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Assessing Inter-Provincial Climate Connectivity in Indonesia Using Detrended Cross-Correlation and Network Analysis

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Abstract

Understanding the spatiotemporal structure of climate variability is critical for implementing effective regional adaptation measures, especially in geophysically complex systems like Indonesia's archipelago. This study utilizes Detrended Fluctuation Analysis (DFA), Detrended Cross-Correlation Analysis (DCCA), and Complex Networks analysis to explore daily recorded temperature, relative humidity, precipitation, solar radiation, and wind velocity for 38 Badan Meteorologi, Klimatologi dan Geofisika (BMKG) provincial stations across Indonesia (January 2010 – December 2025). We use the Autoregressive Fractionally Integrated Moving Average (ARFIMA) model to impute missing values in climate data of Indonesia's 38 provinces. DFA analysis finds that the α values for all study variables are greater than 0.5, confirming that the climate across the entire study region exhibits long-range persistence and that α values increase

systematically as the time scale is extended. Inter-province connectivity between DCCA coefficients $\rho_{\text{DCCA}}(\mathbf{n})$, which are scale-dependent, is near zero at short ($n < 10$ days); both under monsoon and ENSO forcing. This is characterized by the lack of detectable cross-correlation at any timescale from Bali and Nusa Tenggara and Maluku, but the broadest and most persistent coupling of Papua. Timescale-specific hub structures are identified by network analysis: Sumatera Selatan, Kalimantan Selatan, and Papua Selatan emerge as broad cross-island hubs for temperature, humidity, and precipitation/wind, respectively; precipitation and wind exhibit the most extensive cross-island connectivity governed by organized convection and monsoon circulation; solar radiation reveals a stable bimodal topology separating western Java Sea from eastern Pacific cloud regimes. These outcomes offer a multi-scale, multi-variable characterization of Indonesian inter-provincial climate connectivity, with direct practical relevance for both monitoring network optimization and regional climate modeling.

Keywords: DCCA, Climate network, Long-range dependence, Indonesian climate

1 Introduction

The question of climate variability in the tropics is one of the more consequential frontiers in modern climate science as global warming progresses and ongoing anthropogenic forcing leads to a proliferation of extreme weather events [1]. Whether through rising temperatures, changing precipitation regimes, or increasing hydroclimatic instability, such threats to food security, public health, and socioeconomic stability are acute throughout the tropics [2]. It is therefore crucial for the development of effective adaptation and early warning systems to understand the spatiotemporal dynamics of these changes, particularly at regional scales and across intermediate observational timescales. Indonesia, in this context, is both a critical and analytically challenging case study.

Indonesia is the largest archipelago in the world, spanning over 5,000 kilometers across the equator and comprising more than 17,000 islands with heterogeneous topography, land use, and oceanic boundary conditions. Its climate is influenced by a set of large-scale forcing mechanisms, such as the Asian–Australian monsoon system, El Niño–Southern Oscillation (ENSO), and the Indian Ocean Dipole (IOD), which control precipitation, temperature, humidity, and wind patterns at seasonal to interannual timescales [3, 4]. These drivers do not act independently of one another but rather have nonlinear interactions across space and time, resulting in heterogeneous climate responses across the archipelago that break with conventional univariate approaches to regional climate studies [5]. Characterizing the co-variation of climate variables across Indonesian provinces and how these relationships vary over different timescales is therefore pivotal for regional risk assessment, climate monitoring, and policy-making.

For such a pivotal question, the vast majority of climate work in Indonesia has been based either on single-variable studies or on coarsely resolved global model output, which cannot resolve variability at local scales [6, 7]. The Coupled Model Intercomparison Project Phase 6 (CMIP6) and related global climate models offer important

projections of possible future climates [8]. However, broad-scale perspectives need to be underpinned by ground-truthing against empirical, observational data relevant to Indonesia’s uniquely complex atmospheric characteristics. Indonesia’s national meteorological agency, the Badan Meteorologi, Klimatologi dan Geofisika (BMKG), operates a large network of stations that yield densely spatially and temporally continuous climate records throughout the archipelago [9] harnessing such observational data rendering possible a data-driven assessment of the spatiotemporal coupling structure across multiple climate variables and provinces, which is still unresolved and inspires the methodological framework pursued in this study.

One of the main challenges with regional climate data analysis is that observed time series are, in general, nonstationary and often display non-Gaussian statistical characteristics, which violates standard correlation assumptions. Detrended Fluctuation Analysis (DFA) was first proposed by Peng et al. [10], providing a powerful framework to explore the scaling properties and long-range dependence of geophysical processes, allowing us to uncover persistent or anti-persistent dynamics in climate time series without imposing stationarity [11]. Further, the Detrended Cross-Correlation Analysis (DCCA) was developed by Podobnik and Stanley [12] to generalize the DFA method and detect cross-correlations among two nonstationary time series at different timescales simultaneously. The DCCA cross-correlation coefficient, formalized by Zebende [13], provides a normalized, scale-resolved assessment of inter-series coupling that is resistant to trends and distributional assumptions. Examples of DCCA applications to climate data highlight its potential as an analytical tool for describing complex climatological interactions, with studies focusing on phenomena such as scale-dependent coupling structures in temperature fields [14], precipitation systems [15], and cross-scale interaction patterns in multivariate datasets [16].

Supplementation of DCCA with complex network analysis adds another layer of interpretation by geospatializing pairwise correlation coefficients within a graph structure in which nodes are spatial locations, and edges represent the strength of climatic linkages between them [17]. The approaches based on climate networks have proven quite useful for identifying leading regional climatic states, teleconnection modes, and the spatial organization of large-scale climate variability [18, 19]. The networks constructed from DCCA-derived correlation coefficients offer a scale-aware, statistically principled means of characterizing the network topology of regional climate connectivity. This merger has thus far been overlooked in tropical archipelagic systems, such as Indonesia.

While the application of DCCA and network analysis has been growing separately in climate systems, to our knowledge, there has not yet been a comprehensive study of long-range dependence, multiscale interprovincial cross-correlations, and climate network topology for multiple atmospheric variables across the Indonesian archipelago. Current studies focus only on single variables [6, 7] or specific islands/subregions [14], and most are based on reanalysis products rather than station-level observational data [6, 14]. More broadly, island geography and shared membership in a climate zone as structural drivers of inter-province climate connectivity have yet to be systematically quantified within this region. This study fills those gaps by presenting a unified DFA–DCCA–network framework for observing multivariate, province-level

observational data and, for the first time, a comprehensive, data-driven structure of Indonesia’s regional climate connectivity across both spatial and temporal scales.

This study utilized a combined DFA–DCCA–network framework using the BMKG observational dataset covering the last 15 years (2010–2025) for five climate variables (temperature, humidity, rainfall, sun radiation, and wind velocity) across all provinces in Indonesia. The more specific objectives can be divided into three parts: (i) the scaling behaviors and long-range dependence of each climate variable by using DFA, (ii) the extent of inter-provincial cross-correlations at various timescales using DCCA, and (iii) Indonesia’s provincial climate network topology and dominant connectivity hubs. The results will help develop an improved, empirically-based understanding of Indonesia’s regional climate system, which is highly influenced by its geography and has direct relevance to spatially coordinated climate monitoring, early warning systems, and national adaptation policy.

2 Data and Methods

2.1 Study Area and Data Sources

This study focuses on Indonesia, which comprises 38 provinces with diverse topographic, oceanic, and climatic characteristics. The analysis is applied spatially to every province in Indonesia, using meteorological station data.

Meteorological observational data were obtained from the BMKG Open Data Portal (<https://dataonline.bmkg.go.id/>), the authorized data repository of Badan Meteorologi, Klimatologi dan Geofisika [9]. The dataset covers the period from January 2010 to December 2025, providing a 15-year daily-time observational record. It is worth noting that the existing institutional policy limits direct public access via the BMKG portal to a rolling 2-year window; access to long-term records requires account registration, and researchers outside Indonesia may need to submit formal data requests through BMKG’s institutional channels.

Data for air temperature ($^{\circ}\text{C}$), humidity (%), precipitation (mm), sun radiation (hours), and wind velocity (m/s) were combined to represent five principal meteorological variables. These variables were chosen for their physical relevance to Indonesia’s climate system and for their ability to jointly characterize the leading modes of atmospheric variability which show thermodynamic state, moisture content, hydrological forcing, radiative forcing, and dynamic circulation [3, 5]. Together, they allow a full characterization of the spatiotemporal coupling structure of the regional climate across the archipelago.

2.2 Analytical Framework

The analytical framework employed in this research combines three successive methodological components: DFA [10, 11] to characterize the scaling nature of single time series, DCCA [12, 13] to assess inter-province cross-correlation across multiple timescales and complex network analysis to project the resulting correlation structure into a spatial connectivity graph [17–19]. The computational routines themselves are

159 guided by the equations laid out in [20–22]. The mathematical foundations of each
 160 stage are described below.

161 2.3 Detrended Fluctuation Analysis (DFA)

162 Long-range dependence in a time series suggests that wide fluctuations at different
 163 timescales are statistically correlated via a power-law scaling function characterizing
 164 the system. To quantify this property in nonstationary meteorological records for
 165 which conventional autocorrelation analysis is invalid, we use DFA, first developed by
 166 Peng et al. [10], and further extended by Kantelhardt et al. [11].

167 For a meteorological time series $\{Y_i\}_{i=1}^N$ with sample mean $\bar{Y}$, the method begins
 168 by constructing the cumulative deviation profile:

$$X_k = \sum_{i=1}^k (Y_i - \bar{Y}), \quad k = 1, \dots, N \quad (1)$$

169 This step of integration transforms short-scale fluctuations into a slowly varying
 170 signal, whose local trend structure can be systematically removed. The profile X_k is
 171 segmented into non-overlapping segments of length n , and through each segment a
 172 linear polynomial is fitted with the least squares method to model the local trend
 173 $P(n)$. The fluctuation function is then defined as the root-mean-square amplitude of
 174 these detrended residuals over all segments:

$$F(n) = \sqrt{\frac{1}{N} \sum_{k=1}^N (X_k - P(n))^2} \quad (2)$$

175 When long-range correlations are present, $F(n)$ follows a power-law scaling
 176 relationship over a range of segment sizes n :

$$F(n) \propto n^{\alpha_{\text{DFA}}} \quad (3)$$

177 The scaling exponent α_{DFA} is determined by fitting a straight line in log-log space
 178 and fully describes the long-range dependence structure. DFA slopes $\alpha_{\text{DFA}} < 0.5$
 179 are suggestive of anti-persistent behavior, whereby positive deviations at any given
 180 scale are likely to be followed by a negative ones across scales; $\alpha_{\text{DFA}} = 0.5$ describes
 181 an uncorrelated signal (white noise), $0.5 < \alpha_{\text{DFA}} < 1.0$ indicates persistent long-
 182 range correlations among the fluctuations, $\alpha_{\text{DFA}} \approx 1.0$ is 1/f noise (pink noise), $1.0 <$
 183 $\alpha_{\text{DFA}} < 1.5$ imply nonstationary persistent behavior, and $\alpha_{\text{DFA}} \approx 1.5$ is characteristic
 184 of Brownian (integrated white) noise [10, 11].

185 2.4 Detrended Cross-Correlation Analysis (DCCA)

186 We calculate the DCCA cross-correlation coefficient $\rho_{\text{DCCA}}(n)$ to quantify the extent
 187 to which two provincial time series exhibit correlated fluctuations over a continuous
 188 range of timescales.

Let $\{x_i\}$ and $\{y_i\}$ represent two meteorological records of length N , recorded at two different provincial stations for the same variable. Their respective cumulative profiles are:

$$X_k = \sum_{i=1}^k (x_i - \langle x \rangle), \quad Y_k = \sum_{i=1}^k (y_i - \langle y \rangle) \quad (4)$$

For a certain timescale n , both profiles are divided into $(N - n)$ overlapping windows. In each window i , local polynomial trends $\tilde{X}_{k,i}$ and $\tilde{Y}_{k,i}$ are eliminated by least-squares fitting, and the detrended cross-covariance is calculated as:

$$f_{\text{DCCA}}^2(n, i) = \frac{1}{n+1} \sum_{k=i}^{i+n} (X_k - \tilde{X}_{k,i})(Y_k - \tilde{Y}_{k,i}) \quad (5)$$

Averaging over all windows yields the overall detrended cross-covariance function:

$$F_{\text{DCCA}}^2(n) = \frac{1}{N-n} \sum_{i=1}^{N-n} f_{\text{DCCA}}^2(n, i) \quad (6)$$

The individual DFA fluctuation amplitudes for each series, computed analogously as:

$$F_{\text{DFA},x}(n) = \sqrt{\frac{1}{N-n} \sum_{i=1}^{N-n} f_{\text{DCCA},x}^2(n, i)}, \quad F_{\text{DFA},y}(n) = \sqrt{\frac{1}{N-n} \sum_{i=1}^{N-n} f_{\text{DCCA},y}^2(n, i)} \quad (7)$$

serve as normalizing factors, yielding the scale-dependent cross-correlation coefficient [13]:

$$\rho_{\text{DCCA}}(n) = \frac{F_{\text{DCCA}}^2(n)}{F_{\text{DFA},x}(n) \cdot F_{\text{DFA},y}(n)}. \quad (8)$$

By its construction, $\rho_{\text{DCCA}}(n) \in [-1, +1]$, with $+1$ denoting perfect positive long-range cross-correlation, -1 perfect anti-correlation, and 0 the absence of any cross-correlation at scale n ; the coefficient is calculated across a logarithmically spaced array of n values producing an entire cross-correlation profile as a function of timescale. This property renders $\rho_{\text{DCCA}}(n)$ particularly well adapted to tropical climate records where correlation patterns exhibit substantial variability across daily, seasonal, and interannual scales [14–16].

2.5 Network Construction and Analysis

This step enables defining the complete set of inter-provincial $\rho_{\text{DCCA}}(n)$ values, calculated independently for each of the five meteorological variables and all timescales under investigation. These data elements represent a weighted adjacency matrix for building a provincial climate network. Concretely, this network can be defined formally as an undirected weighted graph $G = (V, E)$, where the node set V corresponds to the

213 38 provincial stations and the edge (E) weight between nodes i and j is given by:

$$w_{ij}(n) = \rho_{\text{DCCA}}(n). \quad (9)$$

214 To isolate the climatically most meaningful linkages and avoid a topologically sat-
215 urated network, we impose a sparsification threshold: only edges with absolute weight
216 greater than the 90th percentile of pairwise ρ_{DCCA} values are retained. This top-10%
217 criterion, in agreement with the thresholding approach employed [22] and verified by
218 the field of climate networks [17, 18], leads to a sparse graph whose edges represent
219 strong, statistically significant inter-province climate links.

220 The two-dimensional network topology is described using four graph-theoretic met-
221 rics. Degree centrality identifies provinces with strong climatic coupling to many other
222 provinces, which can act as potential regional climate coherence hubs. The clustering
223 coefficient measures the degree to which climatically connected provinces tend to form
224 locally dense subgroups, indicating regional climate signals in space. The average path
225 length is the average geodesic distance between nodes of a network and is therefore
226 an index of how quickly climate signals can traverse the provincial network. Finally,
227 community detection implemented via a modularity-maximization algorithm defines
228 partitions of the network into internally cohesive groups of provinces, interpreted in
229 the context of island geography and shared membership within climate zones.

230 3 Results

231 Daily meteorological observations were obtained from the BMKG Open Data Portal,
232 covering 38 climatological stations: one per province distributed across the Indonesian
233 archipelago (Fig. 1). The observational record spans January 2010 to December 2025,
234 yielding a maximum of 5,844 daily observations per station per variable.

235 The study examines five principal meteorological variables: wind velocity, air tem-
236 perature, precipitation, relative humidity, and sun radiation. These variables are
237 crucial for cultivating a thorough comprehension of climatic patterns across various
238 Indonesian locations. Moreover, analyzing these metrics facilitates the identification
239 of interconnections among environmental factors that affect weather and climate
240 in Indonesia. Such insights are essential for efficient natural resource management,
241 climate-related planning, and the formulation of adaptive strategies to respond to
242 climatic variability.

243 The degree of data completeness showed significant variation across provinces and
244 meteorological variables (Table 1). Kalimantan Selatan experienced around 10.85%
245 of air temperature data missing, corresponding to 634 days without measurements.
246 Papua Selatan had the highest percentage of missing relative humidity readings, at
247 13.12%, equivalent to around 767 unrecorded days. A significant disparity emerged in
248 the precipitation dataset for Papua Pegunungan: 35.90% of the data, or 2,098 daily
249 records, were missing. Sun radiation data in Sulawesi Tengah showed deficiencies,
250 with 7.26% missing, totaling approximately 424 days. Simultaneously, wind velocity
251 data in Papua Selatan showed a 11.94% deficit, resulting in roughly 698 missing daily
252 measurements. Of all variables, precipitation had the most significant data deficiencies
253 across provinces.

Table 1: Location and missing data summary for the 38 BMKG provincial stations across Indonesian islands

Island	Province	Latitude	Longitude	Percentage of missing value (%)				
				Temperature	Humidity	Precipitation	sun radiation	Wind velocity
Sumatera	Aceh (ACE)	5.52	95.41	3.82	3.75	31.50 [†]	6.05	3.65
Sumatera	Sumatera Utara (SUM)	3.63	98.88	1.02	0.95	13.25	2.95	0.81
Sumatera	Sumatera Barat (SBR)	-0.78	100.28	2.75	2.62	21.80	5.75	0.88
Sumatera	Riau (RIA)	0.46	101.44	0.58	0.52	12.95	6.45	1.32
Sumatera	Kepulauan Riau (KEP)	0.92	104.53	1.05	0.10	13.50	1.82	0.07
Sumatera	Jambi (JAM)	-1.63	103.64	0.65	0.30	20.80	4.35	0.14
Sumatera	Bengkulu (BKL)	-3.86	102.34	0.45	0.35	17.50	1.95	0.05
Sumatera	Sumatera Selatan (SSLT)	-2.90	104.70	1.25	1.82	22.10	2.15	0.65
Sumatera	Bangka Belitung (BBL)	-2.16	106.13	2.92	2.75	9.35	5.85	1.02
Sumatera	Lampung (LPG)	-5.24	105.17	2.72	2.65	30.15 [†]	3.52	1.12
Jawa	Banten (BTN)	-6.11	106.12	0.88	0.85	12.80	2.32	0.42
Jawa	DKI Jakarta (DKI)	-6.15	106.84	0.41	0.28	12.45	2.45	0.03
Jawa	Jawa Barat (JBR)	-6.88	107.59	2.41	2.45	24.50	3.15	0.82
Jawa	Jawa Tengah (JTG)	-6.97	110.37	4.25	5.15	15.35	4.75	1.55
Jawa	DI Yogyakarta (DIY)	-7.73	110.36	7.55	7.55	14.85	3.82	6.52
Jawa	Jawa Timur (JTM)	-7.37	112.78	2.22	2.15	9.65	4.85	0.42
Bali & Nusa Tenggara	Bali (BAL)	-8.74	115.16	1.05	1.02	7.65	1.52	0.12
Bali & Nusa Tenggara	Nusa Tenggara Barat (NTB)	-8.75	116.27	0.91	0.85	9.80	1.02	0.18
Bali & Nusa Tenggara	Nusa Tenggara Timur (NTT)	-10.17	123.66	2.95	2.85	8.05	2.58	0.41
Kalimantan	Kalimantan Barat (KBR)	-0.15	109.40	0.55	0.40	14.10	2.75	0.20
Kalimantan	Kalimantan Tengah (KTG)	-2.22	113.94	1.05	1.01	10.55	6.25	0.51
Kalimantan	Kalimantan Selatan (KSL)	-3.44	114.76	10.85	10.25	18.50	5.55	2.32
Kalimantan	Kalimantan Timur (KTM)	-1.26	116.89	2.52	2.15	8.95	1.45	0.11
Kalimantan	Kalimantan Utara (KUTR)	3.33	117.59	0.55	0.48	12.10	2.25	0.12
Sulawesi	Sulawesi Utara (SUT)	1.54	124.92	6.12	6.05	17.85	4.95	2.05
Sulawesi	Gorontalo (GOR)	0.63	122.85	9.85	9.85	14.80	5.12	2.25
Sulawesi	Sulawesi Tengah (STG)	-0.91	119.91	4.05	3.85	22.05	7.26	0.75
Sulawesi	Sulawesi Barat (SWB)	-3.54	118.97	6.95	6.95	16.50	3.98	1.45
Sulawesi	Sulawesi Selatan (SSL)	-5.06	119.55	2.98	2.85	10.75	1.65	0.22
Sulawesi	Sulawesi Tenggara (SGT)	-4.08	122.41	1.72	1.65	23.50	3.32	0.22
Maluku	Maluku (MAL)	-3.70	128.08	2.15	2.08	12.50	2.12	0.28
Maluku	Maluku Utara (MUT)	0.83	127.38	2.42	2.25	14.25	2.65	0.38
Papua	Papua (PAP)	-2.57	140.51	1.12	1.02	11.95	1.92	0.41
Papua	Papua Barat (PBR)	-0.89	134.06	2.45	2.32	18.10	4.15	4.52
Papua	Papua Selatan (PSEL)	-8.52	140.41	3.85	13.12	22.15	4.15	11.94
Papua	Papua Tengah (PTG)	-3.36	135.49	5.65	5.55	17.65	6.55	2.05
Papua	Papua Pegunungan (PPG)	-4.06	138.95	8.12	7.95	35.90[‡]	3.45	2.75
Papua	Papua Barat Daya (PBD)	-0.89	131.29	5.05	4.85	21.25	3.85	0.48

Note: All missing values were imputed prior to analysis using the Autoregressive Fractionally Integrated Moving Average (ARFIMA) method, which preserves the long-range dependence structure of the time series and has been validated for use with DFA and DCCA under missing data conditions [21]. Bold values indicate the highest missing rates per variable; [†] values $\geq 30\%$ require cautious interpretation; [‡] highest overall missing rate in the dataset (35.90%).



Fig. 1: Spatial distribution of the 38 BMKG provincial meteorological stations across the Indonesian archipelago

Daily meteorological records before analysis underwent Autoregressive Fractionally Integrated Moving Average (ARFIMA) imputation of missing values. It directly accounts for the structure of long-range dependence typical of climatological time series, which is not retained by standard interpolation methods (e.g., linear or spline interpolation). Recently, it was shown that ARFIMA-based imputation preserves the scale-free nature of the original series and produces unbiased estimates of α_{DFA} with missing rates as high as 50% [21]. Given that the maximum missing rate in this study is below this level (35.90% for Papua Pegunungan precipitation), all imputed series are appropriate for the following DFA and DCCA analyses.

3.1 DFA Results

The DFA analysis identifies a crucial statistic, the scaling exponent α_{DFA} , that provides insight into the long-range correlations inherent in climate-related time series. This exponent quantifies the extent of self-affinity in the data, indicating how patterns at more minor time scales reflect those at larger scales, analogous to a fractal in which the complex features of a leaf's veins replicate the configuration of the entire branch. A portion of data that accurately reflects the entirety demonstrates self-affinity, a characteristic of fractal dynamics that highlights the interrelation of temporal patterns.

In Fig. 2, color coding is employed to enhance clarity in showing DFA findings, facilitating intuitive interpretation across various time scales. Light blue indicates

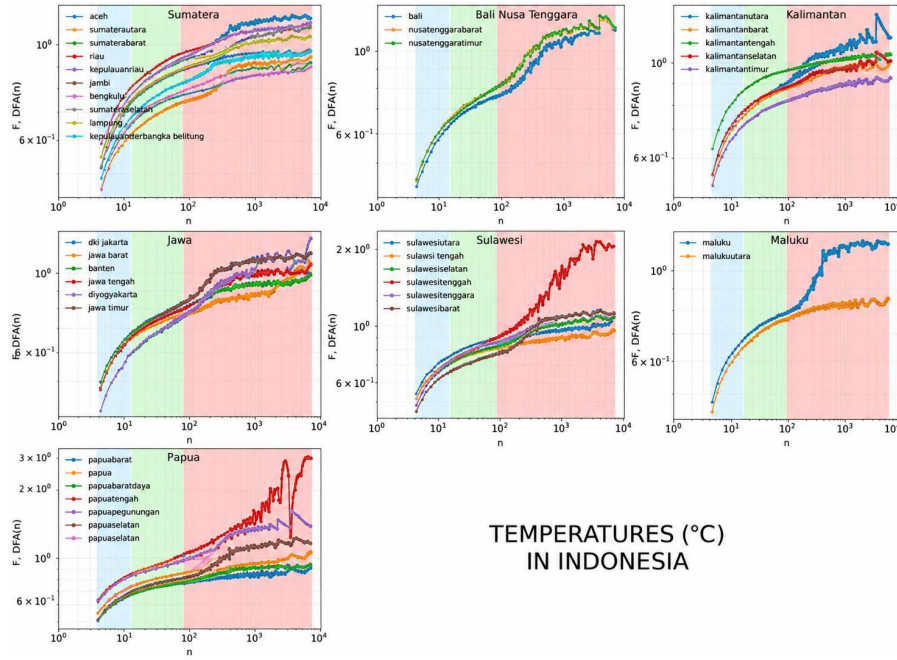


Fig. 2: Detrended fluctuation analysis for temperature for seven islands in Indonesia

short-term scales, illustrating daily-to-weekly variations; green represents medium-term intervals, typically showing monthly fluctuations; and pink indicates long-term spans, spanning seasonal or annual trends. This chromatic methodology facilitates the identification of shifts in fluctuation patterns. It highlights that α_{DFA} values may differ across temporal contexts, underscoring the need to assess long-range correlations within their respective scales to understand the data's intrinsic rhythms comprehensively.

The average air temperature in Indonesia typically ranges from 25 °C to 31 °C, influenced by regional factors and seasonal fluctuations. Numerous provinces exhibit signs of a progressive warming trend. Temperature patterns exhibit significant swings over medium and long-term timeframes, although short-term variations are generally less stable. The temperature time series was analyzed using DFA to investigate these dynamics further, and the resulting fluctuation patterns are illustrated in Fig. 2. It shows that the fluctuation function $F(n)$ ranges from about 0.4 to 2.0, giving an overall fluctuation span of roughly 1.6. This suggests that temperature variability across the observed time scales is moderate, without any sharp or extreme shifts. At shorter time scales, the average DFA exponent $\alpha_{\text{DFA}} = 0.30$, indicating anti-persistent behavior, meaning that temperature values tend to move in the opposite direction of their previous trend. At medium time scales, the average α_{DFA} drops to 0.09, indicating even stronger anti-persistence, in which temperature changes more frequently to reverse course. Over longer time scales, the average α_{DFA} declines further to 0.05, suggesting

that temperature variations become even quicker and more strongly anti-persistent as the time scale increases.

3.2 ρ_{DCCA} Results

This study uses the DCCA to investigate the interrelationships among meteorological and climatic variables across Indonesia. The analysis is performed across various temporal scales from short to long-term and is categorized into seven primary geographical islands: Sumatera, Jawa, Bali and Nusa Tenggara, Kalimantan, Sulawesi, Maluku, and Papua.

Changes in weather, climate, and environmental patterns are explored using BMKG observational data across three time-scale categories. These include daily fluctuations (short-term, $n < 10$), monthly-to-seasonal variations (medium-term, $10 < n < 100$), and longer-term or decadal patterns ($n > 100$). This multi-scale approach enables a comprehensive assessment of how atmospheric processes behave and interact across different temporal horizons in Indonesia's diverse climatic regions.

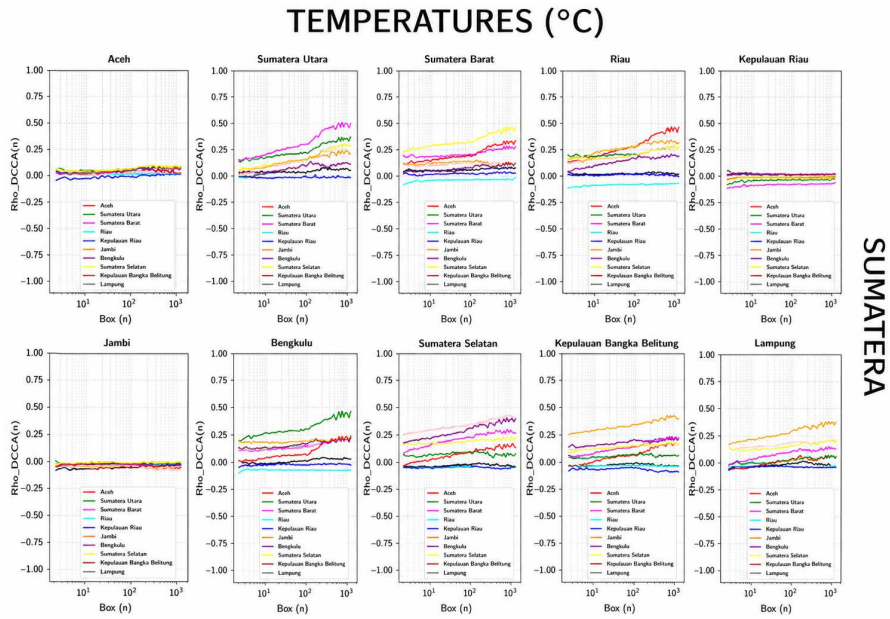


Fig. 3: Cross-correlation for temperature in Sumatera Island

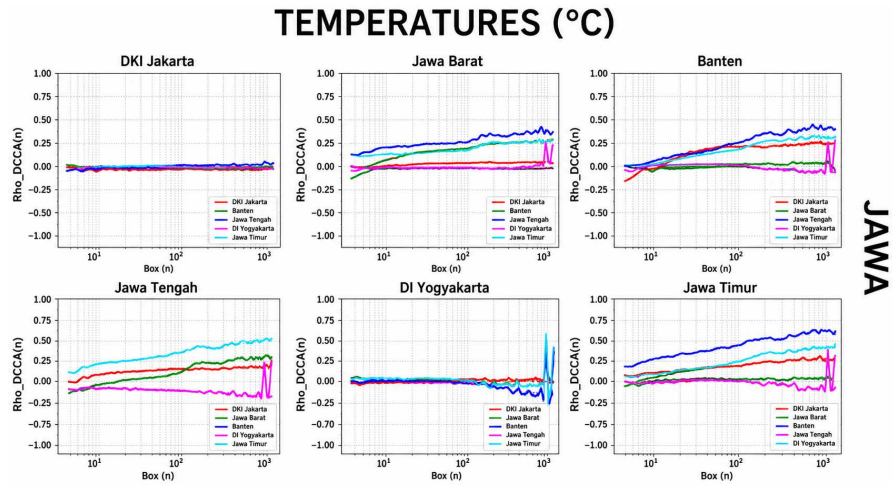


Fig. 4: Cross-correlation for temperature in Jawa Island

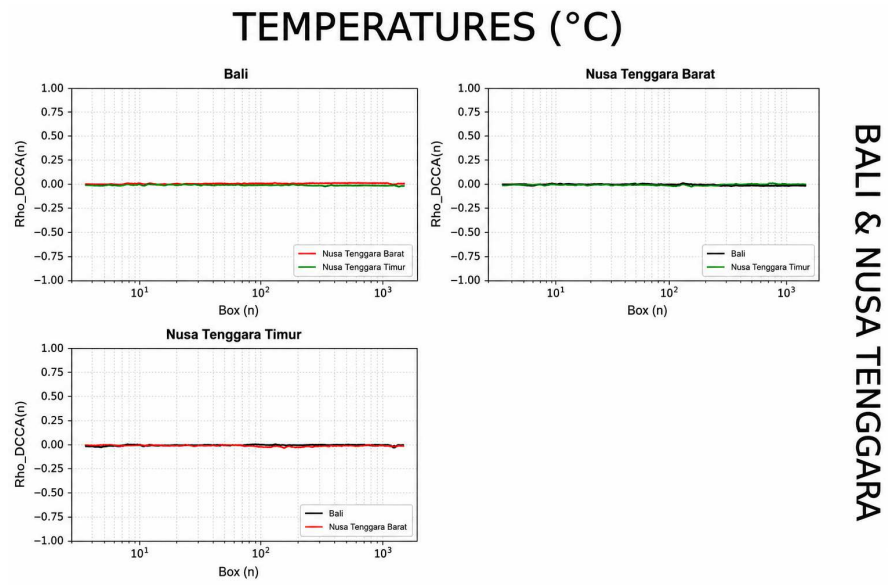


Fig. 5: Cross-correlation for temperature in Bali and Nusa Tenggara Island

TEMPERATURES (°C)

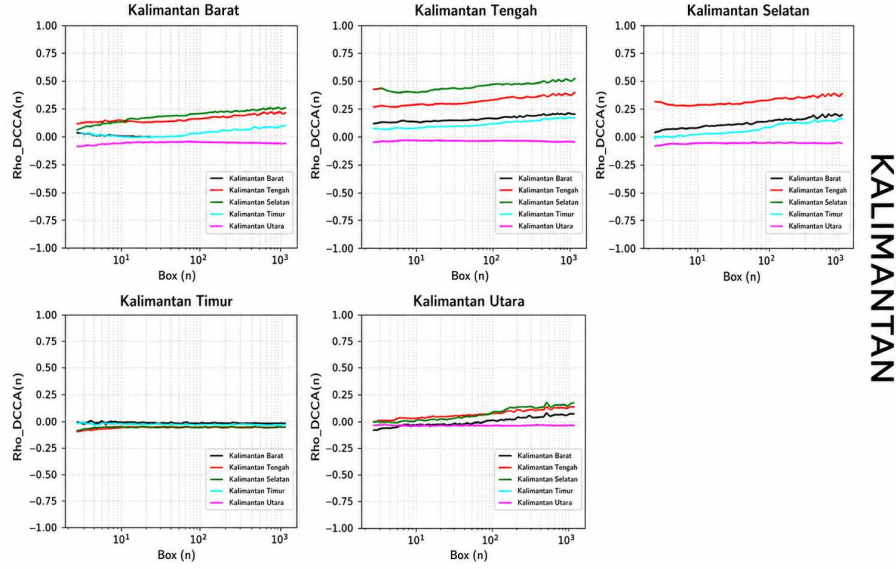


Fig. 6: Cross-correlation for temperature in Kalimantan Island

TEMPERATURES (°C)

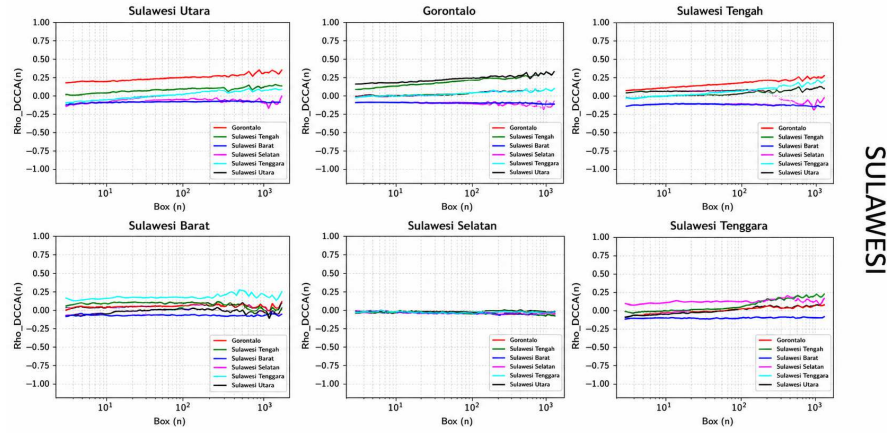


Fig. 7: Cross-correlation for temperature in Sulawesi Island

309 The cross-correlation coefficients $\rho_{\text{DCCA}}(n)$ of daily temperature among Sumat-
 310 era provinces show a similar scale-dependent behavior for all station pairs (Fig. 3).
 311 At short timescales ($n < 10$ days). There is, however, some spatial heterogeneity
 312 in the results: we find relatively greater inter-provincial coupling in Sumatera Barat
 313 and Sumatera Selatan at long timescales, and consistently weaker correlations across
 314 all temporal scales in Kepulauan Riau and Bengkulu. Importantly, this leads to low
 315 ($\rho_{\text{DCCA}}(n) < 0.50$) at all scales, indicating only a moderate range of temperature
 316 synchrony throughout the island rather than strong across the board.

317 Spectra of cross-correlation coefficients over daily temperature among Jawa
 318 provinces are more differentiated with respect to space in comparison to the group of
 319 Sumatera (Fig. 4). DKI Jakarta and DI Yogyakarta have $\rho_{\text{DCCA}}(n) \approx 0$ across all
 320 timescales and all province pairs, meaning effectively no cross-correlation with the rest
 321 of the island on any temporal scale. By contrast, Jawa Tengah and Jawa Timur become
 322 systematically more positively correlated as n increases, peaking at $\rho_{\text{DCCA}} \approx 0.50$
 323 when $n > 100$ days. Jawa Barat and Banten have similarly moderate long-timescale
 324 cross-correlations ($\rho_{\text{DCCA}} \approx 0.25$ – 0.30) with strength decreasing to much lower values
 325 on shorter scales. Together, these results reveal our key finding: a strong west-to-east
 326 gradient in interprovincial temperature coupling, weakest in the western provinces and
 327 strongest in the central-eastern provinces.

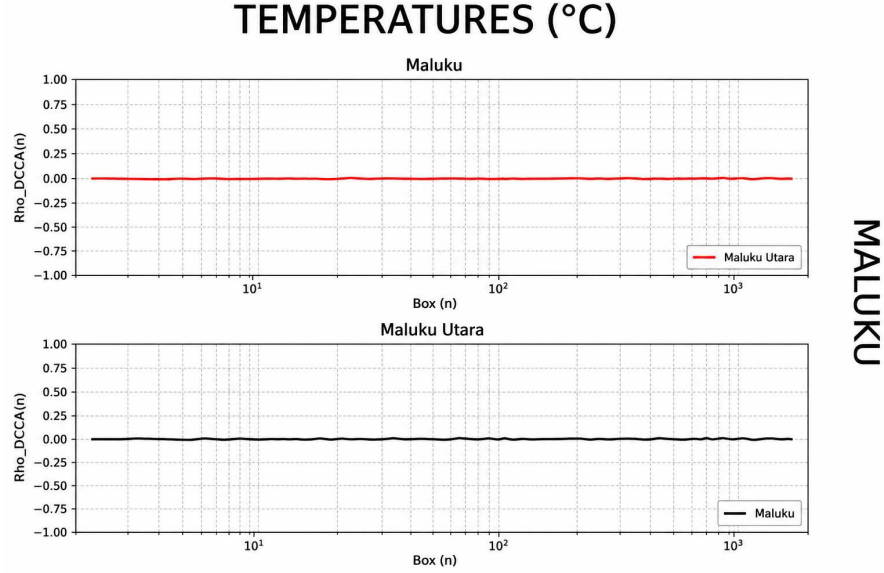


Fig. 8: Cross-correlation for temperature in Maluku Island

328 In all pairwise combinations (Bali–Nusa Tenggara Barat, Bali–Nusa Tenggara
 329 Timur, Nusa Tenggara Barat–Nusa Tenggara Timur) the cross-correlation coefficient
 330 $\rho_{\text{DCCA}}(n)$ for daily temperature among the three Bali and Nusa Tenggara provinces is

TEMPERATURES (°C)

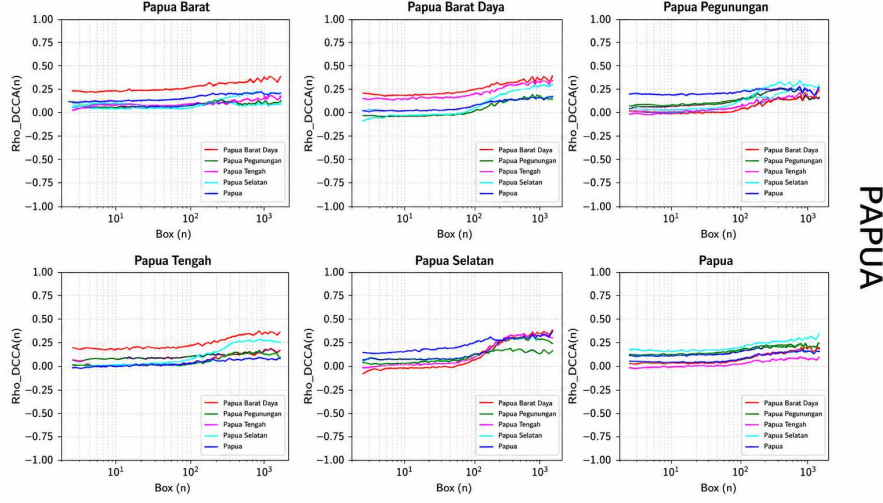


Fig. 9: Cross-correlation for temperature in Papua Island

virtually zero ($\rho_{DCCA}(n) \approx 0$) across the entire range of timescales ($n = 10$ – 1000 days), with no systematic increase in correlation strength as box size increases (Fig. 5). No cross-correlation is observed in either panel across all temporal scales, distinguishing this island group from all others in this study.

The DCCA cross-correlation coefficients $\rho_{DCCA}(n)$ between daily temperature among Kalimantan provinces show a spatially continuous geographical structure (Fig. 6). Cross-correlations are strongest between Kalimantan Tengah and Kalimantan Selatan, where $\rho_{DCCA}(n)$ rises monotonically from a value near zero at short timescales to about 0.45–0.50 for long timescales ($n > 100$ days). We find moderate positive correlations ($\rho_{DCCA} \approx 0.15$ – 0.25) between Kalimantan Barat with Kalimantan Selatan and Kalimantan Tengah at long timescales, and a moderately-stronger coupling of Kalimantan Utara with the western (and central) provinces that strengthens gradually with increasing n . Kalimantan Timur, on the other hand, is fully decoupled from all timescales with $\rho_{DCCA}(n) \approx 0$ across all Kalimantan provinces.

Cross-correlation coefficients $\rho_{DCCA}(n)$ for daily temperature among Sulawesi provinces have a different pattern than all other island groups, especially at short timescales (Fig. 7). In contrast to Sumatera and Jawa — where $\rho_{DCCA}(n) \approx 0$ for small n — pairs of Sulawesi provinces exhibit positive cross-correlations already at short timescales, with the suggestion that $\rho_{DCCA}(n)$ declines rapidly for large n . Along short scales, Sulawesi Utara and Gorontalo show the strongest coupling ($\rho_{DCCA} \approx 0.25$ – 0.40), as do Gorontalo and Sulawesi Tengah ($\rho_{DCCA} \approx 0.25$ – 0.30). Sulawesi Barat and Sulawesi Tenggara exhibit moderate inter-province coupling ($\rho_{DCCA} \approx 0.15$ – 0.25), relatively consistent across timescales. On the other hand, across

the entire range of n for Sulawesi Selatan, we see $\rho_{\text{DCCA}}(n) \approx 0$ to all other Sulawesi provinces.

The cross-correlation between Maluku and Maluku Utara is $\rho_{\text{DCCA}}(n) \approx 0$ over the full range of sample box sizes ($n = 10 - 1000$ days), with no systematic increase with timescale or directional trend in both panels (Fig. 8). No common scaling behavior is seen between the temperature fluctuations of the two provinces at any time scale.

The cross-correlation coefficients $\rho_{\text{DCCA}}(n)$ are significantly positive for daily temperatures across the Papua provinces (Fig. 9). Unlike the pairwise strongest cross-correlations between Maluku, Bali and Nusa Tenggara, all pairs in both Papua provinces show positive cross-correlations that are already evident at short timescales ($n = 100$ days). Papua Tengah has moderate coupling with nearly all provinces, while Papua Pegunungan demonstrates the least strength for cross-correlations across province pairs.

3.3 Network Analysis

The temperature network topology changes significantly along the three timescales studied (Fig. 10). At the short timescale ($n = 10$ days, panel a), the network represents a sparsely-connected structure: Sulawesi Selatan serves as an inter-island hub connecting Kalimantan and Jawa provinces (node in upper portion of the grey box), with the lower area of this network heralding loosely clustered nodes from Jawa, Bali and Nusa Tenggara. Similarly, Papua Pegunungan, Papua, Papua Selatan, and Maluku are still peripheral. On the medium timescale ($n = 100$ days, panel b), a particularly strong mega-cluster emerges that includes almost all Jawa provinces, Bali and Nusa Tenggara, Maluku, Sulawesi Tenggara, and Sulawesi Selatan. At the longest timescale ($n = 1000$ days, panel c), there is an increase in both the number of inter-island connections as well as their structural complexity: Sumatera Selatan acts as a high-degree hub connecting to Kalimantan Timur, Kalimantan Selatan, and several provinces to the South, while Jambi is more central in a backbone of Sumatera connectivity extending Northward through Aceh, Sumatera Utara, Kepulauan Riau and up into Riau. This applies to all three timescales to Papua Pegunungan, Papua, and Maluku.

Unlike the relative structural evolution of temperature, the humidity network retains its own unique features (Fig. 11). At the short timescale $n = 10$ days (panel a), this network is already much more densely connected than its related temperature counterpart, as Sulawesi Selatan connects Kalimantan independently with both Kalimantan Selatan and Kalimantan Barat during very warm days. Sumatera's cluster also includes Jambi and Sumatra Selatan, aligning them immediately with the Jawa provinces.

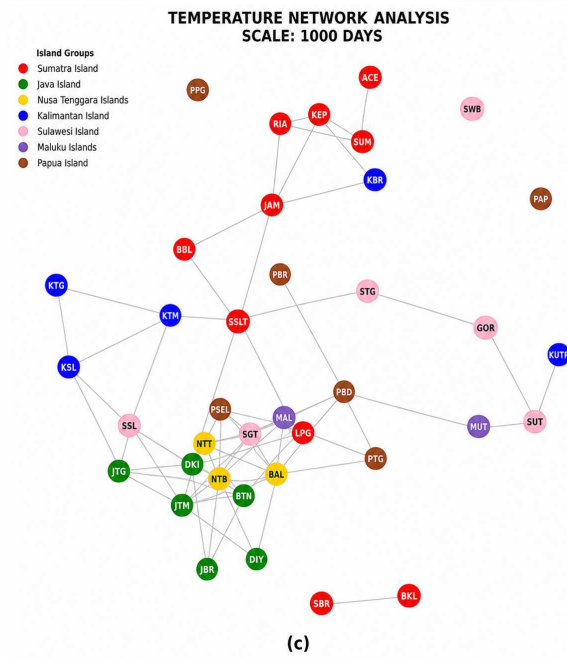
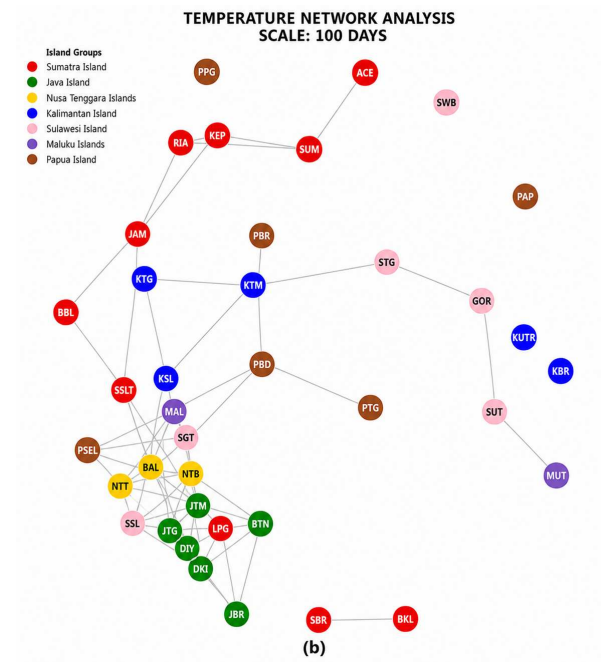
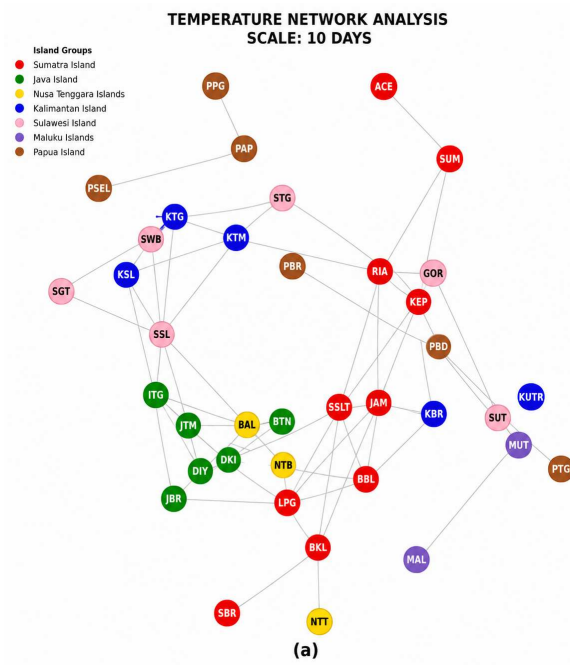


Fig. 10: Network representation of temperature variable for 38 provinces in Indonesia

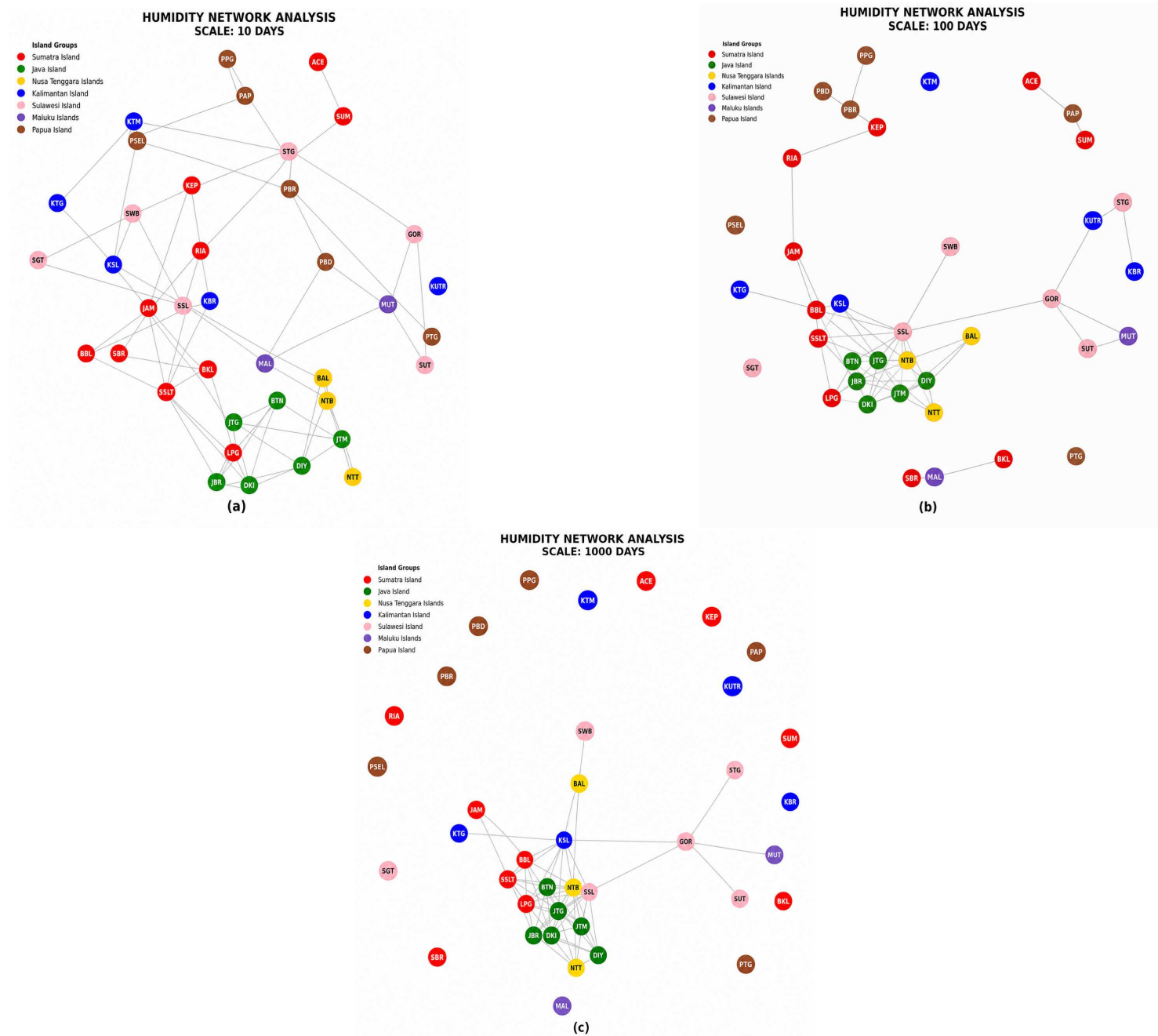


Fig. 11: Network representation of humidity variable for 38 provinces in Indonesia

Bali and Nusa Tenggara are all clustered together into the Jawa cluster. Over the median timescale ($n = 100$ days, panel b), a large central mega-cluster forms, including all Jawa provinces, Bali and Nusa Tenggara, Kalimantan Selatan, Sumatera Selatan, as well as many southern Sumatera stations. Over the longest timescale ($n = 1000$ days, panel c), Kalimantan Selatan takes over as the most connected region in the network from Sumatera Selatan, maintaining strong connections to the Jawa–Bali cluster while also extending farther by developing links with Sumatra and Sulawesi provinces. Papua provinces, northern Sumatra (Aceh, Sumatera Utara), and Maluku (Maluku) are consistently peripheral across all three timescales.

The structural characteristics of the precipitation network are fundamentally different from those of temperature and humidity at all timescales (Fig. 12). At the short timescale ($n = 10$ days, panel a), the network already has a high degree of connectivity, and various cross-island hub counties (Aceh, Sulawesi Utara) are linking Sumatra simultaneously with Java or Papua with other islands. There is no single mega-cluster; connectivity is dispersed through several pathways crossing between islands. Papua Selatan is the most connected cross-island hub, connecting Papua, Kalimantan, Jawa, and eastern Indonesian provinces, with a broadly dispersed spatial network but no dominant central cluster at medium timescales ($n = 100$ days, panel b). On the longest timescale ($n = 1000$ days; panel c), Papua Selatan and Aceh continue to serve as primary cross-island connectors. At the same time, Bali returns to prominence on the list of bridge nodes linking Jawa, Kalimantan, Papua, and Sulawesi. In contrast, the network remains spread across all three timescales, without coalescing into a single compact core.

Across all three timescales, the solar radiation network maintains a statistically stable bimodal structure — an attribute that no other variable possesses (Fig. 13). Short timescale ($n = 10$ days, panel a): The network splits into two loosely coupled sub-networks: an upper cluster connecting Kalimantan (Kalimantan Timur, Kalimantan Selatan, Kalimantan Tengah), Sulawesi (Sulawesi Barat, Sulawesi Tengah, Sulawesi Tenggara, Gorontalo, Sulawesi Utara), Maluku (Maluku, Maluku Utara) and Papua provinces (Papua, Papua Pegunungan, Papua Barat, Papua Barat Daya), with a lower cluster anchored by the tightly interlinked Jawa provinces (DKI Jakarta, DI Yogyakarta, Jawa Barat, Jawa Tengah, Jawa Timur, Lampung); Bali and Nusa Tenggara nodes are intermediate between these two regions in terms of interconnectivity. The main link between the two sub-networks is Sulawesi Selatan. At the medium timescale ($n = 100$ days, panel b), the bimodal structure sharpens, consisting of a compact mega-cluster centered on Sulawesi Selatan and encompassing all Jawa provinces plus Bali and Nusa Tenggara and some Sumatera stations for the lower sub-network while reconfiguring into a Sulawesi–Maluku–Papua–Kalimantan chain with Sulawesi Tengah, Maluku Utara, and Gorontalo as connecting nodes for the upper sub-network. At the maximum timescale ($n = 1000$ days, panel c), Kalimantan Selatan becomes a bridge node linking upper Kalimantan–Papua to the lower southern mega-cluster through Sulawesi Selatan, while core Jawa–Bali and Nusa Tenggara become more densely connected with additional Sumatera provinces. Perhaps unsurprisingly, we find that Papua Selatan and Papua are consistently marked as peripheral across all three time scales.

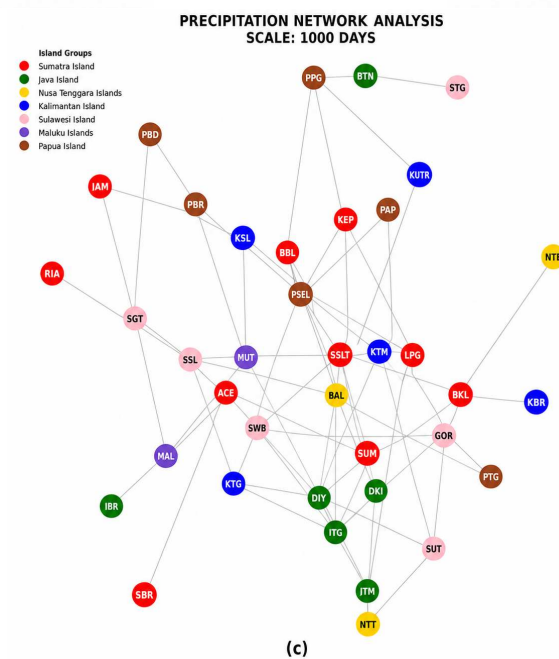
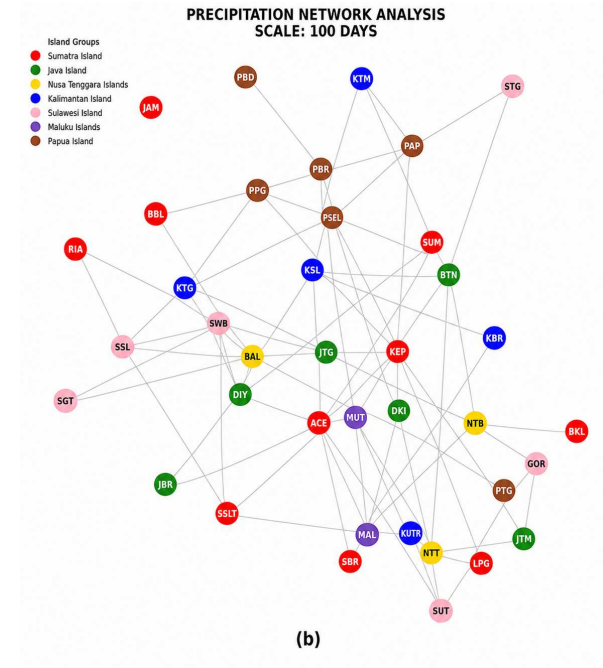
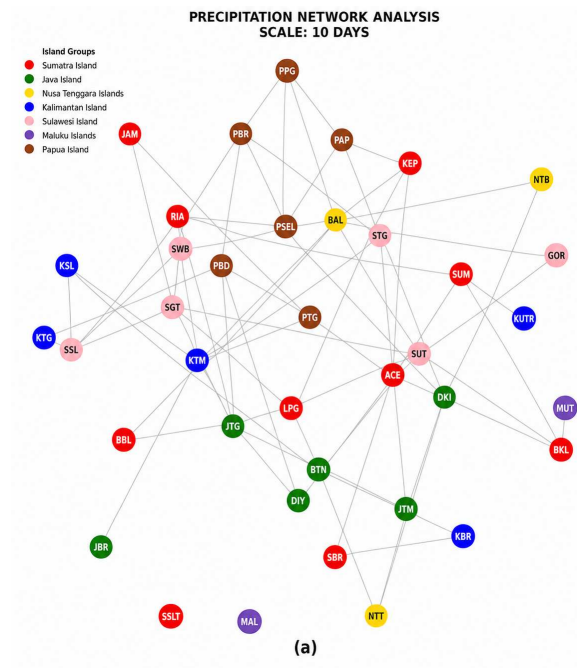


Fig. 12: Network representation of precipitation variable for 38 provinces in Indonesia

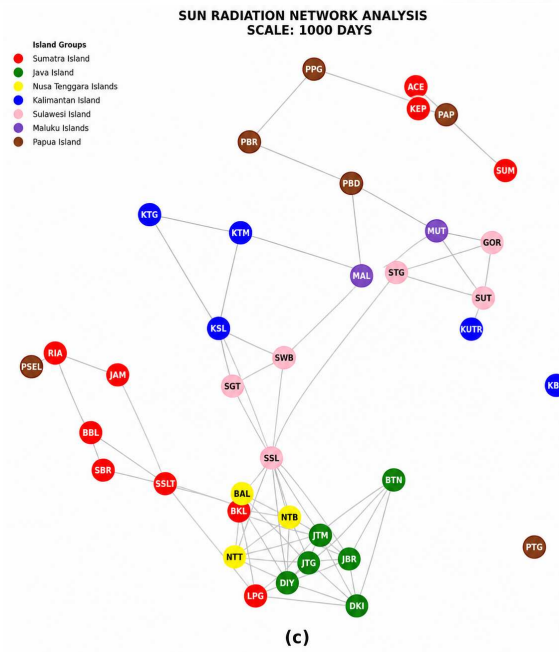
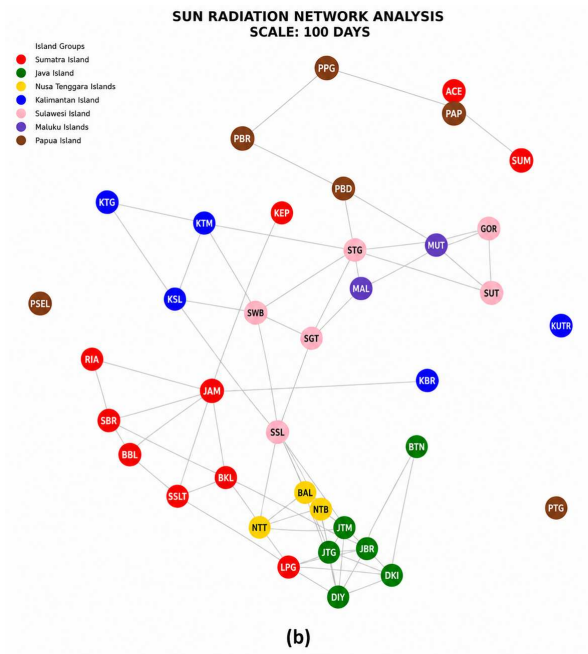
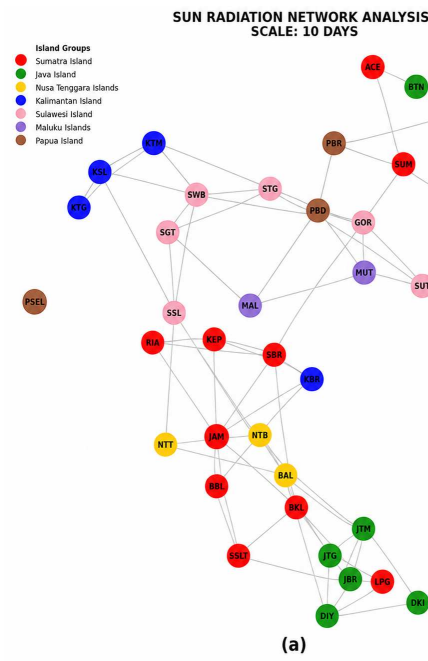


Fig. 13: Network representation of sun radiation variable for 38 provinces in Indonesia

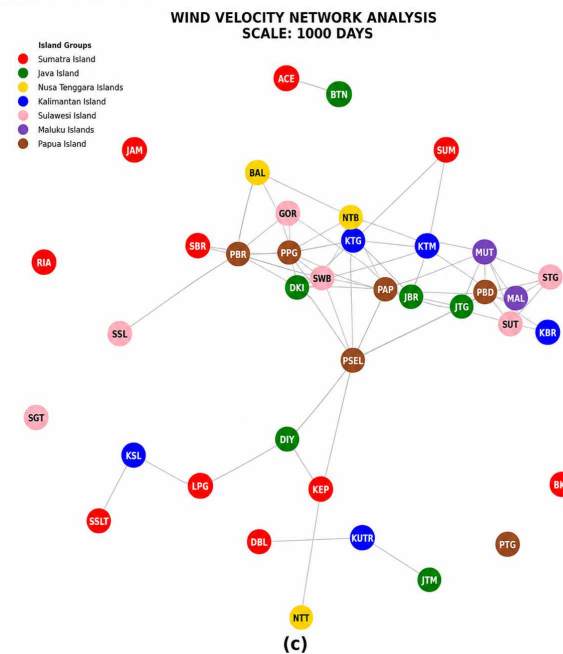
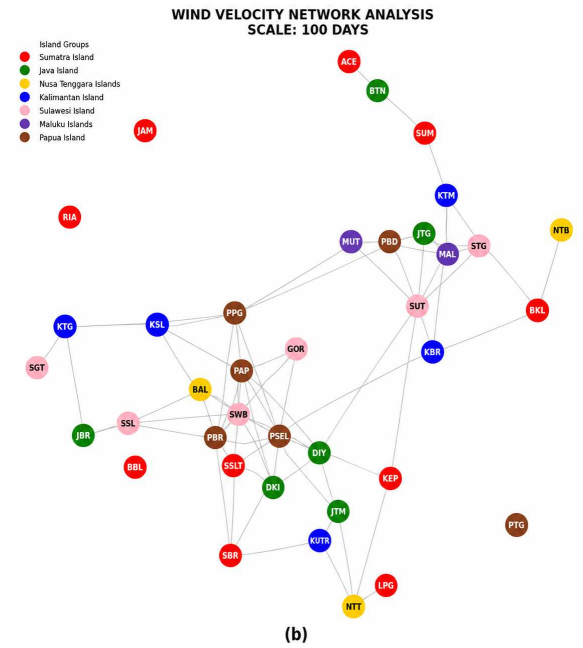
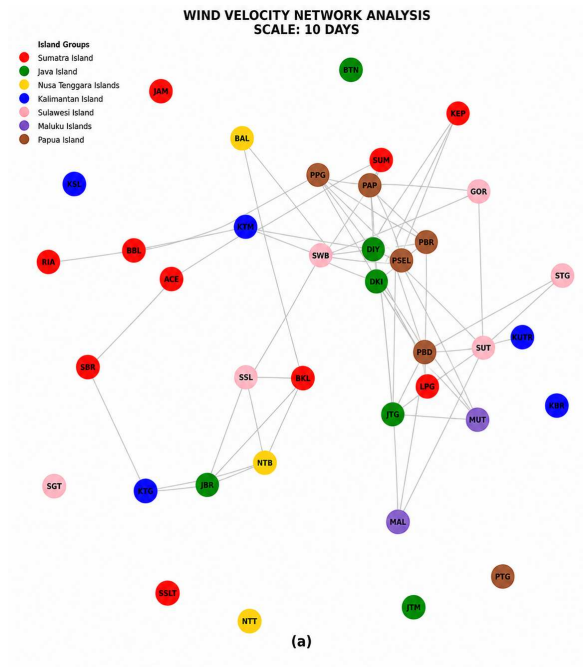


Fig. 14: Network representation of wind velocity variable for 38 provinces in Indonesia

The wind velocity connectivity network is the most spatially heterogeneous among the five variables, with Papua provinces being at more central than peripheral locations across timescales (Fig. 14). For the short timescale ($n = 10$ days, panel a), the network forms a dense cross-island core comprising DI Yogyakarta, DKI Jakarta, Papua Selatan, Papua Barat Daya, Lampung, Jawa Tengah, and Maluku. At the same time, Kalimantan Timur acts as both an important hub for other islands and a major center linking out to Bali, Sulawesi Barat, Papua, Papua Pegunungan, and Papua Barat. At this scale, some peripheral provinces, such as Jambi, Kalimantan Selatan, and Sulawesi Tenggara, are included. In the medium timescale ($n = 100$ days, panel b), the network reorganizes into two loosely coupled sub-networks consisting of an upper cluster connecting Sulawesi Utara, Maluku, Sulawesi Tengah, Maluku Utara, and Kalimantan Timur, while forming a larger lower cluster focused around Papua Selatan, Sulawesi Barat, and Papua, which includes Jawa and Papua provinces with more dispersed Sumatera stations. This scale and multiple provinces remain monopolized by Jambi, Riau, Kalimantan Selatan, Kalimantan Tengah, and Sulawesi Tenggara. At the longest timescale ($n = 1000$ days, panel c), Papua Selatan remains the most connected network hub with maximum node degree in a star-like cross-island configuration connecting simultaneously to Papua Pegunungan, Papua Barat, Sulawesi Barat, DKI Jakarta, DI Yogyakarta, Jawa Barat, Jawa Tengah, Papua, and Papua Barat Daya, along with Maluku, as well as Kalimantan Tengah along with Nusa Tenggara Barat and Maluku Utara spanning six island groups.

4 Discussion

4.1 Scale-Dependent Climate Connectivity in Indonesia

The cross-correlation analysis and network analysis suggest that inter-provincial climate connectivity is structured hierarchically, scale-dependently, which broadly agrees with the known multiscale organization of atmospheric forcing modes in the Indonesian region. In all but the island groups, $\rho_{DCCA}(n) \approx 0$ at short timescales ($n > 100$ days) across these same islands reflects the increasing influence of large-scale atmospheric modes, especially the Asian–Australian monsoon and ENSO, which impose coherent climate signals over large geographic extents on seasonal to interannual timescales [3]. The emergence of megaclasses on intermediate timescales in response to multiple climate stimuli (temperature, humidity, solar radiation) is consistent with macro-scale forcing of monsoonal periods (~ 180 – 365 days), capable of synchronizing climate variability across multiple island groups. The transition from a scaling regime to no correlations, as the box scales through frequency space, is qualitatively consistent with DFA and DCCA theory; cross-correlations are suppressed when forcing frequency (the typical forcing wave-length) is higher than the size of one box, but long-range cross-correlations emerge when the period of forcing weight applies to stationary processes that fill at least size boxes [12, 13].

4.2 Island Geography as a Determinant of Climate Coherence

4.2.1 Sumatera and Jawa: Moderate Intra-Island Coupling

Moderate cross-correlations across Sumatera ($\rho_{\text{DCCA}} < 0.50$ at all scales) imply adequate island-wide coherence (monsoon and ENSO). However, significant province-level thermal heterogeneity exists in the relevant network topology; no single dominant hub exists until $n = 1000$ days. The more fused coupling between the provinces of Sumatera Barat and Sumatra Selatan is due to their interior lowland position, which isolates them from contrasting influences found in surrounding coastal areas, whilst differing mostly only by local reflections, preventing contrasts across and by similar overall large-scale convective regimes. In contrast, both replicatively weak correlations for Kepulauan Riau and Bengkulu can be explained by certain climatic signatures arising from their unusual exposure: maritime (Kepulauan Riau) and coastal Indian Ocean (Bengkulu). In contrast, $\rho_{\text{DCCA}}(n)$ of DKI Jakarta is near zero across all timescales in Jawa. It is strongly peripheral to the temperature and humidity networks at any scale, indicating that all distribution of variation above diurnal can be explained neither by significant regionalities nor local hydro-climatology dynamics likely yielding from urban heat island, whereby a often locally driven warming trend masks large-scale variability associated with the larger-scale monsoon signal. The ordinally weak cross-correlations of DI Yogyakarta are likely the result of orographic blocking by surrounding highlands (Mountaint of Merapi–Merbabu complex) that modify synoptic-scale advection and produce a distinguishable, thermally distinct microclimate. The strong Jawa Tengah–Jawa Timur coupling ($\rho_{\text{DCCA}} \approx 0.50$ at large n), observed as a compact central-eastern cluster in the temperature network, is attributable to their common flat-to-rolling topography and similar exposure to southerly Indian Ocean monsoon flows.

4.2.2 Bali, Nusa Tenggara, and Maluku: Climatically Fragmented Island Groups

The absence of cross-correlation between Bali and Nusa Tenggara, and Maluku at all timescales is the most diagnostic result of the DCCA analysis. It is further supported by these climatic behaviors being consistently peripheral in the network of temperature, humidity, and solar radiation across scales. For Bali and Nusa Tenggara this is physically explained by the totally different climate character of each province: Bali has a very unique volcanic terrain and high land-use modification (due to tourism) creating a thermally distinct local climate; Nusa Tenggara Barat straddles a more or less semi-arid island chain with a clear dry season, meanwhile Nusa Tenggara Timur extends into the eastern Indonesian seas which are under an apparent seasonal monsoon weather pattern that stands in stark contrast to the wetter western islands. These differences are large enough that even the strongest atmospheric modes cannot produce significant cross-correlations [3]. The lack of cross-correlation between Maluku and Maluku Utara, both located within the same geographic archipelago but facing very different sea basins (Maluku opening to the Banda Sea; Maluku Utara opening to the Molucca and Halmahera Seas), implies they have completely independent climate

regimes due to fundamentally different oceanographic forcing and sea surface temperatures. Collectively, these results provide evidence that cohesion in climatic regimes does not extend to temperature or humidity on small eastern Indonesian island groups bounded by complex maritime boundaries, where spatial aggregation at the island level for those variables is inappropriate. At the same time, precipitation and wind display partial integration even among such island groups because of the cross-island range of organized convective systems.

4.2.3 Kalimantan: West–South Clustering and Eastern Isolation

The remarkable Kalimantan Tengah–Kalimantan Selatan coupling ($\rho_{\text{DCCA}} \approx 0.45$ – 0.50 at large n) reflected in the temperature network as an enduring west–south cluster is physically sensible given their proximity on Borneo from both a meteorological (i.e., both provinces are strongly influenced by long-range Jawa Sea monsoon forcing) and a climatological perspective (both provinces share broad lowland equatorial rainforest climate). The progressively weaker coupling to western and northern provinces reflects the separate moisture and radiation regimes of the South China Sea and Celebes Sea, respectively. Among all results across this island group, the DCCA analysis yields, above all, its most physically complicated result: Kalimantan Timur is decoupled from any other Kalimantan province, a finding confirmed by its isolated position in temperature and humidity networks, yet also strongly connected to neighboring islands via the wind network. Its geographic orientation toward the Makassar Strait and Sulawesi Sea (compared to west and south Borneo) exposes it to unique oceanographic, while extensive land-surface modification from massive coal and petroleum extraction may also drive additional local thermal anomalies stronger than the regional climate signal. This role in wind connectivity aligns with the Makassar Strait functioning as a key pathway for interhemispheric monsoon exchange, coupling low-level wind variability across eastern Borneo and surrounding seas.

4.2.4 Sulawesi: Pacific-Facing Northern Provinces as a Coherent Cluster

The positive values of $\rho_{\text{DCCA}}(n)$ at short timescales ($n < 10$ days) between Sulawesi Utara and Gorontalo, which are exclusive to Sulawesi across all island groups in the DCCA analysis, directly relate to the network structure since these northern peninsula provinces show stable connections even at the shortest contiguity timescale. The most plausible cause of this short-scale coupling is the direct exposure of the northern Sulawesi peninsula to both the Pacific Ocean and Celebes Sea, where low-level wind convergence and sea surface temperature variability associated with the Pacific Warm Pool create systematic co-occurring local day-to-day climate anomalies that propagate through adjacent provinces. Sulawesi Selatan’s near-zero $\rho_{\text{DCCA}}(n)$ with all other Sulawesi provinces confirmed by its isolated network position in temperature and unexpected hub role at short timescales for temperature in earlier analyses reflects its geographic isolation on the southwestern peninsula, where exposure to the Flores and Banda Seas as well as a strong bimodal monsoon regime impose fundamentally different climate climatology from northern and central Sulawesi.

558 4.2.5 Papua: ENSO-Dominated Coherent Climate Regime

559 The inter-provincial coupling in Papua, indicated as positive even at short timescales
560 and sustained across all temporal scales from DCCA analysis, is the strongest among
561 any province-pair combination of within-island climate coherence for temperature in
562 this study. This outcome is consistent with Papua's location at the western edge
563 of the Pacific Warm Pool, such that ENSO-driven sea surface temperature anomalies
564 have uniform spatial impacts on atmospheric temperature and humidity across
565 the island. Papua's variable-stylized structural evolution network position is equally
566 revealing, whilst Papua provinces are still peripheral in temperature and humidity
567 networks (characterizing the domination of local orographic and maritime effects for
568 these variables), they occupy central positions in the wind network, with Papua Sela-
569 tan consolidating as the dominant hub ($n = 1000$ days) simultaneously connecting six
570 island groups. This contrast reveals a key difference in the thermodynamic (tempera-
571 ture, humidity) and dynamic (wind) drivers of climate variability in Papua: the former
572 is strongly controlled by local topography and sea-surface conditions that isolate indi-
573 vidual provinces, while the latter is dominated by the large-scale monsoon circulation
574 that makes Papua a structural nexus of interannual wind variability across the Indo-
575 Pacific system. Papua Pegunungan is characterized by weak coupling with the rest of
576 the provinces, which might be attributable to its high-altitude, mountainous terrain,
577 where orographic effects give rise to a lapse-rate-controlled regime that is decoupled
578 from the boundary-layer dynamics governing the lowland coastal provinces.

579 4.3 Variable-Specific Cross-Island Connectivity Mechanisms

580 4.3.1 Temperature and Humidity: Intra-Island Dominance 581 Transitioning to Monsoon-Driven Mega-Clusters

582 The comparable structural evolution of temperature and humidity networks mature
583 from sparse intra-island clusters at short timescales to monsoon-forced mega-clusters
584 at medium timescales is supported by the strong physical coupling between sur-
585 face temperature and atmospheric moisture content through evapotranspiration and
586 boundary-layer thermodynamics. The main difference now is that humidity generates
587 cross-island connectivity one timescale earlier than temperature: a source in Sulawesi
588 Selatan already bridges Kalimantan, Sumatera, and Jawa in the humidity network at
589 $n = 10$ days, whereas it takes $n = 100$ days for comparable links to appear in the tem-
590 perature network. This discrepancy is physically consistent with the fact that moisture
591 transport is driven by large-scale horizontal advection, which acts coherently across
592 island boundaries at all time scales. In contrast, temperature exhibits greater local
593 variability associated with surface properties (e.g., albedo, topography, urban land use)
594 that mask regional signals on short time scales. The retraction of Kalimantan Selatan
595 from its role as the main hub of moisture connectivity at $n = 1000$ days is consistent
596 with model sensitivity to interannual ENSO-driven moisture anomalies transmitted
597 through the Jawa Sea, establishing Kalimantan Selatan as a central node in the
598 interannual moisture transfer pathway across the western Indonesian archipelago.

4.3.2 Precipitation: Synoptic Cross-Island Connectivity Driven by Organized Convection

The comparatively large connectivity of the precipitation network already at $n = 10$ days, with Aceh and Sulawesi Utara being strong cross-island hubs that link simultaneously Sumatera, Jawa, Papua, and Sulawesi (Fig. 12), aligned with previous work indicating fundamentally different mechanisms for rainfall variability compared to temperature and humidity variations. As the ITCZ, MJO, and Borneo vortex are coherent large-scale systems that simultaneously influence non-adjacent provinces on synoptic timescales, Indonesian precipitation is dominated by organized convective systems. The lack of a dominant mega-cluster across all precipitation timescales, in contrast to the compact clusters for temperature and humidity, is consistent with our understanding from previous studies that convective rainfall is an intermittent and spatially heterogeneous process, comprising distant provinces collectively excited by episodic large-scale systems, rather than steady background forcing producing compact thermodynamic clusters. The fact that the unexpected emergence of Papua Selatan is also the most connected hub at medium timescales arises from its unique geographic position, whereby Australian monsoon moisture is advected to the north, and Arafura Sea evaporative fluxes converge with ENSO-modulated convection in the western Pacific over southern Papua, rendering Papua Selatan a structural nexus for precipitation variability across much of the eastern archipelago.

4.3.3 Solar Radiation: Persistent Bimodal Structure Driven by Cloud Regime Partitioning

The bimodal topology of the solar radiation network, consisting of a lower cluster centered on western Jawa and an upper cluster at eastern/northern sites, remains the most geographically interpretable network structure identified in this study and does not have an analog in any other variable across multiple timescales. The incoming solar radiation at the surface in Indonesia is largely regulated by cloud cover in two contrasting regimes. In the lower cluster, coherent insolation anomalies on land in western maritime provinces (Jawa, Bali, Nusa Tenggara, southern Sumatera) are associated with cloud variability driven by organized low-level convergence zones and/or the Java Sea monsoon [5]. In contrast, the eastern and northern provinces (Kalimantan, Sulawesi, Maluku, Papua) are instead dominated by convective cloud regimes associated with direct surface parcel heating and Pacific moisture convergence, resulting in separate radiation climate communities. This bimodal partitioning aligns with the known cloud cover discontinuity across the Indonesian archipelago, related to seasonal shifts of both the ITCZ and the monsoon convergence zones, which systematically alternate clear and overcast conditions between the western and eastern sectors of the country. This supports the emergence of Kalimantan Selatan as a bridge node during $n = 1000$ days, consistent with its intermediate geographic position between the Java Sea and Makassar Strait cloud regimes, which facilitate coupling to these sub-networks at interannual timescales when ENSO modulates cloud cover across Borneo [3].

4.3.4 Wind Velocity: Papua as the Central Hub of Interannual Monsoon Variability

The most structurally distinctive cross-variable contrast in this analysis and a key motivating factor for delineating thermodynamic versus dynamic climate variability is the marked reversal of Papua’s network position, from perimeter temperature and humidity to core wind velocity across all timescales. In Indonesia, wind speed variability is inherently driven by the monsoon circulation system, which acts as a basin-scale phenomenon controlling surface winds across the whole Indo-Pacific region, regardless of the islands’ landscape. Papua’s intermediate role in the wind network mirrors its position at the intersection of the two predominant monsoon systems associated with each ocean: southeasterly trade winds from an Australian anticyclone and northwesterly flow out of a Pacific Warm Pool converge on Papua, resulting in coherence in wind variability throughout this structural hub. The establishment of Papua Selatan as the primary wind network node at $n = 1000$ days contemporaneously connecting to six disparate oceanic island groups in a star-like arrangement reflects an intensification of ENSO’s periodic forcing on the Walker circulation, which actually shifts the location of the main convergence zone between the Indian and Pacific Oceans and subsequently most strongly impacts surface wind features within the western-most Indonesian basin. The continuous isolation of Jambi, Riau, and interior Kalimantan provinces in the wind network serves as a testament to how dramatically low-level winds are forced by the topography surrounding these areas, with local-scale circulation impinging on large-scale monsoon flow to create wind regimes that dynamically decouple these provinces from broad-scale motion associated with the monsoon.

4.4 Persistently Isolated Provinces and Implications for Climate Monitoring

The spatial patterns of $\rho_{\text{DCCA}}(n)$ and network centrality revealed in this study work together to locate two different types of Indonesian provinces that require distinct monitoring needs. The first category provides a set of consistently well-connected hub provinces: Sumatera Selatan for temperature, Kalimantan Selatan for humidity, and Papua Selatan for wind velocity and precipitation that can be used to infer regional climate states across multiple connected provinces at seasonal to interannual resolution, making them strategic nodes in a rationalized monitoring network. The second group consists of consistently peripheral provinces that include Papua Pegunungan, Maluku, DKI Jakarta, Kalimantan Timur, Sulawesi Selatan, including Bali and Nusa Tenggara, and Maluku provinces, where climate dynamics are regulated primarily by local effects such as urban heat islands, high-altitude orography, and complex maritime boundaries that act independently of the large-scale modes synchronizing the rest of the network. For these provinces, for which neighboring stations cannot appropriately represent at any timescale and for any variable, dedicated independent observational infrastructure is required to capture their climate variability. In addition, the variable-dependent hub structure (i.e., a single province is a hub for all five variables simultaneously) indicates that no single monitoring configuration is optimal across all climate variables and that variable-specific designs should be used within an Indonesian provincial observational

network framework. The consistent increase of $\rho_{\text{DCCA}}(n)$ and connection density with the timescale further support our contention that sparse observational networks may be sufficient for climate information between years. In contrast, denser networks are critical for multi-day weather analysis and sub-seasonal seasonal prediction along this archipelago.

5 Conclusion

This study establishes the first continental-scale, multivariate assessment of inter-provincial climate connectivity across 38 provinces in Indonesia, based on DFA, DCCA, and complex network analysis, using 15 years of daily BMKG records. Three conclusions emerge. It first reports that long-range persistence ($\alpha > 0.5$) is universal across all variables and provinces, strengthening systematically from short to long timescales. Second, inter-province coherence is scale-dependent and geographically heterogeneous: correlations are near zero at short timescales and strengthen at seasonal to interannual scales as the monsoon and ENSO impose ever-wider coherence, with Bali and Nusa Tenggara and Maluku remaining fragmentary at all scales. At the same time, Papua displays the strongest and longest-lasting coupling. Third, connectivity architecture is variable-dependent—precipitation and wind reveal cross-island synchrony at subday scales; solar radiation retains a bimodal topological signature separating western Jawa Sea from eastern Pacific cloud regimes across time scales; temperature and humidity transitions at seasonal scales, from intra-island clustering to monsoon-driven mega-clusters.

Concerning temperature, humidity, precipitation, and wind, the practically identified cross-island monitoring hubs are located in Sumatera Selatan (temperature), Kalimantan Selatan (humidity), and Papua Selatan (precipitation/wind); while other provinces designated with some strategic functions required their own independent observational infrastructures, including: Papua Pegunungan, DKI Jakarta, Kalimantan Timur, Sulawesi Selatan, and both Maluku provinces. Future work assessing whether these connectivity structures are stationary across different ENSO epochs and comparing the results with gridded reanalysis products is necessary.

Beyond the Indonesian context, the DFA-DCCA-network framework offers a broadly transferable approach for characterizing multiscale climate connectivity across regions with multistation records. Compared with traditional statistical correlation methods, it can address the long-range dependence and non-stationarity problems that those methods cannot handle, adapt to climate time series that do not meet classical statistical assumptions, and be extended to three research scenarios. The core-periphery network structure identified by this framework can provide empirical evidence for allocating climate monitoring resources in Indonesia: hub provinces can support interannual climate tracking in sparsely monitored regions. In contrast, isolated provinces need to sustain independent investment in observational work to meet the needs of various local and regional development research efforts.

Supplementary information. Supplementary material with map, graphs and tables used in the analysis of climate variables (humidity, precipitation, sun radiation, wind velocity).

726 Declarations

727 **Ethics, Consent to Participate, and Consent to Publish declarations.** Not
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729 **Conflict of Interest.** The authors declare that they have no conflict of interest.

730 **Data availability.** The Indonesian climate data is publicly available from the
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736 Paulo Canas Rodrigues conceived and designed the study, developed the analytical
737 framework, and supervised the interpretation of results. All authors contributed to
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