Heterogeneous Correlation Mapping between Rainfall Variability in Lake Toba and Indian Ocean Sea Surface Temperature*

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***Abstract*—Rainfall variability in the Lake Toba watershed of North Sumatra is influenced by large-scale ocean–atmosphere interactions, particularly those involving sea surface temperatures (SST) in the Indian Ocean. This study applies Heterogeneous Correlation Mapping (HCM) to examine the spatially varying relationship between monthly rainfall at 13 meteorological stations and SST over the Indian Ocean warm pool (5°S–10°N, 60°E–80°E) during 1981–2014. Singular Value Decomposition (SVD) is employed to extract dominant coupled modes of SST–rainfall variability. Results indicate that a six-month lag yields the strongest coupling, with the leading mode explaining 88.5% of the total variance. A clear spatial heterogeneity is observed: stations such as Lumban Julu and Silaen exhibit stronger SST–rainfall correlations, while others show weaker responses, likely due to topographic and local climatic modulation. These findings underscore the importance of accounting for spatial and temporal structures in hydroclimatic teleconnection analysis and offer insights for improving seasonal rainfall prediction in mountainous tropical regions.**

I. INTRODUCTION

The hydrometeorological variability over tropical Southeast Asia is strongly modulated by large-scale ocean–atmosphere interactions [1], [2], [3], particularly those associated with changes in sea surface temperature (SST) across the Indian and Pacific Oceans [4], [5]. In this context, rainfall variability in the Lake Toba region of North Sumatra, Indonesia, is known to be sensitive to remotely forced climate drivers such as the El Niño–Southern Oscillation (ENSO) [6].

Previous studies [7] have examined the influence of SST anomalies on rainfall variability in North Sumatra, such as those captured by Niño3.4. However, these basin-averaged approaches often overlook local-scale variations, particularly in topographically complex regions like the Lake Toba watershed. Moreover, the common assumption of linear and immediate SST–rainfall relationships neglects potential lagged and spatially heterogeneous teleconnections, underscoring the need for more localized and temporally flexible analyses.

This study addresses this gap by applying a Heterogeneous Correlation Mapping (HCM) approach [8], [9], [10] to quantify the spatial distribution of correlation between monthly rainfall at thirteen meteorological stations around Lake Toba and lagged SST values over the Indian Ocean warm pool region. Using singular value decomposition (SVD), which is closely related to empirical orthogonal function (EOF) analysis in climate data applications [11], [12], [13], we identify dominant coupled modes and quantify their spatial manifestation via HCM. The analysis spans the period 1981–2014 and evaluates multiple temporal lags to determine the optimal lead time at which SST exerts the strongest influence on rainfall. Therefore, this study aims to: (1) construct a joint SST–rainfall data matrix for extracting coupled hydroclimatic variability between the Indian Ocean warm pool and Lake Toba rainfall; (2) identify the optimal lag at which SST variability most strongly relates to rainfall variability; (3) map the spatial heterogeneity of rainfall response using HCM; and (4) interpret the implications of the dominant SST–rainfall coupling for regional seasonal rainfall prediction.

The main contribution of this study is the development of a joint SST–rainfall modeling framework that integrates Heterogeneous Correlation Mapping (HCM), Singular Value Decomposition (SVD), and lagged SST analysis. By constructing a joint data matrix from station-based rainfall observations and gridded SST fields, this framework enables the extraction of dominant coupled modes of SST–rainfall variability within a unified decomposition approach. This study further identifies the temporal delay and spatial heterogeneity of the SST influence on rainfall around Lake Toba, providing localized hydroclimatic insight for a topographically complex tropical watershed.

II. METHODS

A. Study Area and Data Sources

Lake Toba, located in the highland region of North Sumatra, Indonesia, stands as the largest volcanic lake in Southeast Asia. Geographically, it spans latitudes $2^\circ 21' 32''$ to $2^\circ 56' 28''$ N and longitudes $98^\circ 26' 35''$ to $99^\circ 15' 40''$ E. Covering a surface area of about 1,124 km^2 and draining a catchment area of roughly 2,486 km^2, Lake Toba lies at an altitude of approximately 903 meters above sea level. It has an average depth of 228 meters and reaches depths exceeding 500 meters in some locations [15], [14], [16].

This study explores the statistical relationship between monthly rainfall observed at 13 meteorological stations surrounding Lake Toba (Figure 1) and sea surface temperature (SST) over the Indian Ocean warm pool (Figure 2). The rainfall dataset was provided by the Indonesian Meteorology, Climatology, and Geophysical Agency (BMKG) for the period 1981–2014.

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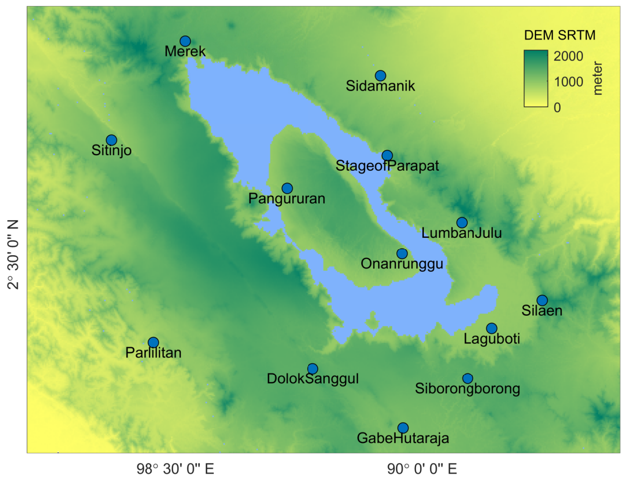

Fig. 1. Study area and spatial distribution of the 13 rainfall stations around Lake Toba used in this study.

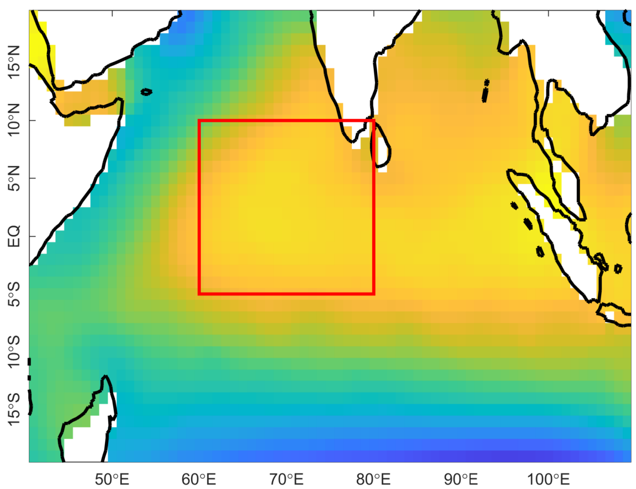

Fig. 2. Climatological mean of sea surface temperature (SST) over the Indian Ocean for the period 1981–2014. The red box indicates the analysis domain used in this study.

SST data were obtained from the Hadley Centre Sea Ice and Sea Surface Temperature dataset (HadISST), with a spatial resolution of $1^\circ \times 1^\circ$. A spatiotemporal subset was extracted for the domain bounded by 5°S–10°N and 60°E–80°E, representing the Indian Ocean warm pool. Data were filtered for the period 1980–2014, consistent with the rainfall dataset. Lagged SST fields were used to account for delayed atmospheric responses, with lag duration set as a parameter in the analysis.

B. Research Workflow

Figure 3 summarizes the methodological workflow used in this study. The rainfall observations from 13 stations were first arranged into a rainfall matrix, while the gridded SST data over the Indian Ocean warm pool were reshaped into an SST matrix with matching monthly temporal resolution. To account for delayed oceanic influence, the SST matrix was shifted using several lag values from 0 to 6 months. For each lag configuration, the rainfall and SST matrices were combined into a joint data matrix, which was then decomposed using SVD to extract the dominant coupled modes. The resulting expansion coefficients were used to evaluate temporal coupling, while the heterogeneous correlation map was computed to identify spatial differences in rainfall response among stations.

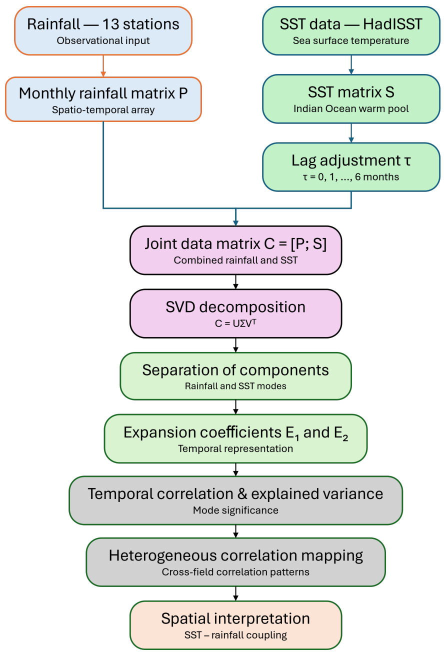

Fig. 3. Methodological workflow for the joint SST–rainfall framework, including data preprocessing, lag adjustment, joint matrix construction, SVD decomposition, temporal coupling analysis, and HCM-based spatial interpretation.

C. Data Preprocessing

The rainfall matrix $\mathbf{P} \in \mathbb{R}^{m \times T}$ was constructed where m is the number of stations (13) and T is the number of months in the analysis period. Similarly, SST values from n valid grid points within the selected domain were reshaped into matrix $\mathbf{S} \in \mathbb{R}^{n \times T}$, resulting in an SST matrix of matching temporal length.

Each row of $\mathbf{P}$ and $\mathbf{S}$ corresponds to a station or grid point, respectively, and each column represents a monthly observation. Lag between SST and rainfall was implemented by temporally shifting the SST matrix by τ months before analysis.

D. Singular Value Decomposition of Joint Matrix

Instead of directly decomposing the cross-covariance matrix between $\mathbf{P}$ and $\mathbf{S}$, we constructed a **joint data matrix** by vertically concatenating both datasets [17]:

$$\mathbf{C} = \begin{bmatrix} \mathbf{P} \\ \mathbf{S} \end{bmatrix} \in \mathbb{R}^{(m+n) \times T} \tag{1}$$

The matrix $\mathbf{C}$ is then decomposed using Singular Value Decomposition (SVD) as:

$$\mathbf{C} = \mathbf{U}\Sigma\mathbf{V}^\top \tag{2}$$

where $\mathbf{U}$ contains the spatial modes for rainfall and SST combined, Σ is a diagonal matrix of singular values σ_i, and $\mathbf{V}$ contains the temporal modes.

E. Mode Separation and Expansion Coefficients

The rainfall-related and SST-related components of the spatial modes were separated as follows:

$$\mathbf{E}_1 = \mathbf{P}^\top \mathbf{U}_P \quad (3)$$

$$\mathbf{E}_2 = \mathbf{S}^\top \mathbf{U}_S \quad (4)$$

where $\mathbf{U}_P$ and $\mathbf{U}_S$ are the top m and bottom n rows of matrix $\mathbf{U}$, respectively. The resulting expansion coefficients $\mathbf{E}_1$ and $\mathbf{E}_2$ represent temporal evolutions of rainfall and SST associated with each mode.

F. Heterogeneous Correlation Mapping (HCM)

For each mode i, the Heterogeneous Correlation Map (HCM) was constructed by computing the Pearson correlation between the i-th SST expansion coefficient $\mathbf{e}_2^{(i)}$ and the rainfall time series at each station [9]:

$$\mathrm{HCM}_j^{(i)} = \mathrm{corr}(\mathbf{e}_2^{(i)}, P_j), \quad j = 1, \ldots, m \quad (5)$$

This results in a spatial map (on station locations) showing how each station's rainfall covaries with the temporal evolution of SST patterns.

G. Explained Variance and Lag Setting

The strength of each mode was quantified using the squared singular values [18], [19]:

$$\mu_i = \frac{\sigma_i^2}{\sum_{j=1}^{r} \sigma_j^2} \times 100\% \quad (6)$$

where r is the number of retained modes (e.g., $r = 100$). The analysis was conducted for several lag values τ (0–6 months), and the mode with the highest rainfall–SST correlation was highlighted for interpretation.

III. RESULTS AND DISCUSSION

A. Determination of Optimal Lag

To determine the appropriate lag between sea surface temperature (SST) in the Indian Ocean warm pool and rainfall variability over Lake Toba, the analysis was performed for lag values ranging from 0 to 6 months. For each lag, the SST time series was shifted by the specified number of months relative to the rainfall series, and the coupled variability was assessed using singular value decomposition (SVD) of the joint matrix (Eq. 1).

Table I summarizes the results for each lag setting. Three key indicators were evaluated: (1) the temporal correlation between the expansion coefficients of SST and rainfall in the first mode, (2) the maximum spatial correlation in the heterogeneous correlation map (HCM), and (3) the percentage of variance explained by the first singular mode μ_1.

TABLE I
SUMMARY OF LAG PERFORMANCE IN TERMS OF TEMPORAL CORRELATION, MAXIMUM SPATIAL CORRELATION IN HCM, AND EXPLAINED VARIANCE μ_1.

Lag	Temporal Corr	Max. Spatial Corr	μ_1 (%)
0	0.024	0.1096	88.3260
1	-0.195	-0.1871	88.2693
2	-0.375	-0.3457	88.2226
3	-0.310	-0.3349	88.2392
4	0.005	0.0748	88.3205
5	0.349	0.3453	88.4098
6	**0.522**	**0.4612**	**88.4547**

The results clearly show that a lag of 6 months yields the strongest coupling between SST and rainfall. It achieves the highest temporal correlation (0.522), the largest maximum spatial correlation in the HCM (0.4612), and the greatest explained variance by the first mode (88.45%). This suggests that SST over the Indian Ocean warm pool region exert a delayed influence on rainfall over the Lake Toba region with an approximate lead time of six months. Accordingly, all subsequent analyses in this study were conducted using the 6-month lag configuration.

B. Explained Variance and Mode Dominance

The singular value decomposition (SVD) of the joint data matrix yielded a set of orthogonal modes that capture the coupled variability between SST and rainfall. Under the optimal lag of six months, the first five singular modes explain a cumulative variance of approximately 94.96%, with the first mode alone contributing 88.45% of the total signal.

Table II presents the detailed breakdown of the percentage of variance explained by each of the first five modes. The sharp drop from the first to the second mode confirms that the dominant coupling structure is effectively captured by the first mode, while higher-order modes contribute marginally.

TABLE II
EXPLAINED VARIANCE (%) BY THE FIRST FIVE SVD MODES AND CUMULATIVE CONTRIBUTION UNDER LAG-6 CONFIGURATION.

Mode	Individual Variance (%)	Cumulative Variance (%)
1	88.45	88.45
2	2.40	90.85
3	1.95	92.80
4	1.14	93.94
5	1.02	94.96

The dominance of the first mode, both statistically and dynamically, justifies its use for further interpretation. This mode reflects the most coherent joint variability between the SST in the Indian Ocean and the rainfall fluctuations over Lake Toba. As such, subsequent temporal and spatial analyses in this study focus on the first mode as the primary coupled pattern of interest.

C. Temporal Coupling between Rainfall and SST

The temporal evolution of the coupled variability between rainfall over Lake Toba and SST over the Indian Ocean warm pool is represented by the first pair of expansion coefficients from the SVD, denoted as $\mathbf{E}_1$ (rainfall) and $\mathbf{E}_2$ (SST). Figure 4 (top panel) illustrates the temporal alignment of both series during the period 1981–2014. The patterns exhibit strong visual coherence, with peaks and troughs that generally occur synchronously, despite originating from different physical domains.

The Pearson correlation between the two time series is 0.5372, indicating a moderate to strong linear association. To further characterize the nature of this dependence, a Gaussian copula [20], [21] was applied to the bivariate distribution of the expansion coefficients. The contour plot in the bottom-left panel of Figure 4 shows the elliptical structure of the joint density, consistent with a Gaussian dependency model.

The bottom-right panel presents a simple linear regression between the SST and rainfall expansion coefficients. The resulting relationship is expressed as:

$$\text{Rainfall} = 68.64 \times \text{SST} - 1784.5, \tag{7}$$

confirming a positive linear association. The upward slope of the regression line reinforces the interpretation that warmer SSTs in the Indian Ocean tend to precede wetter conditions over the Lake Toba region.

The positive regression slope indicates that higher SST-related expansion coefficients are associated with higher rainfall-related expansion coefficients. This suggests that warmer SST conditions over the Indian Ocean warm pool tend to correspond to wetter rainfall conditions over the Lake Toba region under the dominant coupled mode.

The correlation coefficient of 0.5372, while not exceptionally high, is statistically meaningful given the complex nature of atmospheric processes over the Maritime Continent. This region is characterized by competing influences from local convection, monsoonal flow, and remote teleconnections such as ENSO and the Indian Ocean Dipole (IOD). The presence of a moderate yet robust lagged correlation indicates that the SST signal, particularly from the warm pool area, may be acting through an indirect pathway, possibly modulating large-scale circulations that influence moisture convergence over northern Sumatra.

From a dynamical perspective, the six-month lead of SST suggests a delayed atmospheric response, which is plausible considering the persistence and memory of ocean temperatures relative to the more transient nature of rainfall variability. This supports the hypothesis that warm SST enhance convective activity in the equatorial Indian Ocean, which in turn alters the regional circulation and affects rainfall patterns downstream.

Furthermore, the elliptical shape of the Gaussian copula contours suggests that the relationship is approximately symmetric and lacks significant non-linear tail dependence. This validates the use of linear diagnostics such as correlation and regression in this setting, while also confirming that the leading mode of variability is dominated by a consistent joint structure rather than intermittent extremes.

D. Spatial Coupling via Heterogeneous Correlation Map

To assess the spatial heterogeneity of rainfall response to SST off the Western Coast of North Sumatra, we constructed a Heterogeneous Correlation Map (HCM) using the correlation between the first temporal mode of SST variability and the monthly rainfall time series at each of the thirteen stations around Lake Toba. This analysis was conducted using a six-month lag, which was previously identified as the optimal temporal offset for capturing the SST–rainfall teleconnection.

As shown in Figure 5, all stations exhibit positive correlations, confirming that elevated SSTs in the Indian Ocean warm pool region are generally associated with increased rainfall across the watershed. However, the strength of the coupling varies spatially, reflecting differences in topography, exposure, and local climatic modulation.

The highest correlation is observed at Lumban Julu (0.46), located in the eastern sector of the basin. This suggests that rainfall in this region is strongly modulated by remote SST in the Indian ocean. Other stations showing relatively strong coupling include Silaen (0.39), Parlilitan (0.37), Sidamanik (0.36), and Dolok Sanggul (0.36). These sites are situated in various parts of the watershed but demonstrate similar responsiveness to the SST-driven variability, possibly due to favorable orientation relative to prevailing moisture fluxes or reduced topographic shielding.

Moderate correlations are observed at Onan Runggu, Stageof Parapat, and Siborongborong (each at 0.35), suggesting stable but slightly weaker connections. Meanwhile, the lowest correlations are recorded at Pangururan and Laguboti (0.31), Gabe Hutaraja (0.32), Merek and Sitinjo (0.33), indicating that rainfall variability at these stations may be influenced more dominantly by local convective processes or orographic effects than by large-scale SST signals. The overall pattern confirms a consistent but spatially modulated SST–rainfall teleconnection across the Lake Toba region. This spatial variation is important for understanding hydrological sensitivity and for the development of regionally tailored seasonal prediction models.

E. Qualitative Comparison with Previous Studies

The findings of this study are consistent with previous studies showing that rainfall variability in Indonesia is strongly affected by large-scale ocean–atmosphere interactions, particularly ENSO- and IOD-related SST variability [4], [5]. Similar evidence was also reported for North Sumatra, where ENSO was shown to influence seasonal and annual rainfall variability with spatially varying impacts across different topographic regions [7]. However, most previous studies have commonly relied on basin-averaged climate indices, such as Niño3.4 or IOD indices, whereas the present study directly analyzes gridded SST fields over the Indian Ocean warm pool and relates them to station-level rainfall around Lake Toba. This allows the SST–rainfall relationship to be examined in a more spatially explicit manner.

Compared with earlier correlation-based studies, the present study provides two additional insights. First, the strongest SST–rainfall coupling occurs at a six-month lag, indicating that Indian Ocean SST variability may contain useful lead-time information for seasonal rainfall prediction in the Lake Toba region. Second, the HCM results show that the rainfall response is not spatially uniform. Stations such as Lumban Julu and Silaen show stronger SST-related responses, whereas Pangururan and Laguboti exhibit weaker correlations. This

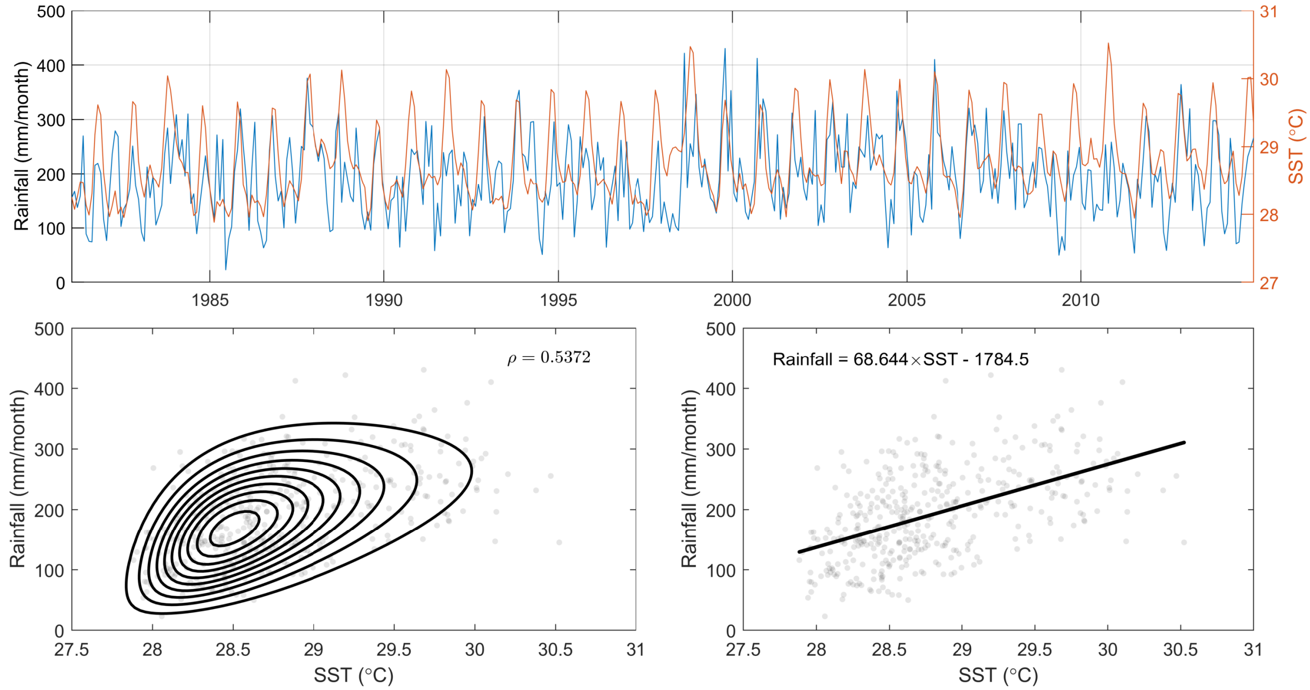

Fig. 4. Temporal coupling between rainfall and SST. **Top:** Time series of the first expansion coefficients from SVD for rainfall ($\mathbf{E}_1$, blue) and SST ($\mathbf{E}_2$, orange). **Bottom left:** Dependence structure using Gaussian copula density contours. **Bottom right:** Linear regression relationship between SST and rainfall expansion coefficients.

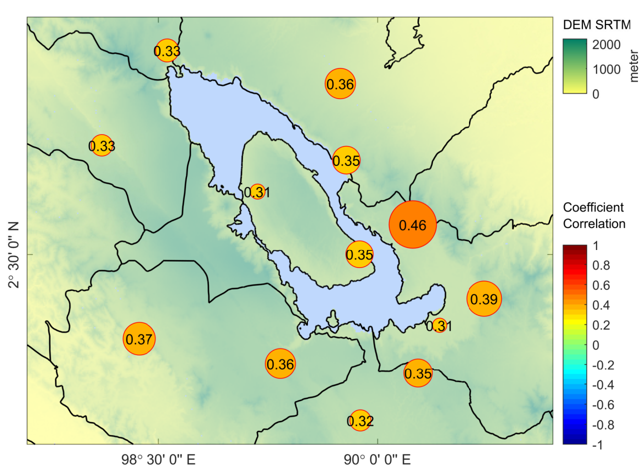

Fig. 5. Heterogeneous Correlation Map (HCM) showing the correlation between the first temporal mode of SST variability and rainfall at 13 stations around Lake Toba. Marker size and color indicate the strength of correlation, overlaid on a DEM background (SRTM).

spatial contrast supports previous findings that rainfall variability in Indonesia is modulated not only by large-scale SST forcing but also by regional and local factors, including topography and local atmospheric processes [22], [7].

The use of SVD in this study is also consistent with previous hydroclimatic studies that applied EOF/SVD-based methods to extract dominant coupled modes from high-dimensional climate data [10]. In contrast to broader-scale SVD studies of Indonesian monsoon rainfall, this study applies the SVD–HCM framework to a localized mountainous watershed and combines it with lagged SST analysis. Moreover, previous HCM applications in Indonesia have mainly focused on the association between climate indicators and hotspots [9], while the present study applies HCM to station-based rainfall variability. Therefore, the novelty of this study lies not in the separate use of SVD or HCM, but in their integration into a localized SST–rainfall framework that identifies the dominant temporal mode, the optimal lag, and the spatially heterogeneous rainfall response across the Lake Toba watershed.

IV. CONCLUSION

This study applied Heterogeneous Correlation Mapping (HCM) in conjunction with Singular Value Decomposition (SVD) to investigate the spatially variable relationship between Indian Ocean sea surface temperatures (SST) and rainfall variability over the Lake Toba watershed. By focusing on physically defined SST over the Indian Ocean warm pool (5°S–10°N, 60°E–80°E) and monthly rainfall from 13 meteorological stations during 1981–2014, the analysis revealed a dominant coupled mode that captures 88.45% of the variance, with the optimal lag identified at six months.

The findings demonstrate that rainfall in the Lake Toba region responds to SST variability in a spatially heterogeneous and temporally delayed manner. Stations such as Lumban Julu and Silaen exhibit stronger teleconnection patterns, while others show more localized variability, likely modulated by topographic and atmospheric factors. The observed linear and positive association between SST and rainfall—confirmed by correlation, Gaussian copula analysis, and regression—supports the potential of SST-based predictors in regional rainfall forecasting.

Methodologically, this study demonstrates that the integration of a joint SST–rainfall matrix, SVD-based coupled mode extraction, and HCM provides a useful framework for identifying both temporal lead-lag relationships and spatially heterogeneous rainfall responses in complex tropical watersheds.

These insights emphasize the importance of incorporating both spatial detail and temporal lag structure into hydroclimatic modeling, especially for data-sparse and topographically complex environments. The methodology and findings of this study provide a foundation for the development of tailored seasonal climate prediction tools and adaptive water resource management strategies in mountainous tropical regions such as North Sumatra.

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