interannual SON anomalies of the two products correlate at $r = 0.889$ with $KGE = 0.83$, and the SON seasonal skill is reproduced when CHIRPS replaces POWER as the target, so the operational conclusions do not depend on the reanalysis. A direct comparison with the co-located station (WMO 97260) via NOAA ISD/GSOD was attempted but its daily record is too incomplete (26.6% of days) for interannual validation; multi-decadal BMKG gauge validation, which requires an institutional data agreement, remains outstanding, and the reported skill should be read as an upper bound for a single grid cell.

Second, the onset definition is coarse. At monthly resolution, twenty-three of forty-three onsets fall in November, which compresses the target and probably understates achievable onset skill. A daily POWER retrieval with the BMKG dekadal criterion (three consecutive dekads of at least 50 mm) is the appropriate refinement, and is the most promising avenue for improving the operational product.

Third, the DMI series available from NOAA PSL is HadISST-based and terminates in April 2025, which excludes 2025 from the seasonal analysis. Since the IOD proved to be a non-contributor at this location, this leaves the conclusions unchanged, though a real-time operational implementation would require an OISST-based dipole index.

Fourth, the record is 43 to 44 years. The epoch comparison can resolve only $\Delta r \gtrsim 0.25$, and the bootstrap confidence intervals

on the skill scores are correspondingly wide. Claims about non-stationarity of this teleconnection, in either direction, are not supportable at this sample size, and we make none.

Conclusion

For Sumbawa Regency, the multi-month optimal time lags that a conventional cross-correlation analysis reports between ENSO indices and local rainfall do not exist. The naive method attributes significance to non-causal negative lags, where rainfall would lead the index, and places the naive Niño 3.4 maximum at a negative lag; after Box-Jenkins pre-whitening, only the concurrent SOI signal survives ($r = 0.239$), and the concurrent oceanic signals disappear along with the lagged ones. The apparent climate memory of these indices is the persistence of the indices themselves.

Predictability nevertheless exists, at seasonal aggregation rather than in monthly lag structure. The June-August mean SOI forecasts SON rainfall with an out-of-sample R^2 of 0.405 and a skill score of +0.247 against climatology, predicts the onset month with a skill score of +0.219, and supports a categorical warning for below-normal rainfall with a critical success index of 0.53 against a chance value of 0.20 and a Brier skill score of +0.422. A single index, issued at the end of August, carries almost all of this information; Niño 3.4 and the IOD add nothing, and a nonlinear learner does not outperform linear regression. No change in teleconnection strength between 1982-2003 and 2004-2025 is detectable.

Two recommendations follow. Operationally, regional meteorological and agricultural agencies in West Nusa Tenggara can construct a defensible seasonal outlook for Sumbawa from the JJA-mean SOI alone, communicated as a probabilistic shift in the odds of a below-normal wet-season onset, with the explicit caveat that roughly two in five dry seasons

will be missed. Methodologically, cross-correlation studies of climate teleconnections at district scale should report the negative-lag diagnostic and apply pre-whitening as a matter of routine; where they have not, their reported optimal lags, and any machine-learning feature sets built upon them, should be treated as unverified.

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Author Contribution

This work is reported following the CRediT taxonomy. Romi Aprianto: Conceptualization, Methodology, Software, Formal analysis, Data curation, Visualization, Writing - original draft. Akbar Tawaqqal: Investigation, Writing – review & editing. Syaharuddin: Validation, Supervision, Writing - review & editing. All authors have read and agreed to the submitted version of the manuscript.

Conflict of Interest

The authors declare no conflict of interest.

References

- Aldrian, E., & Susanto, R. D. (2003). Identification of three dominant rainfall regions within Indonesia and their relationship to sea surface temperature. *International Journal of Climatology*, 23(12), 1435–1452. <https://doi.org/10.1002/joc.950>
- Amirudin, A. A., Salimun, E., Tangang, F., Juneng, L., & Zuhairi, M. (2020). Differential influences of teleconnections from the Indian and Pacific Oceans on rainfall variability

- in Southeast Asia. *Atmosphere*, 11(9), 886. <https://doi.org/10.3390/atmos11090886>
- Aprianto, R., Tawaqqal, A., & Syaharuddin. (2026a). ENSO and IOD teleconnection with Sumbawa rainfall: Reproducible pipeline and data (Version 1) [Data set]. Zenodo. <https://doi.org/10.5281/zenodo.21636374>
- Aprianto, R., Tawaqqal, A., & Syaharuddin. (2026b). ENSO and IOD teleconnection with Sumbawa rainfall: Reproducible pipeline and data (revised version) [Data set]. Zenodo. <https://doi.org/10.5281/zenodo.21636373>
- As-syakur, A. R., Tanaka, T., Osawa, T., & Mahendra, M. S. (2013). Indonesian rainfall variability observation using TRMM multi-satellite data. *International Journal of Remote Sensing*, 34(21), 7723–7738. <https://doi.org/10.1080/01431161.2013.826837>
- As-syakur, A. R., Adnyana, I. W. S., Mahendra, M. S., Arthana, I. W., Merit, I. N., Kasa, I. W., Ekayanti, N. W., Nuarsa, I. W., & Sunarta, I. N. (2014). Observation of spatial patterns on the rainfall response to ENSO and IOD over Indonesia using TRMM Multisatellite Precipitation Analysis (TMPA). *International Journal of Climatology*, 34(15), 3825–3839. <https://doi.org/10.1002/joc.3939>
- Benjamini, Y., & Hochberg, Y. (1995). Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing. *Journal of the Royal Statistical Society: Series B*, 57(1), 289–300. <https://doi.org/10.1111/j.2517-6161.1995.tb02031.x>
- Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2016). *Time series analysis: Forecasting and control* (5th ed.). Wiley.
- Bretherton, C. S., Widmann, M., Dymnikov, V. P., Wallace, J. M., & Bladé, I. (1999). The effective number of spatial degrees of freedom of a time-varying field. *Journal of Climate*, 12(7), 1990–2009. [https://doi.org/10.1175/1520-0442\(1999\)012<1990:TENOSD>2.0.CO;2](https://doi.org/10.1175/1520-0442(1999)012<1990:TENOSD>2.0.CO;2)
- Cai, W., Ng, B., Geng, T., Jia, F., Wu, L., Wang, G., Liu, Y., Gan, B., Yang, K., Santoso, A., Lin, X., Li, Z., Liu, Y., Yang, Y., Jin, F.-F., Collins, M., & McPhaden, M. J. (2023). Anthropogenic impacts on twentieth-century ENSO variability changes. *Nature Reviews Earth & Environment*, 4(6), 407–418. <https://doi.org/10.1038/s43017-023-00427-8>
- Camps-Valls, G., Fernández-Torres, M. Á., Cohrs, K.-H., Höhl, A., Castelletti, A., Pacal, A., Robin, C., Martinuzzi, F., Papoutsis, I., Prapas, I., Pérez-Aracil, J., Weigel, K., Gonzalez-Calabuig, M., Reichstein, M., Rable, M., Giuliani, M., Mahecha, M. D., Popescu, O.-I., Pellicer-Valero, O. J., Ouala, S., Salcedo-Sanz, S., Sippel, S., Kondylatos, S., Happé, T., & Williams, T. (2025). Artificial intelligence for modeling and understanding extreme weather and climate events. *Nature Communications*, 16, 1919. <https://doi.org/10.1038/s41467-025-56573-8>
- Chen, C., Sahany, S., Moise, A. F., Chua, X. R., Hassim, M. E., Lim, G., & Prasanna, V. (2023). ENSO-rainfall teleconnection over the Maritime Continent enhances and shifts eastward under warming. *Journal of Climate*, 36(14), 4635–4663. <https://doi.org/10.1175/JCLI-D-23-0036.1>
- Chen, Y., Teo, F. Y., Wong, S. Y., Chan, A., Weng, C., & Falconer, R. A.

- (2025). Monsoonal extreme rainfall in Southeast Asia: A review. *Water*, 17(1), 5. <https://doi.org/10.3390/w17010005>
- Ebisuzaki, W. (1997). A Method to Estimate the Statistical Significance of a Correlation When the Data Are Serially Correlated. *Journal of Climate*, 10(9), 2147–2153. [https://doi.org/10.1175/1520-0442\(1997\)010<2147:AMTETS>2.0.CO;2](https://doi.org/10.1175/1520-0442(1997)010<2147:AMTETS>2.0.CO;2)
- El Hafyani, M., El Himdi, K., & El Adlouni, S. E. (2024). Improving monthly precipitation prediction accuracy using machine learning models: A multi-view stacking learning technique. *Frontiers in Water*, 6, 1378598. <https://doi.org/10.3389/frwa.2024.1378598>
- Fredyan, R., & Kusuma, G. P. (2022). Spatiotemporal convolutional LSTM with attention mechanism for monthly rainfall prediction. *Communications in Mathematical Biology and Neuroscience*, 2022, 105. <https://doi.org/10.28919/cmbn/7761>
- Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., & Michaelsen, J. (2015). The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific Data*, 2, 150066. <https://doi.org/10.1038/sdata.2015.66>
- Gelaro, R., McCarty, W., Suárez, M. J., Todling, R., Molod, A., Takacs, L., Randles, C. A., Darmenov, A., Bosilovich, M. G., Reichle, R., Wargan, K., Coy, L., Cullather, R., Draper, C., Akella, S., Buchard, V., Conaty, A., da Silva, A. M., Gu, W., Kim, G.-K., Koster, R., Lucchesi, R., Merkova, D., Nielsen, J. E., Partyka, G., Pawson, S., Putman, W., Rienecker, M., Schubert, S. D., Sienkiewicz, M., & Zhao, B. (2017). The Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2). *Journal of Climate*, 30(14), 5419–5454. <https://doi.org/10.1175/JCLI-D-16-0758.1>
- Ghosh, R., & Shepherd, T. G. (2023). Storylines of Maritime Continent dry period precipitation changes under global warming. *Environmental Research Letters*, 18(3), 034017. <https://doi.org/10.1088/1748-9326/acb788>
- Gibson, P. B., Chapman, W. E., Altinok, A., Monache, L. D., DeFlorio, M. J., & Waliser, D. E. (2021). Training machine learning models on climate model output yields skillful interpretable seasonal precipitation forecasts. *Communications Earth & Environment*, 2, 174. <https://doi.org/10.1038/s43247-021-00225-4>
- Hanifa, R., & Wiratmo, J. (2024). ENSO and IOD Influence on Extreme Rainfall in Indonesia: Historical and Future Analysis. *Agromet*, 38(2), 78–87. <https://doi.org/10.29244/j.agromet.38.2.78-87>
- Hariadi, M. H., van der Schrier, G., Steeneveld, G.-J., Sutanto, S. J., Sutanudjaja, E., Ratri, D. N., Sopaheluwakan, A., & Tank, A. K. (2024). A high-resolution perspective of extreme rainfall and river flow under extreme climate change in Southeast Asia. *Hydrology and Earth System Sciences*, 28(9), 1935–1956. <https://doi.org/10.5194/hess-28-1935-2024>
- Haylock, M. R., & McBride, J. (2001). Spatial coherence and predictability of Indonesian wet season rainfall. *Journal of Climate*, 14(18), 3882–3887. [https://doi.org/10.1175/1520-0442\(2001\)014<3882:SCAPOI>2.0.CO;2](https://doi.org/10.1175/1520-0442(2001)014<3882:SCAPOI>2.0.CO;2)

- Heede, U. K., & Fedorov, A. V. (2023). Colder eastern equatorial Pacific and stronger Walker circulation in the early 21st century: Separating the forced response from natural variability. *Geophysical Research Letters*, 50(3), e2022GL101020. <https://doi.org/10.1029/2022GL101020>
- Hidayat, R., Apip, A., Dasril, A. P., Taufik, M. (2025). Climate teleconnection triggers prolonged dry season in tropical maritime continent. *Theoretical and Applied Climatology*, 156, 626. <https://doi.org/10.1007/s00704-025-05852-x>
- Khalid, M. R., Ahmed, S., & Abdullah, A. (2024). Assessing NASA-POWER precipitation product in predicting surface flow: Lower Jhelum River case study. *Air, Soil and Water Research*, 17, 11786221241280753. <https://doi.org/10.1177/11786221241280753>
- Kosovelj, K., & Zaplotnik, Ž. (2023). Indices of Pacific Walker circulation strength. *Atmosphere*, 14(2), 397. <https://doi.org/10.3390/atmos14020397>
- Kurniadi, A., Weller, E., Min, S.-K., & Seong, M.-G. (2021). Independent ENSO and IOD impacts on rainfall extremes over Indonesia. *International Journal of Climatology*, 41(6), 3640–3656. <https://doi.org/10.1002/joc.7040>
- Kurniadi, A., Weller, E., Kim, Y.-H., & Min, S.-K. (2023). Evaluation of Coupled Model Intercomparison Project Phase 6 model-simulated extreme precipitation over Indonesia. *International Journal of Climatology*, 43(1), 174–196. <https://doi.org/10.1002/joc.7744>
- Kurniadi, A., Weller, E., Salmond, J., & Aldrian, E. (2024). Future projections of extreme rainfall events in Indonesia. *International Journal of Climatology*, 44(1), 160–182. <https://doi.org/10.1002/joc.8321>
- Ling, F., Luo, J. J., Li, Y., Tang, T., Bai, L., Ouyang, W., & Yamagata, T. (2022). Multi-task machine learning improves multi-seasonal prediction of the Indian Ocean Dipole. *Nature Communications*, 13(1), 7681. <https://doi.org/10.1038/s41467-022-35412-0>
- Loveday, N., Taggart, R., & Khanarmuei, M. (2024). A user-focused approach to evaluating probabilistic and categorical forecasts. *Weather and Forecasting*, 39(8), 1163–1180. <https://doi.org/10.1175/WAF-D-23-0201.1>
- Madushan, H., Jayaratne, C., & Wijemannage, A. (2025). Evaluation of NASA POWER daily rainfall products against ground observations in Sri Lanka. *Remote Sensing in Earth Systems Sciences*, 8, 264–272. <https://doi.org/10.1007/s41976-024-00173-5>
- Marzuki, M., Ramadhan, R., Yusnaini, H., Vonnisa, M., Muharsyah, R., Nugraha, Y., Sari, A. Y., & Erajalita, A. (2025). Long-term spatial-temporal variability, trends and extreme rainfall events over Indonesia based on 43 years of CHIRPS data. *International Journal of Climatology*, 45(14), e70107. <https://doi.org/10.1002/joc.70107>
- Materia, S., García, L. P., van Straaten, C., O, S., Mamalakis, A., Cavicchia, L., Coumou, D., de Luca, P., Kretschmer, M., & Donat, M. (2024). Artificial intelligence for climate prediction of extremes: State of the art, challenges, and future perspectives. *WIREs Climate Change*, 15(6), e914. <https://doi.org/10.1002/wcc.914>
- Moron, V., Robertson, A. W., & Boer, R. (2009). Spatial coherence and seasonal predictability of monsoon onset over Indonesia. *Journal of Climate*, 22(3), 840–850.

- <https://doi.org/10.1175/2008JCLI2435.1>
- Necker, T., Wolfgruber, L., Kugler, L., Weissmann, M., Dorninger, M., & Serafin, S. (2024). The fractions skill score for ensemble forecast verification. *Quarterly Journal of the Royal Meteorological Society*, 150(764), 4457–4477. <https://doi.org/10.1002/qj.4824>
- Nguyen-Thanh, H., Ngo-Duc, T., & Herrmann, M. (2023). The distinct impacts of the two types of ENSO on rainfall variability over Southeast Asia. *Climate Dynamics*, 61(5), 2155–2172. <https://doi.org/10.1007/s00382-023-06673-2>
- Nugroho, A. R., Tamagawa, I., & Harada, M. (2022). Spatiotemporal analysis on the teleconnection of ENSO and IOD to the stream flow regimes in Java, Indonesia. *Water*, 14(2), 168. <https://doi.org/10.3390/w14020168>
- Price, I., Sanchez-Gonzalez, A., Alet, F., Andersson, T. R., El-Kadi, A., Masters, D., Ewalds, T., Stott, J., Mohamed, S., Battaglia, P., Lam, R., & Willson, M. (2025). Probabilistic weather forecasting with machine learning. *Nature*, 637(8044), 84–90. <https://doi.org/10.1038/s41586-024-08252-9>
- Ramadhan, R., Marzuki, M., Yusnaini, H., Muharsyah, R., Suryanto, W., Sholihun, S., & Vonnisa, M. (2023). A preliminary assessment of the GSMAp version 08 products over Indonesian Maritime Continent against gauge data. *Remote Sensing*, 15(4), 1115. <https://doi.org/10.3390/rs15041115>
- Risbey, J. S., Squire, D. T., Baldissera, Pacchetti, M., Black, A. S., Chapman, C. C., Dessai, S., Irving, D. B., Matear, R. J., Monselesan, D. P., Moore, T. S., Richardson, D., Sloyan, B. M. & Tozer, C. R. (2022). Common issues in verification of climate forecasts and projections. *Climate*, 10(6), 83. <https://doi.org/10.3390/cli10060083>
- Saleh, A., Tan, M. L., Yaseen, Z. M., & Zhang, F. (2024). Integrated machine learning models for enhancing tropical rainfall prediction using NASA POWER meteorological data. *Journal of Water and Climate Change*, 15(12), 6022–6042. <https://doi.org/10.2166/wcc.2024.719>
- Shravankumar, S.M., Paliwal, V., & Lavanya, B. (2026). Evaluating Seasonal Variability in Rainfall Forecast Accuracy Using Comparative Regression Modelling Approaches. *Water Resources Management*, 40(9), 401. <https://doi.org/10.1007/s11269-026-04597-0>
- Sparks, A. H. (2018). nasapower: A NASA POWER global meteorology, surface solar energy and climatology data client for R. *Journal of Open Source Software*, 3(30), 1035. <https://doi.org/10.21105/joss.01035>
- Sulaiman, A., Osaki, M., Takahashi, H., Yamanaka, M. D., Susanto, R. D., Shimada, S., Kimura, K., Hirano, T., Wetadewi, R. I., Sisva, S., Kato, T., Kozan, O., Kubo, H., Awaluddin, A., & Tsuji, N. (2023). Peatland groundwater level in the Indonesian maritime continent as an alert for El Niño and moderate positive Indian Ocean Dipole events. *Scientific Reports*, 13, 939. <https://doi.org/10.1038/s41598-023-27393-x>
- Supari, S., Tangang, F., Salimun, E., Aldrian, E., Sopaheluwakan, A., & Juneng, L. (2018). ENSO modulation of seasonal rainfall and extremes in Indonesia. *Climate Dynamics*, 51(7–8), 2559–2580. <https://doi.org/10.1007/s00382-017-4028-8>
- Tan, M. L., Armanuos, A. M., Ahmadianfar, I., Demir, V., Heddarn, S., Al-Areeq, A. M., Abba, S. I.,

- Halder, B., Lilinc, H. C., & Yaseen, Z. M. (2023). Evaluation of NASA POWER and ERA5-Land for estimating tropical precipitation and temperature extremes. *Journal of Hydrology*, 624, 129940. <https://doi.org/10.1016/j.jhydrol.2023.129940>
- Tayyeh, H. K., & Mohammed, R. (2023). Analysis of NASA POWER reanalysis products to predict temperature and precipitation in Euphrates River basin. *Journal of Hydrology*, 619, 129327. <https://doi.org/10.1016/j.jhydrol.2023.129327>
- Wang, G., Cai, W., & Santoso, A. (2024a). Simulated thermocline tilt over the tropical Indian Ocean and its influence on future sea surface temperature variability. *Geophysical Research Letters*, 48(6), e2020GL091902. <https://doi.org/10.1029/2020GL091902>
- Wang, G., Cai, W., Santoso, A., Abram, N., Ng, B., Yang, K., Geng, T., Doi, T., Du, Y., Izumo, T., Ashok, K., Li, J., Li, T., McKenna, S., Sun, S., Tozuka, T., Zheng, X., Liu, Y., Wu., L., Jia, F., Hu, S., & Li, X. (2024b). The Indian Ocean Dipole in a warming world. *Nature Reviews Earth & Environment*, 5(8), 588–604. <https://doi.org/10.1038/s43017-024-00573-7>
- Wang, G., Cai, W., & Santoso, A. (2024c). Variability of the Indian Ocean Dipole post-2100 reverses to a reduction despite persistent global warming. *Nature Communications*, 15, 5023. <https://doi.org/10.1038/s41467-024-49401-y>
- Wani, O. A., Mahdi, S. S., Yeasin, M., Kumar, S. S., Gagnon, A. S., Danish, F., Al-Ansari, N., El-Hendawy, S. & Mattar, M. A. (2024). Predicting rainfall using machine learning, deep learning, and time series models across an altitudinal gradient in the North-Western Himalayas. *Scientific Reports*, 14, 27876. <https://doi.org/10.1038/s41598-024-77687-x>
- Watanabe, M., Iwakiri, T., Dong, Y., & Kang, S. M. (2023). Two competing drivers of the recent Walker circulation trend. *Geophysical Research Letters*, 50(23), e2023GL105332. <https://doi.org/10.1029/2023GL105332>
- Watanabe, M., Kang, S. M., Collins, M., Hwang, Y.-T., McGregor, S., & Stuecker, M. F. (2024). Possible shift in controls of the tropical Pacific surface warming pattern. *Nature*, 630(8016), 315–324. <https://doi.org/10.1038/s41586-024-07452-7>
- Wei, Z., & Yuan, N. (2024). Identifying climate memory impacts on climate network analysis: A new approach based on fractional integral techniques. *Climate Dynamics*, 62(5), 3465–3476. <https://doi.org/10.1007/s00382-023-07076-z>
- Wilks, D. S. (2019). *Statistical methods in the atmospheric sciences* (4th ed.). Elsevier. <https://doi.org/10.1016/C2017-0-03921-6>
- Wu, M., Li, C., Collins, M., Li, H., Chen, X., Zhou, T., & Zhang, Z. (2024). Early emergence and determinants of human-induced Walker circulation weakening. *Nature Communications*, 15, 9161. <https://doi.org/10.1038/s41467-024-53509-6>
- Yang, R., Hu, J., Li, Z., Mu, J., Yu, T., Xia, J., Li, X., Dasgupta, A., & Xiong, H. (2024). Interpretable machine learning for weather and climate prediction: A review. *Atmospheric Environment*, 338, 120797. <https://doi.org/10.1016/j.atmosenv.2024.120797>

- Zhang, Y., Li, J., Diao, Y., Wang, Q., Wu, R., Liu, T., Jin, Y., Hou, Z., & Wang, H. (2024). Reconciling roles of the South China Sea summer monsoon and ENSO in prediction of the Indian Ocean dipole. *Environmental Research Letters*, 19(1), 014041. <https://doi.org/10.1088/1748-9326/ad122a>
- Zehri, S., Yulihastin, E., Marpaung, F., Adiputra, A., Mushoddik, M., Purwadani, N. N., & Gammamerdianti, G. (2025). Diverse impact of 2023 El Niño on weather patterns over the Indonesian Maritime Continent. *Journal of Southern Hemisphere Earth System Science*, 75(2), ES25005. <https://doi.org/10.1071/ES25005>
- Zhou, L., & Zhang, R.-H. (2023). A self-attention-based neural network for three-dimensional multivariate modeling and its skillful ENSO predictions. *Science Advances*, 9(10), eadf2827. <https://doi.org/10.1126/sciadv.adf2827>