

Spatial and Temporal Characteristics of Total Cloud Cover Over Bali, Indonesia, Using ERA5 Reanalysis Data (2016–2025)

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Abstract

Clouds play a fundamental role in regulating the Earth's radiation balance and hydrological cycle; however, the climatological characteristics of Total Cloud Cover (TCC) over Bali remain insufficiently documented despite the island's complex topography and pronounced monsoonal climate. This study investigates the spatial and temporal characteristics of TCC across six representative locations in Bali using monthly ERA5 reanalysis data for the 2016–2025 period. Spatial climatology was characterized using descriptive statistics, while seasonal variability, long-term trends, and the relationship between TCC and the Oceanic Niño Index (ONI) were evaluated using Ordinary Least Squares (OLS) regression, the Mann–Kendall test, Sen's slope estimator, and monthly Spearman rank correlation analysis.

The results reveal pronounced spatial variability in cloud cover across Bali. Mean TCC ranged from 63.3% in Buleleng to 81.5% in Bangli, indicating persistently cloudier conditions over the mountainous interior than the surrounding coastal regions. A distinct seasonal cycle was observed at all stations, with higher cloud cover during the wet season and lower cloud cover during the dry season under the dominant influence of the Australian–Asian monsoon. Trend analyses consistently indicated no statistically significant long-term changes in TCC during 2016–2025, as confirmed by both OLS regression and the Mann–Kendall test ($p > 0.05$). The relationship between ONI and TCC exhibited marked seasonal variability, with the strongest positive correlations occurring during October ($\rho = 0.45–0.73$), whereas considerably weaker or negative correlations were observed during the peak dry season, suggesting that ENSO-related cloud variability is most evident during the monsoon transition period.

This study provides an updated climatological description of Total Cloud Cover over Bali and highlights the combined roles of local topography, the Australian–Asian monsoon, and ENSO in shaping regional cloud-cover variability. The findings provide a useful reference for regional climate monitoring, seasonal forecasting, and climate-sensitive sectors, including agriculture, water-resource management, renewable energy, aviation, and tourism.

Introduction

Clouds play a fundamental role in the Earth's climate system by regulating the exchange of incoming shortwave solar radiation and outgoing longwave terrestrial radiation, thereby controlling the planetary radiation budget and the global hydrological cycle (Ramanathan et al., 1989; Stephens, 2005; Bony et al., 2015; IPCC, 2021). Variations in cloud cover strongly influence surface energy balance, atmospheric circulation, precipitation, and local weather conditions, with important implications for agriculture, water resource management, renewable energy, aviation, and disaster risk reduction (Stephens, 2005; Wild et al., 2015). Consequently, understanding the spatial and temporal variability of cloud cover is essential for improving regional climate assessments and supporting sustainable environmental management.

Indonesia is located within the Maritime Continent, one of the world's most active tropical convective regions, where atmospheric conditions are governed by complex interactions among the atmosphere, ocean, and land surface (Ramage, 1968; Chang et al., 2005). Regional climate variability is influenced by

several large-scale climate systems, including the Australian–Asian monsoon, the El Niño–Southern Oscillation (ENSO), the Madden–Julian Oscillation (MJO), and the Indian Ocean Dipole (IOD) (Chang et al., 2005; McPhaden et al., 2006; Zhang, 2005; Saji et al., 1999). Among these climate drivers, ENSO represents one of the dominant sources of interannual climate variability. El Niño events generally suppress atmospheric convection and reduce moisture availability over Indonesia, whereas La Niña events enhance convection and cloud development through increased low-level moisture convergence (McPhaden et al., 2006; Aldrian & Susanto, 2003). While these atmospheric responses have been extensively investigated using rainfall observations (Haylock & McBride, 2001; Hendon, 2003) and Outgoing Longwave Radiation (OLR) as a proxy for tropical convection (Bannu et al., 2008), direct investigations of Total Cloud Cover (TCC) remain comparatively limited, particularly over small tropical islands with complex terrain.

Bali represents an ideal natural laboratory for investigating cloud variability because of its pronounced topographic complexity. The island is characterized by a volcanic mountain range extending across its central region, where elevations increase rapidly from coastal lowlands to mountainous terrain exceeding 1,400 m above sea level. These steep elevation gradients modify atmospheric circulation through orographic lifting, adiabatic cooling, localized thermodynamic processes, and rain-shadow effects, producing substantial spatial heterogeneity in cloud formation and persistence (Barry, 2008; Whiteman, 2000; Houze, 2012; Kirshbaum et al., 2018; Roe, 2005). In addition, land–sea breeze circulations and mesoscale atmospheric processes further contribute to pronounced spatial and seasonal variations in cloud development across the island.

Previous climatological studies in Indonesia have predominantly focused on rainfall variability, monsoon dynamics, and surface temperature changes (Aldrian & Susanto, 2003; Hamada et al., 2002; Hendon, 2003; Haylock & McBride, 2001; Supari et al., 2018). Numerous studies have quantified the influence of ENSO on rainfall anomalies (Haylock & McBride, 2001; Hendon, 2003; McPhaden et al., 2006), whereas others have employed OLR as an indirect indicator of tropical convection (Bannu et al., 2008). In contrast, studies that directly examine Total Cloud Cover as an atmospheric variable remain relatively scarce (Stengel et al., 2020), especially at the scale of small mountainous tropical islands such as Bali. Existing studies have also rarely integrated spatial distribution, seasonal variability, interannual variability, long-term trends, and teleconnection analyses within a single cloud-climatology framework, resulting in an incomplete understanding of cloud-cover variability across the region.

The availability of high-resolution atmospheric reanalysis datasets has created new opportunities for regional cloud-climatology research. ERA5, developed by the European Centre for Medium-Range Weather Forecasts (ECMWF), provides physically consistent atmospheric variables with high spatial and temporal resolution and has demonstrated reliable performance in numerous climatological applications, including studies over the Indonesian Maritime Continent (Hersbach et al., 2020). However, a comprehensive assessment of ERA5-derived Total Cloud Cover over Bali that simultaneously examines its spatial characteristics, seasonal cycle, interannual variability, long-term trends, and relationship with ENSO has not yet been reported.

To address these knowledge gaps, this study presents a comprehensive climatological assessment of ERA5-derived Total Cloud Cover over Bali during 2016–2025. Unlike previous studies that primarily emphasized rainfall variability or indirect indicators of atmospheric convection, this study directly investigates cloud-cover variability by integrating analyses of spatial distribution, seasonal variability, interannual variability, long-term trends using ordinary least squares (OLS) regression, the Mann–Kendall test, and Sen's slope estimator, together with the relationship between monthly Total Cloud Cover anomalies and the Oceanic Niño Index (ONI). This integrated framework provides an updated cloud-climatology baseline for Bali and improves understanding of how local topographic controls, monsoonal circulation, and ENSO jointly influence cloud-cover variability over a tropical mountainous island.

The objectives of this study are to:

1. Characterize the spatial distribution and climatological characteristics of Total Cloud Cover across six representative locations in Bali.
2. Evaluate the seasonal and interannual variability of Total Cloud Cover during the 2016–2025 period.
3. Assess long-term trends in Total Cloud Cover using ordinary least squares (OLS) regression, the Mann–Kendall test, and Sen's slope estimator.
4. Examine the monthly relationship between the Oceanic Niño Index (ONI) and Total Cloud Cover using Spearman rank correlation analysis.

The findings provide an updated climatological baseline of Total Cloud Cover over Bali and offer insights into the combined influence of topography, monsoonal circulation, and ENSO on cloud-cover variability within the Maritime Continent. These results contribute to regional climate monitoring and seasonal climate prediction while supporting climate-sensitive sectors such as agriculture, water resource management, renewable energy, aviation, and tourism.

Data and Methods

2.1 Study Area

This study focuses on Bali Island, Indonesia, a tropical insular region characterized by complex land-sea boundaries and complex topographic configurations. Situated within the southern maritime continent, Bali's atmospheric dynamics are heavily governed by the macro-scale monsoonal wind reversal, local land-sea breezes, and distinct topographic gradients (Chang et al., 2005; Barry, 2008). The island features an extensive elevation range, extending from coastal lowlands up to rugged volcanic massifs exceeding 1,400 meters above sea level (m a.s.l.), as delineated by the digital elevation framework.

To capture the spatial heterogeneity of atmospheric parameters across these microclimatic zones, six strategic observation locations were designated: Denpasar, Buleleng, Karangasem, Jembrana, Tabanan, and Bangli. These locations span diverse physiographic settings, ranging from coastal lowlands directly exposed to maritime air masses to elevated inland regions where topographic blocking and orographic

lifting strongly influence cloud development and convective precipitation (Houze, 2012; Kirshbaum et al., 2018).

2.2 Data Sources

2.2.1 Total Cloud Cover (TCC) Dataset

Atmospheric fields were obtained from the fifth-generation European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis dataset (ERA5), accessed through the Copernicus Climate Data Store (CDS). ERA5 combines millions of atmospheric observations from satellites, radiosondes, aircraft, ships, buoys, and surface stations using a state-of-the-art four-dimensional variational (4D-Var) data assimilation system to provide a physically consistent global atmospheric reanalysis (Hersbach et al., 2020). Total Cloud Cover (TCC) represents the fraction of a grid cell covered by clouds throughout the atmospheric column and is expressed as a percentage (%). Monthly mean TCC fields derived from ERA5 reanalysis data covering the period from January 2016 to December 2025 were used in this study. Spatial extraction was performed using the nearest-neighbor method at the native ERA5 horizontal resolution of $0.25^{\circ} \times 0.25^{\circ}$ (approximately $27.5 \text{ km} \times 27.5 \text{ km}$ near the equator). The nearest-neighbor approach was selected to preserve the original ERA5 grid values and avoid artificial smoothing associated with spatial interpolation over Bali's highly heterogeneous terrain.

2.2.2 Large-Scale Climate Indices

To evaluate macro-scale oceanic-atmospheric teleconnections affecting regional cloud fields, the Oceanic Niño Index (ONI) was retrieved from the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center. The ONI tracks the 3-month running mean of Sea Surface Temperature (SST) anomalies in the Niño 3.4 region (5°N – 5°S , 120° – 170°W) of the tropical Pacific Ocean (NOAA, 2025; McPhaden et al., 2006).

2.3 Data Preprocessing and Spatial Extraction

The ERA5 NetCDF datasets were processed using Python programming language with the xarray, pandas, NumPy, GeoPandas, SciPy, and Matplotlib libraries. Total Cloud Cover (TCC) values were extracted from the ERA5 grid using the nearest-neighbor approach based on the geographical coordinates of the six observation stations listed in Table 1. This approach preserves the original ERA5 grid values without introducing artificial smoothing effects associated with spatial interpolation, thereby providing a more representative characterization of localized atmospheric conditions over Bali's complex topography (Hersbach et al., 2020).

Prior to statistical analysis, the extracted TCC datasets underwent a series of quality-control procedures to ensure data consistency. Monthly records were examined for missing values and physically unrealistic observations outside the valid ERA5 TCC range (0–1). No missing values or invalid records were identified throughout the study period. Consequently, no temporal interpolation or gap-filling procedures were required prior to statistical analysis. The original TCC fractions were subsequently converted into

percentages (%) and aggregated into monthly mean time series, resulting in 120 continuous monthly observations for each station between January 2016 and December 2025 (720 observations in total across all stations).

Table 1
Geographical coordinates and spatial metadata of the selected atmospheric observation stations in Bali, Indonesia.

Station	Latitude (°S)	Longitude (°E)	Elevation (m a.s.l.)	Topographic Setting
Buleleng	8.11	115.09	10	Northern Coastal Slope / Leeward Zone
Bangli	8.27	115.35	423	Central Highlands / Elevated Basin
Jembrana	8.35	114.62	13	Western Coastal Lowlands
Karangasem	8.45	115.62	91	Eastern Volcanic Flank / Windward Zone
Tabanan	8.54	115.12	125	Southern Foothills / Transitional Zone
Denpasar	8.65	115.22	32	Southern Coastal Lowlands / Urban Canopy

Note: Geographical coordinates are referenced to the World Geodetic System 1984 (WGS 84) geographic coordinate system. Elevation values (m a.s.l.) were extracted directly from the Digital Elevation Model (DEM) used in this study. Windward and leeward classifications are assigned relative to the prevailing moisture-bearing airflow during the Northwest and Southeast monsoon seasons.

Monthly climatological means were then classified into four seasonal categories following the operational climatological definition of the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG): West Monsoon (December–February), First Transitional Season (March–May), East Monsoon (June–August), and Second Transitional Season (September–November). This seasonal aggregation reduces high-frequency weather variability while preserving the dominant seasonal and interannual climate signals associated with the regional monsoon system.

To quantify departures from the climatological state, monthly TCC anomalies ($TCC'_{i,j}$) were calculated using:

$$TCC'_{i,j} = TCC_{i,j} - \overline{TCC_j}$$

Where $TCC_{i,j}$ denotes the monthly mean Total Cloud Cover for year i and month j , while $\overline{TCC_j}$ represents the corresponding 10-year monthly climatological mean (2016–2025). This anomaly calculation removes the mean seasonal cycle, allowing the analysis to focus on interannual cloud-cover

variability associated with large-scale climate forcing rather than predictable seasonal fluctuations (Wilks, 2019).

2.4 Seasonal Classification and Temporal Stratification

To investigate seasonal variability in Total Cloud Cover (TCC) associated with the Indonesian monsoon system (Chang et al., 2005; Aldrian & Susanto, 2003), the monthly TCC time series was classified into two macro-seasonal periods representing the dominant hydroclimatic regimes over Bali.

The Wet Season was defined as December–March (DJFM), corresponding to the peak influence of the Northwest Monsoon, which is characterized by enhanced low-level moisture transport, atmospheric convergence, and intensified convective cloud development across southern Indonesia. Conversely, the Dry Season was defined as April–November (AMJJASON), encompassing the Southeast Monsoon and both transitional seasons, during which relatively drier atmospheric conditions and reduced convective activity generally prevail over the study region. This two-season classification follows the regional climatological characteristics of Bali and provides sufficiently large sample sizes for robust seasonal statistical analysis.

To examine recent temporal variability, the study period was further divided into two equal five-year intervals: 2016–2020 and 2021–2025. This temporal stratification facilitates a balanced comparison between the earlier and more recent periods while minimizing biases associated with unequal sample sizes. The approach also enables the identification of potential shifts in cloud-cover characteristics during the most recent decade without implying long-term climatic trends.

2.5 Statistical Analysis

2.5.1 Descriptive Statistics

Descriptive statistical analyses were first performed to characterize the spatial and temporal variability of Total Cloud Cover (TCC) across the six observation stations. The arithmetic mean (μ) and temporal standard deviation (σ) were calculated to quantify the central tendency and variability of monthly cloud cover throughout the study period. In addition, frequency histograms were constructed to examine the distributional characteristics of TCC, including skewness, modality, dispersion, and seasonal variability among stations. These descriptive statistics provide an overview of regional cloud-cover behavior and establish the statistical basis for subsequent trend and teleconnection analyses.

2.5.2 Linear Trend Analysis

Long-term temporal variations in monthly TCC were evaluated using a combination of parametric and non-parametric trend analysis techniques. Ordinary Least Squares (OLS) regression was employed to estimate the magnitude and direction of linear trends throughout the study period according to:

$$TCC_t = \beta_0 + \beta_1 t + \epsilon_t$$

where TCC_t is the monthly Total Cloud Cover (%) at time t , β_0 is the regression intercept, β_1 represents the linear trend magnitude (% year⁻¹), and ϵ_t denotes the residual error term. The statistical significance of the regression slope was evaluated using a two-tailed Student's t -test for the regression slope at the 95% confidence level ($p < 0.05$) (Wilks, 2019). OLS regression provides an estimate of the overall direction and magnitude of long-term linear changes in cloud cover.

To complement the parametric regression analysis, monotonic trends were further assessed using the non-parametric Mann–Kendall (MK) trend test (Mann, 1945; Kendall, 1975). The Mann–Kendall test was selected because it does not require normally distributed data, is robust against non-normality, and is less sensitive to outliers commonly encountered in climatological time series. Statistical significance was evaluated at the 95% confidence level ($\alpha = 0.05$) based on the standardized test statistic.

The magnitude of monotonic trends was subsequently quantified using Sen's slope estimator, which calculates the median slope of all pairwise combinations of observations and provides a robust estimate of long-term trend magnitude (Sen, 1968). Positive Sen's slope values indicate increasing cloud-cover conditions over time, whereas negative values indicate decreasing cloud-cover conditions.

The combined application of OLS regression, the Mann–Kendall test, and Sen's slope estimator provides complementary information regarding trend magnitude, statistical significance, and robustness, thereby improving the reliability of long-term trend assessment under varying statistical characteristics of climatological time series. The correlation analysis was conducted independently for each observation station using monthly anomaly series.

2.5.3 Teleconnection Analysis

The relationship between large-scale climate variability and cloud-cover conditions over Bali was evaluated using Spearman's rank correlation coefficient (ρ) (Spearman, 1904). This non-parametric method is widely used in hydroclimatological studies because it does not require assumptions of normality or linearity (Spearman, 1904; Wilks, 2019). Monthly Total Cloud Cover anomalies were correlated with the Oceanic Niño Index (ONI) to quantify the strength and direction of the association between ENSO variability and regional cloud-cover conditions. Correlation coefficients range from -1 to $+1$, where positive values indicate that increasing ONI is associated with increasing TCC, whereas negative values indicate an inverse relationship. Statistical significance was assessed at the 95% confidence level ($p < 0.05$).

Results

3.1 Spatial Characteristics of Mean Total Cloud Cover

Mean Total Cloud Cover (TCC) exhibited pronounced spatial variability across Bali during the 2016–2025 study period, with station-averaged values ranging from **63.3% to 81.5%** (Table 2). Overall, inland

stations consistently recorded higher mean cloud-cover values than coastal stations, highlighting the influence of Bali's complex topography on the spatial distribution of cloud cover.

Table 2

Basic descriptive statistics of monthly Total Cloud Cover (TCC) across six observation stations in Bali during 2016–2025. Mean and standard deviation (SD) are expressed as percentages (%).

Station Name	Mean TCC (%)	Standard Deviation (%)
Bangli	81.5	11.0
Karangasem	70.5	15.0
Tabanan	69.6	15.7
Denpasar	66.2	16.6
Jembrana	66.9	18.6
Buleleng	63.3	19.0
<i>Note: TCC data were derived from the ERA5 atmospheric reanalysis dataset at monthly temporal resolution for January 2016–December 2025.</i>		

Among the six observation stations, Bangli recorded the highest mean TCC (81.5%), followed by Karangasem (70.5%) and Tabanan (69.6%), whereas Buleleng exhibited the lowest mean cloud cover (63.3%). Denpasar and Jembrana showed intermediate mean values of 66.2% and 66.9%, respectively. The difference of 18.2 percentage points between Bangli and Buleleng indicates substantial spatial heterogeneity in cloud-cover conditions across Bali.

Temporal variability also differed among stations. Buleleng (19.0%) and Jembrana (18.6%) exhibited the largest monthly variability, suggesting stronger fluctuations in cloud-cover conditions throughout the year. In contrast, Bangli showed the lowest temporal variability (11.0%), indicating relatively persistent cloud-cover conditions. Karangasem, Tabanan, and Denpasar displayed intermediate standard deviations ranging from 15.0% to 16.6%, reflecting moderate month-to-month variability.

3.2 Seasonal Variability of Total Cloud Cover

Monthly Total Cloud Cover (TCC) exhibited a distinct seasonal cycle across all six observation stations during the 2016–2025 period (Figs. 2 and 3). Although the magnitude of cloud cover varied among stations, the temporal evolution was remarkably consistent throughout Bali, with cloud cover increasing during the wet season and decreasing during the dry season.

Across all stations, TCC increased from December to March, corresponding to the peak of the Northwest Monsoon, and gradually decreased from April to November, reaching minimum values during July–September. Despite this common seasonal evolution, clear spatial differences were evident. Bangli consistently maintained the highest cloud-cover values throughout the year, followed by Karangasem and Tabanan, whereas Buleleng persistently recorded the lowest TCC values. Denpasar and Jembrana

exhibited intermediate cloud-cover conditions between the inland highland stations and the northern coastal region.

The seasonal contrast is further illustrated by the frequency distributions shown in Fig. 3. During the wet season, monthly TCC values were concentrated primarily between 70% and 90%, indicating persistently cloudy conditions across Bali. In contrast, the dry season exhibited a broader distribution extending toward lower TCC values, reflecting reduced cloud cover and greater month-to-month variability.

The wet-minus-dry difference distribution (Fig. 3e) was dominated by positive values, confirming that cloud cover during the wet season consistently exceeded that of the dry season across the six observation stations. This result highlights the strong seasonal control exerted by the regional monsoon system on cloud-cover variability.

Figures 3c and 3d compare the TCC distributions between the early (2016–2020) and recent (2021–2025) periods. The overall distribution remained broadly similar over the decade, with most observations concentrated within the intermediate-to-high cloud-cover range. Nevertheless, the recent period showed a slightly higher frequency of large TCC values. This subtle change is further reflected by the recent-minus-early difference distribution (Fig. 3f), which is centered close to zero but exhibits a slight positive shift, suggesting a modest increase in cloud-cover occurrence during 2021–2025 relative to 2016–2020.

3.3 Interannual Variability of Total Cloud Cover and ENSO Conditions

Interannual variability in Total Cloud Cover (TCC) was assessed using annual anomalies relative to the 2016–2025 climatological mean and compared with the temporal evolution of the Oceanic Niño Index (ONI) over the same period (Figs. 4 and 5).

Annual TCC anomalies exhibited a remarkably consistent temporal evolution across the six observation stations. Positive anomalies occurred simultaneously in 2017, 2021, 2022, and 2025, whereas negative anomalies were consistently observed during 2018–2020 and 2023–2024. Although the magnitude of anomalies varied slightly among stations, the timing of positive and negative departures remained highly coherent, indicating that interannual cloud-cover variability was governed primarily by large-scale regional climate forcing rather than local effects.

Among all years, 2019 exhibited the largest negative TCC anomalies across nearly all stations, whereas the strongest positive anomalies occurred during 2022 and 2025, when annual cloud cover exceeded the climatological mean at most locations. Overall, interannual differences were substantially greater than the spatial differences in anomaly magnitude among stations, emphasizing that year-to-year climate variability dominated over local-scale variability.

The ONI time series indicates pronounced ENSO variability throughout the study period. Following the decay of the 2015–2016 El Niño, ONI fluctuated between neutral, La Niña, and El Niño conditions. A prolonged La Niña episode persisted from late 2020 to early 2023, reaching approximately -1.2°C ,

followed by a strong El Niño event during 2023–2024, with ONI exceeding + 2.0°C, before gradually returning toward neutral conditions in 2025.

A visual comparison of Figs. 4 and 5 suggests a general correspondence between interannual TCC anomalies and ENSO conditions. Positive cloud-cover anomalies occurred more frequently during La Niña episodes, whereas negative anomalies were generally associated with El Niño conditions. However, this relationship was not uniform throughout the study period. For example, pronounced negative TCC anomalies were observed in 2019, despite only moderate ONI values, suggesting that additional regional or local atmospheric processes may also have influenced interannual cloud-cover variability. These observations indicate a potential ENSO influence on cloud-cover variability, which is evaluated quantitatively using Spearman's rank correlation in the following section.

3.4 Long-Term Trend Analysis of Total Cloud Cover

Long-term changes in monthly Total Cloud Cover (TCC) during 2016–2025 were evaluated using Ordinary Least Squares (OLS) regression, together with the Mann–Kendall (MK) trend test and Sen's slope estimator (Table 3). These complementary approaches were used to assess the direction, magnitude, and statistical significance of long-term cloud-cover variability.

Table 3

Results of Ordinary Least Squares (OLS) regression, Mann–Kendall (MK) trend test, and Sen's slope estimator for monthly Total Cloud Cover (TCC) across six observation stations in Bali during 2016–2025.

Station	Mean TCC (%)	OLS Slope (% year ⁻¹)	OLS p-value	MK Trend	MK p-value	Kendall's τ	Sen's Slope (% year ⁻¹)
Denpasar	66.20	0.0954	0.8569	No trend	0.9295	0.006	0.0328
Buleleng	63.33	-0.0615	0.9188	No trend	0.7872	-0.017	-0.1831
Karangasem	70.50	0.0576	0.9042	No trend	0.9873	-0.001	-0.0064
Jembrana	65.93	-0.0657	0.9117	No trend	0.7525	-0.020	-0.1788
Tabanan	69.57	-0.0078	0.9875	No trend	0.8614	-0.011	-0.0883
Bangli	81.50	-0.0446	0.8988	No trend	0.8542	-0.011	-0.0612

Note: OLS = Ordinary Least Squares linear regression; MK = Mann–Kendall trend test. OLS slope and Sen's slope are expressed in % yr⁻¹. p-values represent the statistical significance of the trend at the 95% confidence level ($p < 0.05$). Positive slope values indicate increasing Total Cloud Cover (TCC), whereas negative values indicate decreasing TCC.

The OLS regression revealed only very weak long-term trends in monthly TCC across all observation stations. Estimated slopes ranged from $-0.066\% \text{ year}^{-1}$ at Jembrana to $0.095\% \text{ year}^{-1}$ at Denpasar, with both positive and negative values observed among stations. However, none of the regression slopes were statistically significant ($p > 0.05$), indicating no detectable linear trend in cloud cover during the study period.

The Mann–Kendall test produced results consistent with the OLS analysis. All stations were classified as "No trend", with MK p -values ranging from 0.753 to 0.987, well above the significance threshold of 0.05. Likewise, Kendall's τ coefficients remained close to zero at all stations, indicating the absence of a statistically significant monotonic increase or decrease in monthly cloud cover.

Sen's slope estimates further confirmed the negligible magnitude of long-term change, ranging from $-0.183\% \text{ year}^{-1}$ at Buleleng to $0.033\% \text{ year}^{-1}$ at Denpasar. The close agreement among the OLS regression, Mann–Kendall test, and Sen's slope estimator consistently indicates that no statistically significant long-term trend in monthly Total Cloud Cover was detected across Bali during 2016–2025.

3.5 Monthly Relationship between Oceanic Niño Index and Total Cloud Cover

Monthly Spearman rank correlation coefficients were calculated to evaluate the relationship between the Oceanic Niño Index (ONI) and Total Cloud Cover (TCC) at each observation station during 2016–2025 (Table 4). The monthly analysis was performed to investigate how the strength and direction of the ONI–TCC relationship varied throughout the annual cycle.

Table 4

Spearman rank correlation coefficients between the Oceanic Niño Index (ONI) and monthly Total Cloud Cover (TCC) at six observation stations in Bali during 2016–2025.

Month	Denpasar	Buleleng	Karangasem	Jembrana	Tabanan	Bangli
Jan	0.08	0.13	0.06	0.19	0.11	0.19
Feb	0.35	0.31	0.41	0.13	0.28	0.29
Mar	0.34	0.21	0.14	0.24	0.24	0.19
Apr	0.59	0.36	0.31	0.34	0.39	0.32
May	0.34	0.25	0.40	0.54	0.40	0.50
Jun	0.12	-0.12	-0.04	-0.12	0.09	-0.41
Jul	0.05	-0.08	-0.11	-0.20	-0.24	-0.25
Aug	-0.30	-0.14	0.08	-0.14	0.09	0.18
Sep	-0.28	-0.21	-0.15	-0.04	0.03	0.14
Oct	0.45	0.56	0.73	0.50	0.66	0.53
Nov	0.39	0.20	0.22	0.22	0.23	0.49
Dec	0.53	0.31	0.32	0.19	0.30	0.38
Note: Positive correlation coefficients indicate a direct relationship between the Oceanic Niño Index (ONI) and Total Cloud Cover (TCC), whereas negative coefficients indicate an inverse relationship.						

The correlation analysis revealed a pronounced seasonal dependence in the relationship between ONI and TCC. Correlation coefficients varied substantially in both magnitude and direction throughout the year, indicating that the association between ENSO variability and cloud-cover conditions over Bali changes with the seasonal evolution of the regional climate.

The strongest and most spatially coherent positive correlations occurred during October, when all six observation stations exhibited moderate-to-strong positive relationships. Correlation coefficients ranged from $\rho = 0.45$ in Denpasar to $\rho = 0.73$ in Karangasem, with similarly high values observed at Tabanan ($\rho = 0.66$), Buleleng ($\rho = 0.56$), Bangli ($\rho = 0.53$), and Jembrana ($\rho = 0.50$). This consistent pattern indicates that the association between ONI and TCC reached its maximum during October across the study area.

Positive correlations generally persisted during November and December, although their magnitudes decreased and became more spatially variable among stations. Moderate positive relationships were also evident during April and May, suggesting that ENSO-related cloud-cover variability was most apparent during the transition between the wet and dry monsoon regimes rather than during the peak monsoon seasons.

In contrast, the relationship weakened considerably during June–August, when most correlation coefficients remained below $|p| = 0.30$. Several stations even exhibited moderate negative correlations, particularly Bangli ($p = -0.41$) in June and Denpasar ($p = -0.30$) in August, indicating that the relationship between ONI and cloud cover became weaker and less spatially consistent during the dry season. Likewise, correlations during January–March and September were generally weak across all stations, suggesting only a limited association between monthly ONI variability and cloud-cover conditions during these periods.

The monthly correlation analysis indicates that the association between ONI and Total Cloud Cover is strongly season-dependent. The strongest positive correlations consistently occurred during October, whereas considerably weaker and occasionally negative relationships were observed during other months. These findings suggest that the response of cloud-cover variability to ENSO is likely modulated by the seasonal evolution of the Indonesian monsoon together with local atmospheric processes.

Discussion

4.1 Topographic Influence on the Spatial Distribution of Total Cloud Cover

The spatial differences in mean Total Cloud Cover (TCC) across Bali indicate that cloud climatology is strongly modulated by local topographic conditions in addition to large-scale atmospheric circulation. Although the six observation stations are distributed within a relatively small island, inland stations consistently exhibited higher mean TCC than coastal stations (Table 2), demonstrating pronounced spatial heterogeneity in cloud-cover conditions.

This spatial pattern is consistent with the influence of orographic lifting, whereby moist maritime air is forced to ascend over Bali's mountainous interior, resulting in adiabatic cooling, condensation, and enhanced cloud formation (Houze, 2012). The highest mean TCC recorded at Bangli (81.5%), followed by Karangasem (70.5%), supports this mechanism because both locations are characterized by elevated terrain where upslope airflow favors persistent cloud development. Similar relationships between elevation and cloud occurrence have been reported for other tropical mountainous regions, where complex terrain enhances convection and prolongs cloud persistence (Kirshbaum et al., 2018).

In contrast, the lower mean TCC observed at Buleleng, Denpasar, and Jembrana suggests that cloud formation is less strongly enhanced by terrain. Buleleng, located on the northern coast of Bali, is frequently influenced by rain-shadow conditions generated by the central mountain range during periods of southeasterly monsoon flow. Descending air on the leeward side suppresses condensation and reduces cloud formation, contributing to the lowest mean TCC among the six stations. Coastal locations are also more strongly influenced by land–sea breeze circulations, which increase short-term variability in cloud development relative to the more persistent cloudiness observed over the mountainous interior (Whiteman, 2000).

These results indicate that the spatial variability of cloud cover over Bali cannot be explained solely by regional monsoonal forcing. Instead, the observed cloud-cover pattern reflects the interaction between large-scale atmospheric circulation and local terrain, emphasizing the importance of topographic controls when interpreting cloud climatology over tropical islands with complex physiography.

4.2 Seasonal Variability of Total Cloud Cover in Relation to the Monsoon System

The pronounced seasonal cycle of Total Cloud Cover observed across Bali reflects the dominant influence of the Australian–Asian monsoon system on regional atmospheric conditions. Monthly TCC increased consistently during December–March and decreased during April–November at all observation stations (Figs. 2 and 3), indicating that the timing of seasonal cloud variability is primarily controlled by the annual reversal of the regional monsoon circulation.

During the wet season, northwesterly monsoon flow transports warm and moisture-rich air from the surrounding tropical oceans toward the Indonesian Maritime Continent, promoting deep convection and widespread cloud formation (Aldrian & Susanto, 2003). In contrast, the dry season is dominated by relatively cooler and drier southeasterly airflow originating from the Australian continent, suppressing convective activity and reducing cloud-cover conditions across Bali. This seasonal evolution agrees with previous studies describing monsoon-driven variability in cloudiness and precipitation throughout the Maritime Continent (Chang et al., 2005; Qian, 2008).

Although all stations exhibited a similar seasonal cycle, cloud-cover magnitude remained consistently higher over inland mountainous areas than over coastal regions throughout the year. This persistent difference suggests that topographic effects modulate the intensity of cloud development without substantially altering the seasonal timing imposed by the monsoon system. In other words, the monsoon determines when cloud cover increases or decreases, whereas local terrain influences how much cloud cover develops at each location.

The frequency distributions further indicate that seasonal variability involves changes in both the mean and variability of cloud-cover conditions. Wet-season observations were concentrated within the high TCC range, indicating persistently cloudy conditions across much of Bali. In contrast, the broader distribution observed during the dry season reflects larger month-to-month fluctuations in cloud cover, suggesting that local atmospheric processes become relatively more important when large-scale moisture availability is reduced.

These findings demonstrate that seasonal cloud-cover variability over Bali is governed by the combined influence of monsoonal circulation and local topographic modulation. The monsoon establishes the annual cycle of cloudiness, whereas terrain enhances spatial contrasts in cloud persistence across the island.

4.3 Long-Term Trend Stability of Total Cloud Cover

The combined trend analyses indicate that Total Cloud Cover (TCC) over Bali remained statistically stable throughout 2016–2025. Ordinary Least Squares (OLS) regression, the Mann–Kendall test, and Sen's slope estimator consistently showed that none of the six observation stations exhibited a statistically significant long-term trend (Table 3). The agreement among these complementary methods strengthens confidence that the absence of significant trends is robust and not dependent on the assumptions of a single statistical approach.

The lack of detectable long-term trends suggests that cloud-cover variability during the study period was primarily governed by seasonal and interannual climate variability rather than by persistent long-term change. As shown in the Results, pronounced year-to-year fluctuations were evident in the annual anomaly series, yet these fluctuations oscillated around the climatological mean without producing a significant long-term increase or decrease in TCC. Similar behavior has been reported in tropical regions, where strong monsoonal variability and recurring large-scale climate oscillations often mask weaker long-term trends (IPCC, 2021).

The relatively short observational period should also be considered when interpreting these findings. Although a 10-year record is adequate for describing recent climatological variability, it is generally insufficient for detecting robust climate trends that evolve over multiple decades (IPCC, 2021). Consequently, the absence of statistically significant trends should be interpreted as evidence of short-term stability rather than as confirmation that long-term changes in cloud climatology are absent.

The stability identified in this study provides an updated climatological baseline for Bali during 2016–2025. This baseline can serve as a reference for future studies using longer observational records to determine whether cloud-cover conditions remain stable or begin to exhibit detectable long-term changes under a changing climate.

4.4 ENSO Influence on Interannual Cloud Variability

The monthly correlation analysis indicates that the relationship between ENSO and Total Cloud Cover (TCC) over Bali varies substantially throughout the annual cycle. Rather than exerting a uniform influence, the association between ONI and TCC was strongest during the monsoon transition periods and considerably weaker during the mature phases of the wet and dry monsoons. This seasonal dependence suggests that the atmospheric response to ENSO is strongly modulated by the background circulation over the Indonesian Maritime Continent (McPhaden et al., 2006; Aldrian & Susanto, 2003).

The strongest positive correlations occurred consistently during October, when all six observation stations exhibited moderate-to-strong positive relationships with ONI. Karangasem recorded the highest monthly correlation ($\rho = 0.73$), while similarly positive relationships were observed at the remaining stations. October coincides with the transition from the dry season to the onset of the northwest monsoon, a period during which large-scale atmospheric circulation undergoes substantial seasonal reorganization. Under these conditions, tropical Pacific sea surface temperature anomalies may exert a stronger influence on regional moisture transport and cloud formation. Similar seasonally varying ENSO

teleconnections have been reported throughout the Maritime Continent (Aldrian & Susanto, 2003; Chang et al., 2005).

In contrast, the weak correlations observed during June–August indicate that ENSO played a comparatively smaller role in explaining monthly cloud-cover variability during the peak dry season. During this period, the prevailing southeasterly monsoon transports relatively dry and stable air from the Australian continent, limiting deep convection across Bali (Chang et al., 2005). Consequently, local controls, including topographic forcing, land–sea breeze circulations, and mesoscale atmospheric processes, are likely to exert a greater influence on cloud development than remote ENSO forcing.

Moderate positive correlations during April and May further suggest that ENSO also contributes to cloud-cover variability during the transition from the wet season to the dry season, although the observed relationships were generally weaker than those identified in October. Together, these findings indicate that the influence of ENSO on cloud-cover variability depends on the prevailing seasonal circulation rather than remaining constant throughout the year.

These results demonstrate that cloud-cover variability over Bali is controlled by the interaction between large-scale climate variability and regional atmospheric processes. ENSO contributes to the observed interannual variability, but its influence is expressed differently across seasons as the Australian–Asian monsoon and local atmospheric dynamics modulate the regional cloud response.

4.5 Practical Implications

The climatological characteristics identified in this study have several implications for weather and climate applications in Bali. The pronounced seasonal cycle of Total Cloud Cover (TCC) confirms the dominant role of the Australian–Asian monsoon in regulating regional cloudiness, while the observed seasonal dependence of the ONI–TCC relationship indicates that ENSO influences cloud-cover variability more strongly during the monsoon transition periods than during the mature wet and dry seasons.

The climatological baseline established for 2016–2025 also provides a useful reference for monitoring future changes in cloud-cover conditions. Such baseline information may support seasonal climate monitoring and benefit climate-sensitive sectors, including agriculture, water-resource management, aviation, tourism, and solar-energy assessment, where cloud variability directly affects environmental conditions and operational planning (Stephens, 2005; Wild et al., 2015; WMO, 2023).

4.6 Study Limitations

Several limitations should be considered when interpreting the findings of this study.

First, the analysis covers only the 2016–2025 period. Although this record adequately represents recent cloud-cover variability, it is relatively short for detecting long-term climatic trends that typically emerge over several decades. Consequently, the absence of statistically significant trends should be interpreted as evidence of short-term stability rather than an indication that long-term changes are absent.

Second, the analysis relied exclusively on the ERA5 reanalysis dataset. Although ERA5 has demonstrated good performance in numerous climatological applications (Hersbach et al., 2020), uncertainties remain because reanalysis products depend on numerical model parameterizations and data assimilation. Future validation using satellite-derived cloud products or ground-based observations would improve confidence in the representation of cloud-cover conditions, particularly over Bali's complex mountainous terrain.

Finally, this study focused primarily on the relationship between ENSO and cloud-cover variability. Other large-scale climate modes, including the Indian Ocean Dipole (IOD) and the Madden–Julian Oscillation (MJO), were not explicitly examined and may also contribute to the observed variability. Considering these climate drivers would provide a more comprehensive understanding of atmospheric variability over Bali.

4.7 Future Research

Future research should extend the observational record to evaluate long-term changes in cloud-cover climatology over Bali. Incorporating longer ERA5 records together with satellite observations and ground-based measurements would enable more robust assessments of long-term variability and improve confidence in the derived cloud-cover characteristics.

Further studies should also investigate the combined influence of multiple climate modes, including the Indian Ocean Dipole (IOD), the Madden–Julian Oscillation (MJO), and regional monsoon variability, to better explain the mechanisms governing cloud-cover variability over the Indonesian Maritime Continent.

In addition, integrating cloud-cover analyses with other hydroclimatic variables, such as precipitation, surface temperature, and solar radiation, would provide a more comprehensive understanding of regional climate variability. Such analyses could also support improvements in seasonal climate prediction and climate adaptation strategies for tropical island environments.

Conclusion

This study examined the spatial and temporal characteristics of Total Cloud Cover (TCC) over Bali using monthly ERA5 reanalysis data for 2016–2025. The results demonstrate that cloud-cover variability across the island is jointly controlled by local topographic conditions and large-scale atmospheric circulation.

Spatial analyses revealed clear differences in mean TCC among the six observation stations. Inland mountainous areas, particularly Bangli, consistently exhibited higher cloud cover than coastal regions, whereas Buleleng recorded the lowest mean TCC, highlighting the importance of orographic processes in regulating cloud formation over Bali. A pronounced seasonal cycle was observed at all stations, with higher cloud cover during the wet season and lower cloud cover during the dry season, while local terrain modulated the magnitude of cloud-cover variability under the same monsoonal forcing.

Trend analyses based on Ordinary Least Squares (OLS) regression, the Mann–Kendall test, and Sen's slope estimator consistently indicated the absence of statistically significant long-term changes in TCC during the study period. Instead, cloud-cover variability was dominated by seasonal and interannual fluctuations. Monthly Spearman correlation analysis further demonstrated that the relationship between the Oceanic Niño Index (ONI) and TCC was strongly season-dependent, with the strongest positive correlations generally occurring during October, suggesting that ENSO-related cloud variability is most evident during the monsoon transition period.

The climatological baseline established in this study provides a useful reference for future investigations of cloud-cover variability over Bali. These findings also contribute to regional climate monitoring and seasonal forecasting, with potential applications in climate-sensitive sectors such as agriculture, water-resource management, aviation, tourism, and renewable-energy planning. Future studies should extend the observational record, incorporate additional climate drivers such as the Indian Ocean Dipole (IOD) and the Madden–Julian Oscillation (MJO), and evaluate ERA5-derived cloud-cover estimates using independent satellite and ground-based observations.

Declarations

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author Contribution

P.E.T.R. conceived and designed the study, conducted the data processing and statistical analysis, prepared the figures and tables, and wrote the initial manuscript. A.M. contributed to the supervision of the research, interpretation of the results, and critical revision of the manuscript. Both authors reviewed and approved the final manuscript.

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Data Availability

The ERA5 reanalysis data used in this study are publicly available through the Copernicus Climate Data Store (CDS). The Oceanic Niño Index (ONI) data are publicly available from the NOAA Climate Prediction Center. The data processing and analysis procedures are described in the manuscript.

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Figures

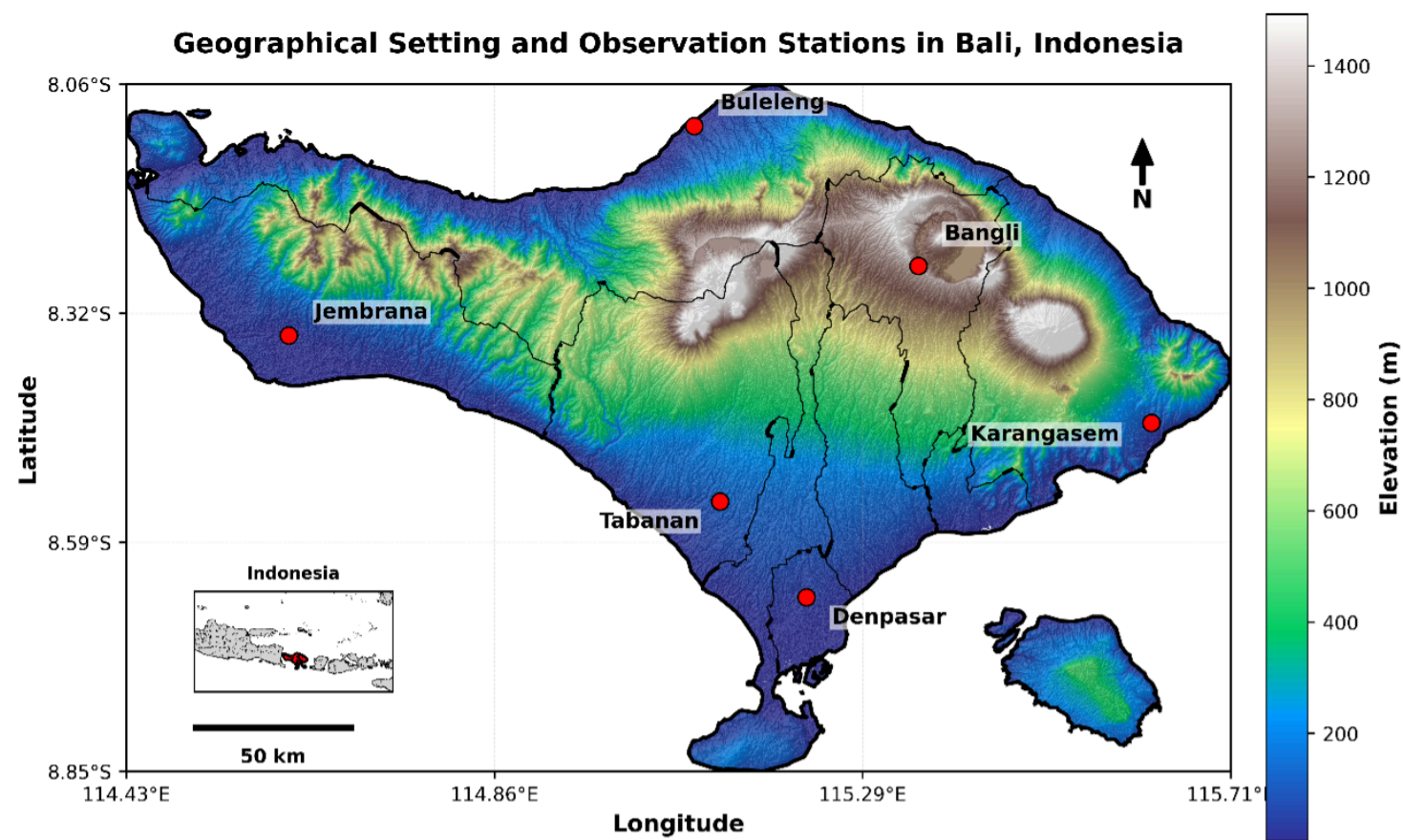


Figure 1

Geographical setting and spatial distribution of the six atmospheric observation stations across Bali Island, Indonesia. The topographic relief and elevation gradients (meters above sea level) are derived from the Digital Elevation Model (DEM), while internal boundaries delineate the administrative regencies. The inset map indicates the geographical location of Bali within the Indonesian Maritime Continent.

Monthly Total Cloud Cover over Bali from ERA5 (2016-2025)

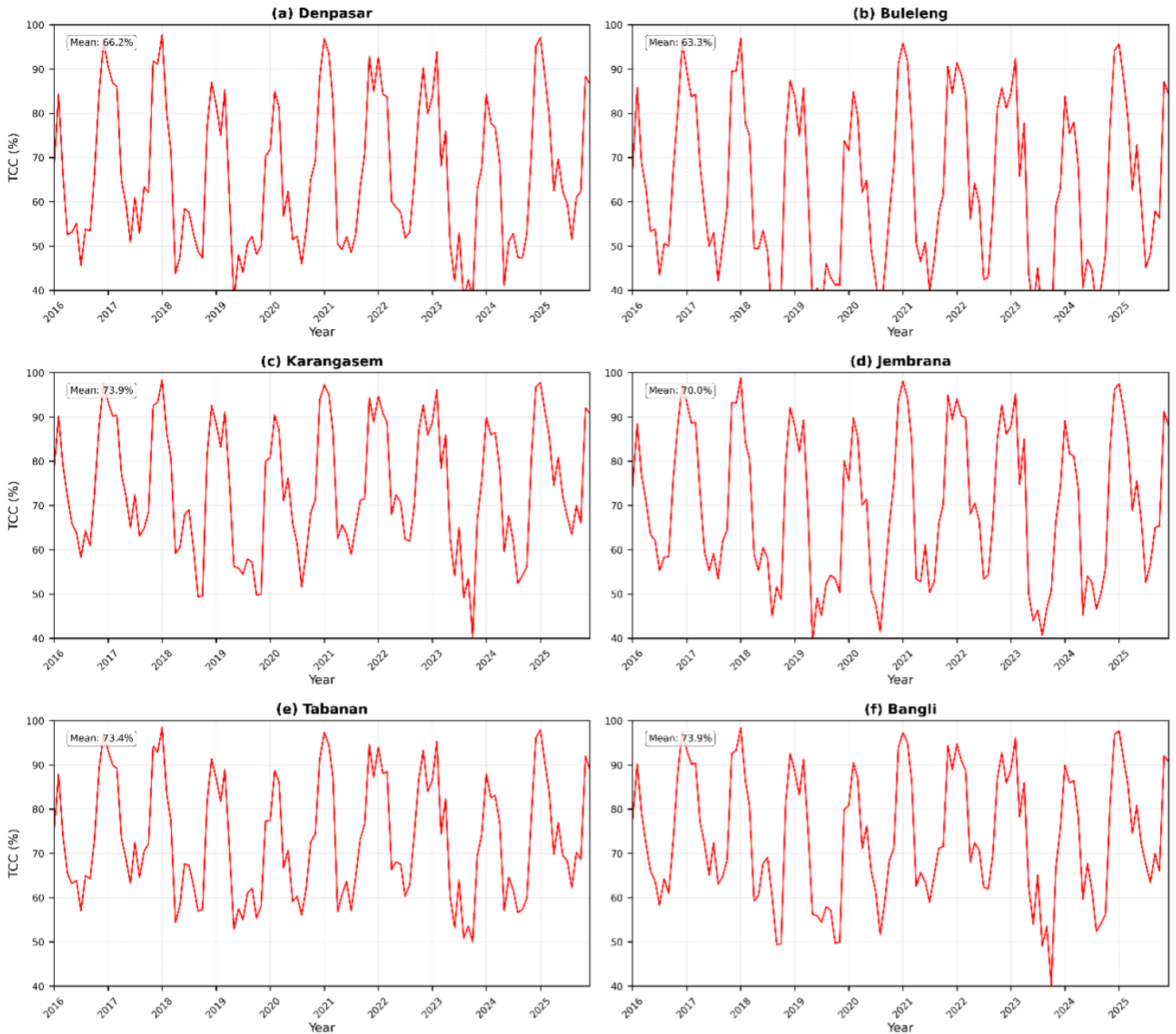


Figure 2

Monthly Total Cloud Cover (TCC, %) derived from the ERA5 atmospheric reanalysis dataset for six observation stations in Bali during 2016–2025: (a) Denpasar, (b) Buleleng, (c) Karangasem, (d) Jembrana, (e) Tabanan, and (f) Bangli. The red lines represent monthly TCC variability, while the inset box in each subplot indicates the corresponding decadal mean TCC. The y-axis is standardized between 40% and 100% to facilitate comparison among stations.

Total cloud cover climatology over Bali (2016-2025)

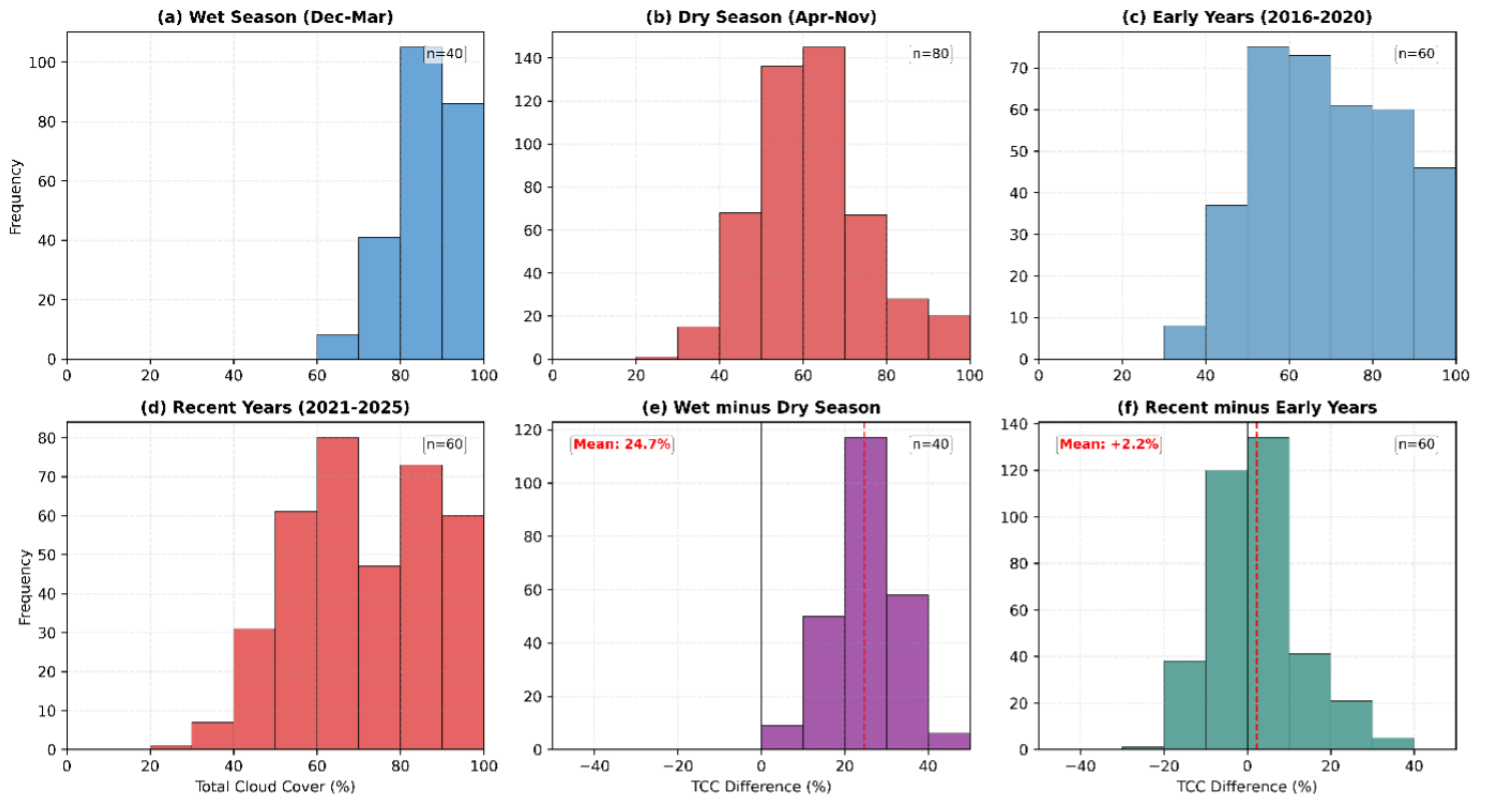


Figure 3

Frequency distributions of monthly Total Cloud Cover (TCC) over Bali during 2016–2025. Panels (a) and (b) show the TCC distributions during the wet season (December–March) and dry season (April–November), respectively. Panels (c) and (d) compare the distributions between the early (2016–2020) and recent (2021–2025) periods. Panels (e) and (f) present the corresponding distributions of wet-minus-dry and recent-minus-early TCC differences. Monthly observations from the six study locations were aggregated to characterize the seasonal and interannual variability of cloud cover across Bali.

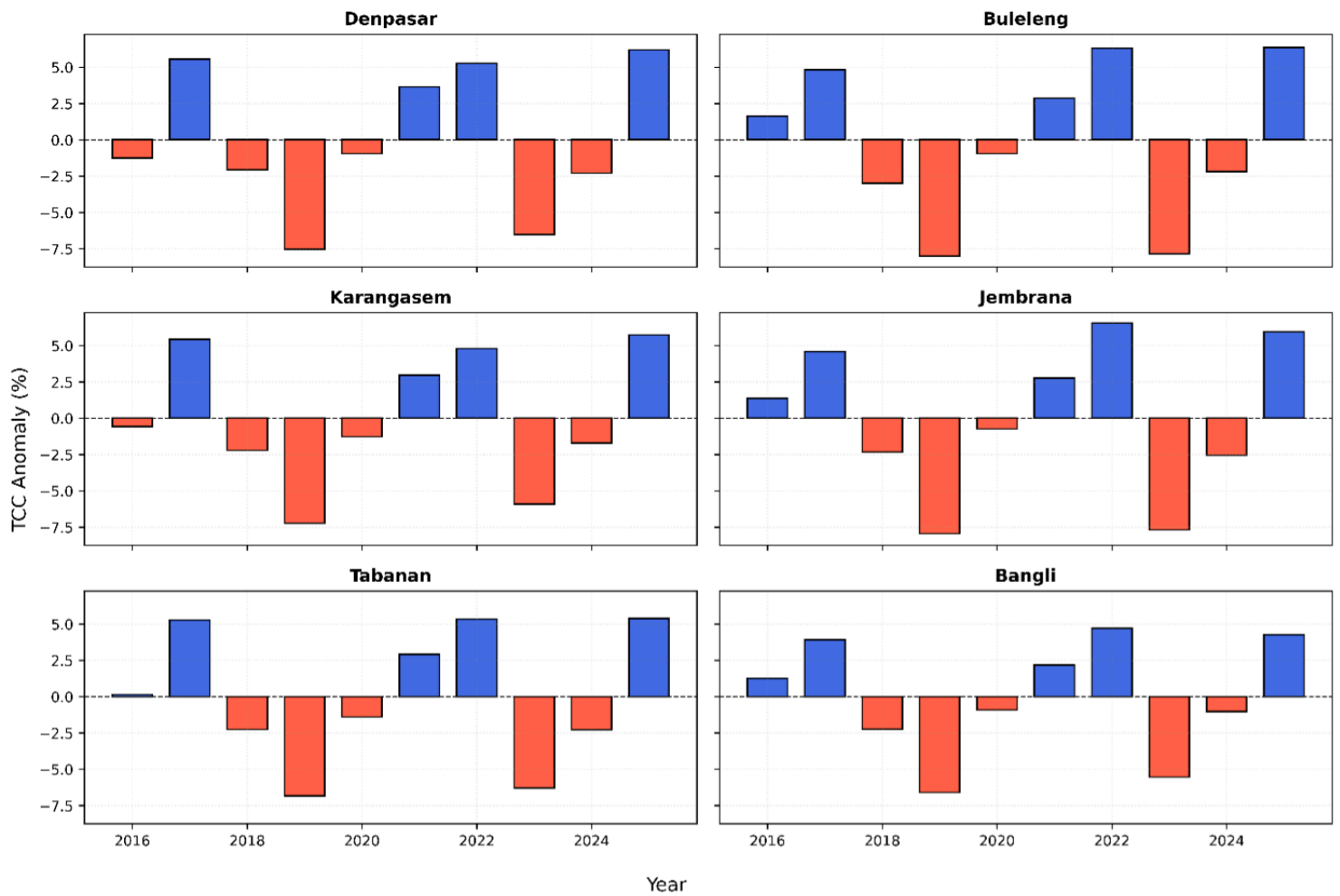


Figure 4

Annual Total Cloud Cover (TCC) anomalies (%) relative to the 2016–2025 climatological mean for six observation stations in Bali: (a) Denpasar, (b) Buleleng, (c) Karangasem, (d) Jembrana, (e) Tabanan, and (f) Bangli. Positive anomalies (blue) indicate cloud cover above the long-term mean, whereas negative anomalies (red) indicate below-normal cloud cover. The dashed horizontal line represents the climatological baseline.

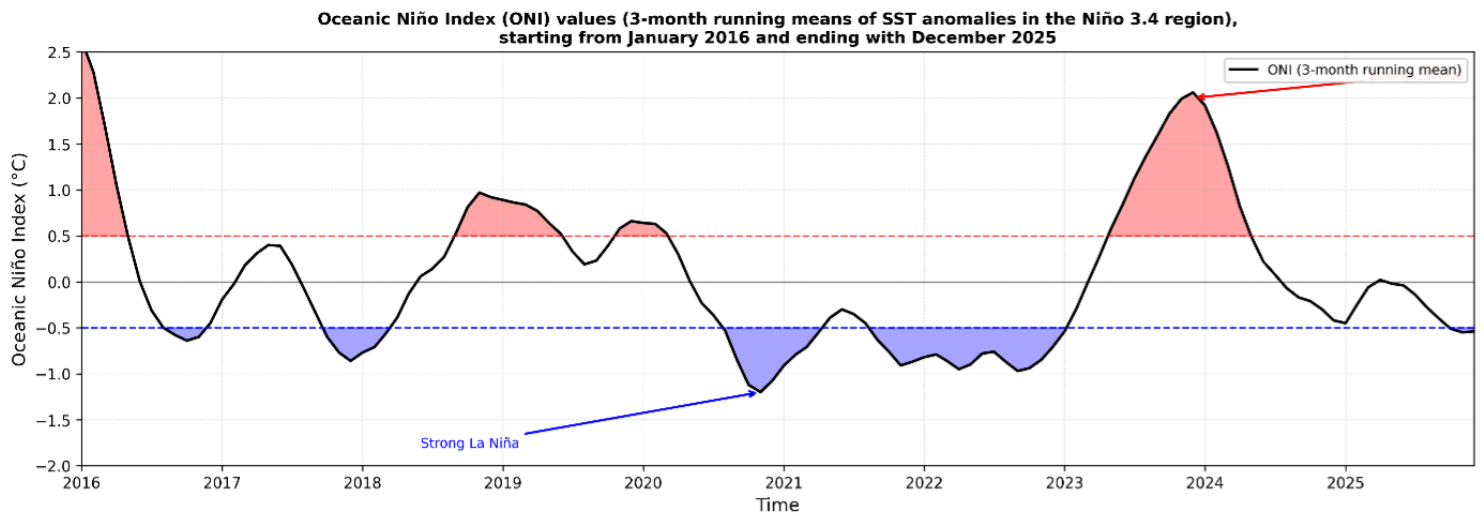


Figure 5

Monthly Oceanic Niño Index (ONI) during 2016–2025 based on three-month running mean sea-surface temperature anomalies over the Niño 3.4 region. Red shading denotes El Niño conditions ($ONI > +0.5\text{ }^{\circ}\text{C}$), blue shading denotes La Niña conditions ($ONI < -0.5\text{ }^{\circ}\text{C}$), and unshaded periods represent neutral conditions.