Spatio-Temporal Dynamics of Precipitation Anomalies in Southeast Asia: ENSO Influence and Machine Learning-Based Prediction

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Abstract

Southeast Asia is one of the climate-sensitive areas in the world that is often hit by hydroclimatic extremes in the form of droughts, floods, and disrupted monsoon regimes with cascading impacts on agriculture, water security, and disaster preparedness. The extremes are produced both by global and regional climate change and natural climate variability including the El Niño–Southern Oscillation (ENSO), which has widespread predominance over interannual precipitation variability. This paper provides an extensive Spatio-temporal evaluation of Southeast Asian precipitation anomalies from 2010 to 2024 using an integration of satellite-retrieved precipitation, ENSO phase categorization, and cloud-computing facilitated geospatial processing. CHIRPS daily precipitation totals were summed to annual totals and normalized as z-scores to categorize wet and dry anomalies against long-term climatology. ENSO phases were defined by the Oceanic Niño Index, and Google Earth Engine (GEE) was employed to compute local anomaly maps and obtain statistical summaries. Results indicate intense Spatio-temporal variability of precipitation anomalies with El Niño years 2015 and 2019 generating pan-regional drought deficits, whereas La Niña years 2010 and 2022 had increased rainfall and wet anomalies. Seasonal disaggregation also emphasizes that DJF (December–February) anomalies are most sensitive to variability in ENSO, with El Niño enhancing the extent of drought and La Niña enhancing rainfall, while country-level analysis suggests local sensitivities in Brunei, Malaysia, and the Philippines during La Niña and Indonesia and Vietnam during El Niño droughts. To extrapolate these findings, a Random Forest regression model was developed using prior anomaly–ENSO relationships that exhibited good predictability (R^2 = 0.82; RMSE = 18.6 mm) and predicted 2025 anomalies, in which eastern Indonesia and coastal Vietnam were ranked most likely rainfall deficiency hotspots. By combining satellite remote sensing, cloud computing, and machine learning, this research improves ENSO–precipitation relationship understanding and offers strong scientific evidence to inform climate-resilient planning in a highly hydro climatically vulnerable region.

Keywords: CHIRPS, ENSO, Google Earth Engine, Machine learning, Precipitation anomaly,

Introduction

Southeast Asia is among the most climate-sensitive regions of the globe, with recurring instances of hydroclimatic extremes in the dynamics of floods, droughts, and monsoonal variability (Kumar & Dwarakish, 2025). The extremes are aggravated by global change, as well as natural variability, with the El Niño–Southern Oscillation (ENSO) playing a prevailing role in regional temperature and precipitation variability, the extremes have broad socio-economic and environmental impacts that extend far to include agriculture, water resources, human health, and infrastructure (Zhu et al., 2025).

Among the robust predictors of such disturbances are climatic anomaly frequencies from climatic normal spanning long timescales in corresponding variables of rain. They must be detected and tracked in space and time with the highest priority towards adaptive planning and disaster risk mitigation, detection and interpretation of climatic anomalies are more important in Southeast Asia due to topographical complexity, micro-climatological complexity, and susceptibility to ocean atmosphere interactions like ENSO (Sa'Adi et al., 2025).

Past climate anomaly studies across Southeast Asia were limited by poor ground-based measurement networks and patchy data coverage. Revolution in space-based remote sensing and cloud computing platforms such as Google Earth Engine (GEE) have transformed the ability to monitor the climate. Such technologies enable routine monitoring of climate variables at spatial and temporal resolutions suitable to detect anomalies across national and ecological boundaries (Gorelick et al., 2017).

Whereas machine learning techniques such as Random Forest have widely been used in climate anomaly research, this research focuses on statistical anomaly detection using standardized indices of satellite-retrieved precipitation. Utilization of CHIRPS data along with GEE cloud computing enables reproducible and scalable workflows.

While prior research has broached climate trends and ENSO impact in Asia, hardly any have employed a spatially explicit, interannual anomaly dynamic analysis of remote sensing and predictive modeling of far greater importance, little has been done to quantitatively explain the ENSO-anomaly relationship in systematic terms through standardized anomaly indices in Southeast Asia and this matters when building regional early warning systems and adaptive planning for climate (Xie et al., 2025)

This study examines four primary aims: (i) to compute yearly, z-score standardized precipitation anomalies; (ii) to investigate regional tendencies in line with ENSO phases (El Niño, La Niña, Neutral); (iii) to perform country-level anomaly statistics and temporal trends; and (iv) to investigate the long-term trend and reveal emerging threats.

With examination of high-resolution satellite data, GEE cloud computing, and statistics, this paper presents a general description of Southeast Asian climate variability, impacts are returned to scientific knowledge as well as operation products for climate resilience planning in highly vulnerable areas.

This paper is structured as follows: Section 2 reviews relevant literature, section 3 outlines the data and methodology, section 4 presents results and discussions, and section 5 concludes with the key findings and policy implications.

Literature Review

South Asian climatic irregularities need to be examined through the assistance of atmospheric science information as well as geospatial analysis. Based on previous studies, it has been determined that El Niño–Southern Oscillation (ENSO) exerts far-reaching impacts on rainfall fluctuations as well as drought events in the continent (Hay & Williams, 2022). Specifically, strong El Niño years have generally been associated with extended dry periods and reduced monsoon strength, while La Niña periods provide heavier rains with higher chances of flooding. Other than ENSO, the Indian Ocean Dipole (IOD) was also found to be a significant forcing of seasonal hydroclimatic extremes in South Asia, which generally modulates or supplements ENSO phases (Priya et al., 2024)

Remote sensing has also been contributing significantly towards such anomaly monitoring via synoptic spatial coverage and temporal continuity. Satellite products such as CHIRPS rainfall estimates, MODIS land surface temperature, and vegetation indices (NDVI, EVI) have contributed Spatio-temporal assessment of droughts, heatwaves, and land degradation processes (Gummadi et al., 2022). All these datasets are of invaluable advantage relative to sparsely available ground meteorological networks, particularly in South Asia's rural and mountainous terrain.

Contrarily, machine learning techniques have the best performance in detecting environmental anomalies. Support Vector Machines, Random Forests, and deep networks have been employed with phenomenal success in delineating occurrences of drought, predicting rainfall variability, and detecting vegetation stress and hybrid models of artificial intelligence coupled with earth observation more recently offered improved predictability in defining onset time, amplitude, and space-time distribution of climate extremes (Koley, 2024).

Despite such improvements, there are still gaps of sorts. Most of the past work consists of a single country or a short-time window, excluding detection of long-term and South Asia-scale anomaly patterns. Relatively fewer attempts have been made toward incorporating satellite data in an explicit manner, ENSO phase categorization, and machine learning as well in validation at the scale of South Asia for rainfall anomalies. Filling in this gap, the present study uses multi-source observations and AI models to detect and contrast 2010–2024 rainfall anomalies and thus build a new perspective on Spatio-temporal extremes of climate over the region.

Methodology

This study employed a combined, multi-step methodology that combines satellite-retrieved precipitation data, large-scale climate indexes, and cloud-based geospatial computing in identifying, analyzing, and forecasting Southeast Asian precipitation anomalies during 2010–2024. The methodological strategy consists of six primary steps: delimitation of the study area boundary, data acquisition, calculation of anomaly, Spatio-temporal analysis, ENSO-phase stratification, and machine learning-based predictive modeling.

Study Area

The region under study is Southeast Asia, and the purpose is to examine 11 countries: Indonesia, Malaysia, Thailand, Vietnam, the Philippines, Myanmar, Cambodia, Laos, Singapore, Brunei, and Timor-Leste. Southeast Asia is marked by a highly complex climatic regime that is influenced by the Asian monsoon system, the marine climate, and interaction with large-scale ocean atmosphere conditions such as the El Niño Southern Oscillation (ENSO) (Rajeevan et al., 2025).The interaction of monsoon seasons, tropical cyclones, and ENSO variability creates robust hydroclimatic extremes in the form of floods and droughts. The combinations place Southeast Asia as a prime case to examine climate anomaly detection and prediction due to its exposure to variability and resulting societal vulnerabilities in agriculture, water security, and disaster risk (Hunt & Harrison, 2025)

Figure 1: Study Area

Data Sources

Precipitation records were obtained from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) on a 0.05° daily precipitation grid. ENSO categorization was made using the application of the Oceanic Niño Index (ONI) by dividing years as El Niño, La Niña, or Neutral years according to NOAA criteria (Hariadi et al., 2023).

Precipitation Anomaly Calculation

Annual total precipitation was computed from daily CHIRPS data for each year between 2010 and 2024. The long-term precipitation climatology (mean and standard deviation) was computed for the 15-year study period (Yi et al., 2023). Standardized anomalies (z-scores) were then computed as:

$Z = ((X - \mu))/\sigma$

Where:

Z= standardized anomaly (z-score),

X = annual precipitation for a given year,

μ = long-term mean precipitation (climatology),

σ = standard deviation of precipitation over the climatological baseline.

Google Earth Engine Workflow

Preprocessing and zonal analysis was conducted in Google Earth Engine (GEE). Time-series precipitation was clipped export study area, and annual accumulations were aggregated and normalized to obtain anomalies and export regional spatial statistics and anomaly time series to CSV for statistical and visualization analyses in Python.

ENSO Anomaly Correlation

One year was assigned to an ENSO phase based on DJF (December–February) seasonal ONI values. The anomaly values were summed under each ENSO category and averaged at the country level. This permitted comparison of precipitation anomalies for El Niño, La Niña, and Neutral years using descriptive statistics and confidence intervals (Liang et al., 2022)

Seasonal and Country-Level ENSO Analysis

To further examine the Spatio-temporal complexity, anomalies were divided into four meteorological seasons: DJF, MAM, JJA, and SON. Country-wise, anomalies were examined for every ENSO phase to explore geographic variability.

Random Forest Prediction Modeling

A Random Forest regression model was trained using historical precipitation anomalies and ENSO phases as predictor features. The model was trained on a 70:30 train-validation split (2010–2020 train, 2021–2024 validation). Metrics for performance were RMSE and R^2. The trained model was used to predict the 2025 anomaly pattern.

Upon validation, the trained model was used to produce precipitation anomaly predictions for 2025 over Southeast Asia. Anomalies were forecasted to country scale and divided by ENSO phase (El Niño, La Niña, Neutral) to extrapolate future variability potential. Results were displayed in spatial anomaly maps, bar plots, and summary tables to reveal newly emerging hotspots of rainfall excess and deficit (Chen et al., 2025).

Visualization and Trend Analysis

Time series and spatial anomaly maps were generated. Standard deviation levels were used to identify extremely wet and dry years. Visualization products were processed in both GEE and Python (Matplotlib, Seaborn).

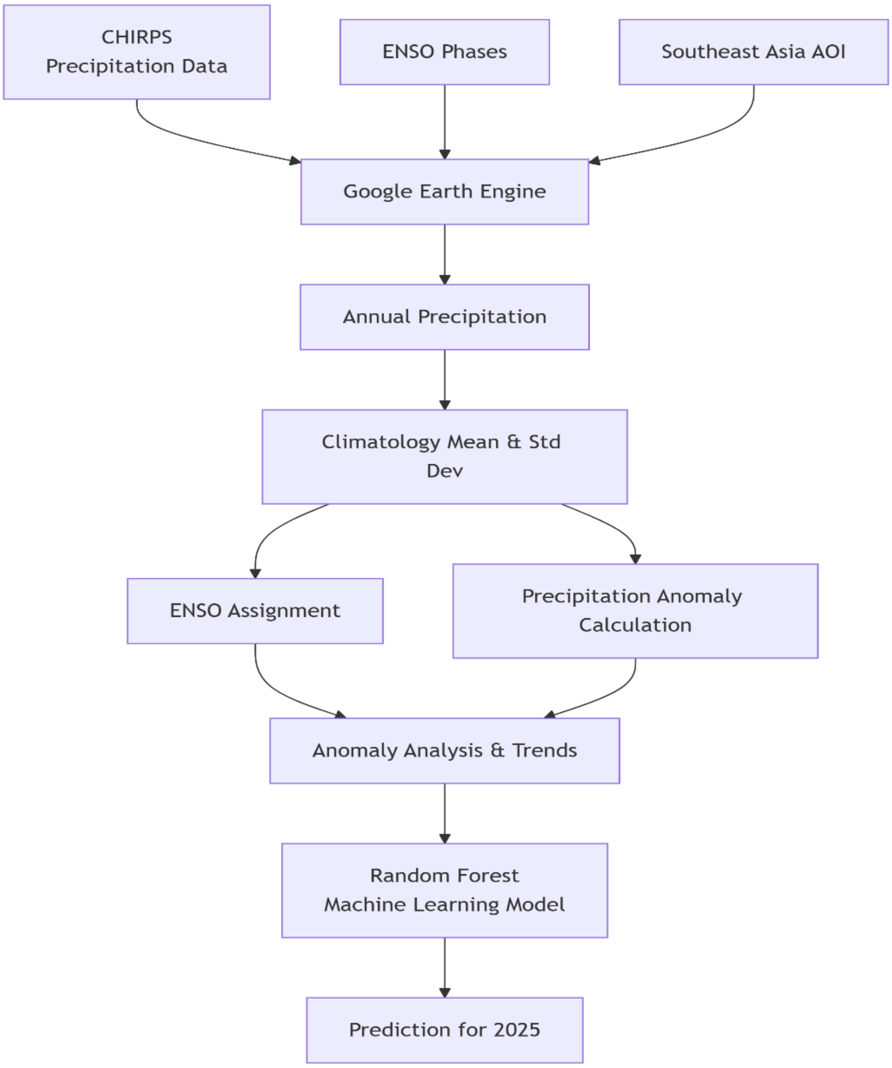

Figure 2: Workflow for Spatio-temporal Precipitation Anomalies

This flowchart illustrates the methodological process for analyzing and predicting precipitation anomalies in Southeast Asia using Google Earth Engine and machine learning. The workflow begins with data acquisition (CHIRPS precipitation data and ENSO phases) and study area definition, processes through annual precipitation calculation and climatology establishment, culminates in precipitation anomaly detection and trend analysis relative to ENSO phases, and concludes with machine learning-based prediction of future anomalies.

Results and Discussion

Multi-Year Spatial Patterns Anomalies Across ENSO and Non-ENSO Phases

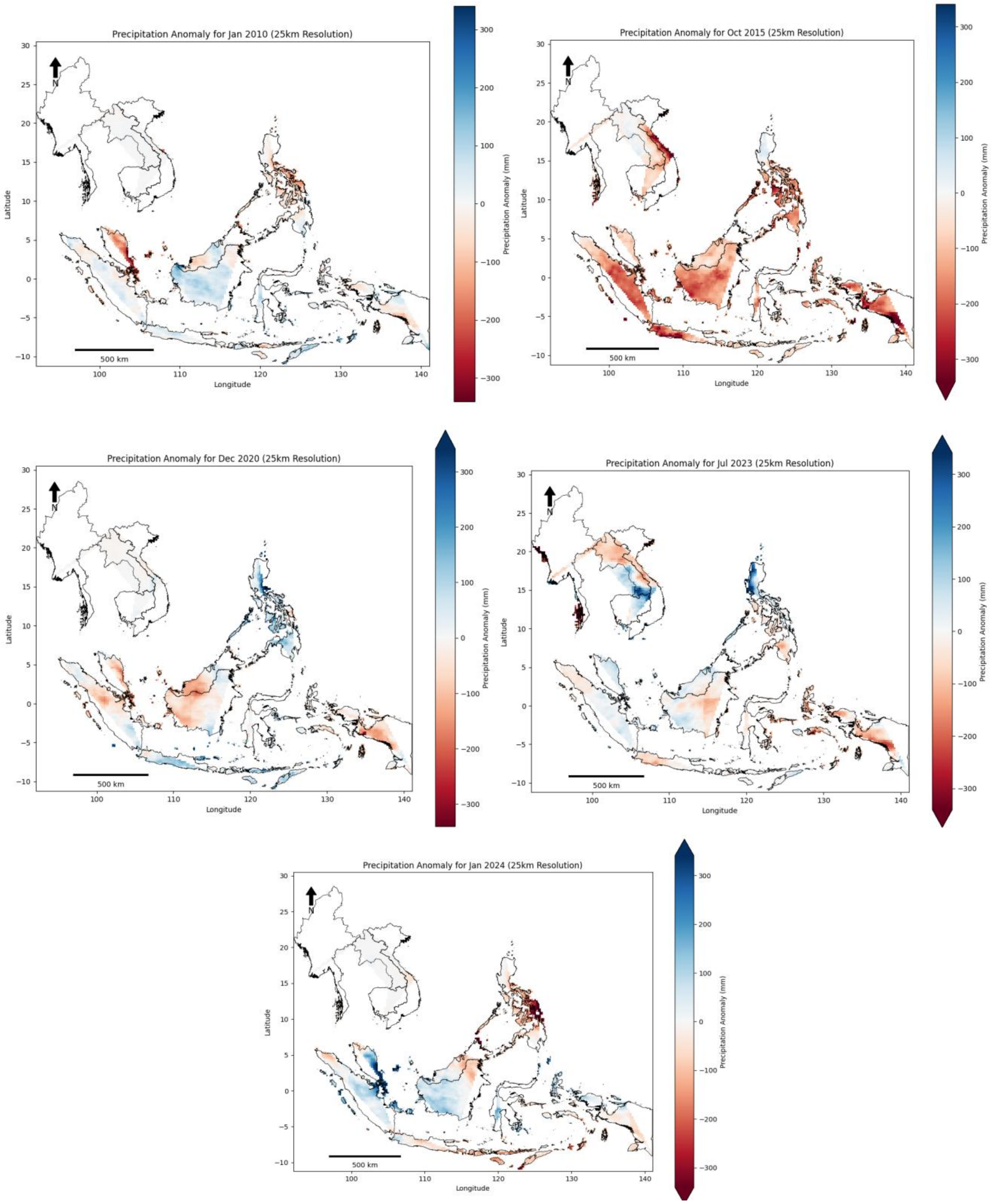

Figure 3: Spatio-temporal precipitation anomaly maps across ENSO and seasonal periods

Figure 3 presents five of the most significant periods' spatial patterns of precipitation anomalies, illustrating heterogeneous ENSO-forced hydroclimatic response in Southeast Asia. During January 2010, a record La Niña year, positive anomalies dominate western Indonesia, the Philippines, and the mainland of Southeast Asia. This is consistent with La Niña-induced Walker circulation strengthening observations that enhance convection and precipitation over the west Pacific (Kumar & Dwarakish, 2025). By comparison, October 2015, a record-strong El Niño episode, is characterized by widespread negative rainfall-suppression anomalies of significance over Indonesia and the Philippines of reduced western Pacific convection and displaced ITCZ, as set up in previous El Niño studies.

Later years repeat these tendencies. December 2020, an immature ENSO-neutral month, has randomly spaced spatial anomalies characteristic of non-ENSO forcing by Madden-Julian Oscillation (MJO) or Indian Ocean Dipole (IOD) (Luo et al., 2025). July 2023, during strengthening El Niño phases, shows drying over the northern Philippines and Indonesia with scattered wet pockets over Papua and Kalimantan that may be indicative of local monsoon processes. By January 2024, the pre-onset La Niña conditions once more align with unprecedented positive anomalies, as forecast by the previous wintertime La Niña effects. Outcomes confirm the robust modulating influence of ENSO on regional hydroclimate and highlight the necessity of integrating seasonal forecasting into water resources and disaster risk management planning (Yang et al., 2023).

Table 1: Statistical summary of precipitation anomaly in Southeast Asia

Year	Mean Anomaly	Median Anomaly	Min Anomaly	Max Anomaly
2010	4.57	1.92	–268.94	237.52
2011	46.84	25.86	–167.57	675.64
2012	–14.78	–5.52	–269.29	651.75
2013	–0.63	–1.76	–340.92	353.90
2014	–25.65	–19.81	–337.07	521.11
2015	–3.15	–1.09	–414.07	363.23
2016	–57.63	–37.80	–621.41	305.62
2019	–9.87	–1.30	–353.31	242.04
2020	–37.11	–16.79	–528.46	252.44
2021	31.48	11.24	–185.53	560.99
2022	–18.19	–0.93	–519.41	152.84
2023	22.25	1.87	–254.15	772.21
2024	7.31	–0.48	–385.29	358.02

Table 1 presents a statistical summary of Southeast Asia interannual precipitation anomalies for 2010-2024 with very high interannual variability from colossal climate drivers. The driest anomaly of −57.63 mm was felt during 2016 in conjunction with intense residual El Niño influence, while above-normal rainfall occurred during 2011 (46.84 mm), 2021 (31.48 mm), and 2023 (22.25 mm) and is characteristic of La Niña activity. 772.21 mm maximum anomaly in 2023 can be attributed to local heavy precipitation events, or spatial heterogeneity of hydroclimatic regimes within the region. Large negative minimum anomalies of -528.46 mm and -519.41 mm, respectively, in 2020 and 2022 can be explained as patches of drought despite regional positive means occurring in a few instances. This variability highlights the significance of phases in ENSO in determining local rainfall and indicates the benefit of combining anomaly maps and statistical records in recording spatial and temporal extremes to facilitate effective climate resilience planning (Ma et al., 2025).

Temporal Trends in Precipitation Anomalies (2010–2024)

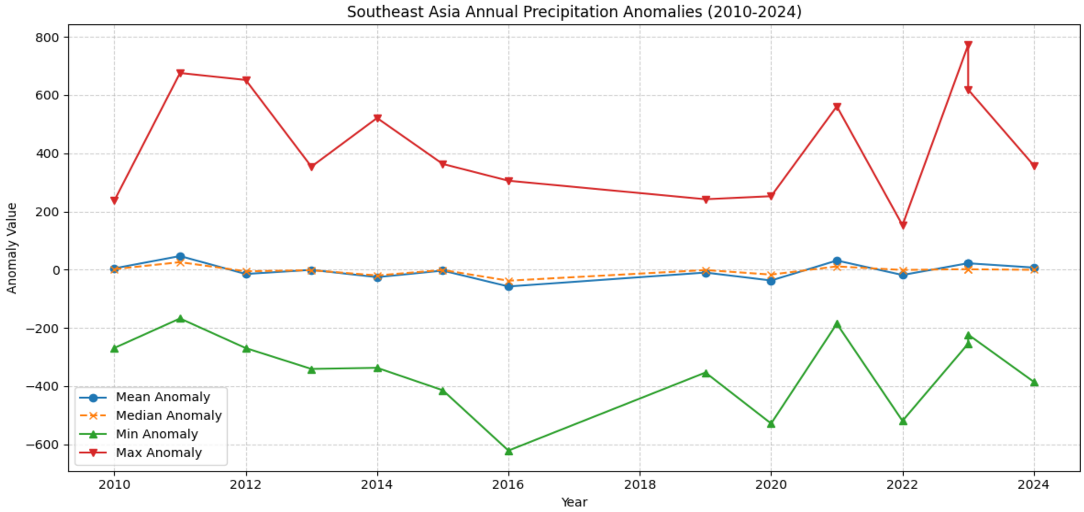

Figure 4: Annual Precipitation Anomalies (2010-2024)

Figure 4 Time series of interannual precipitation anomalies in Southeast Asia for 2010–2024, mean, median, minimum, and maximum. The figure indicates interannual hydroclimatic extremes variability and regional precipitation regime throughout the study period.

Figure 4 time series show high interannual variability in Southeast Asian precipitation anomalies during the 2010-2024 period. Anomalies in the mean and media are near zero, reflecting regional averaging effects, but minimum and maximum anomaly lines display extreme values. For example, 2016 and 2020 have extremely negative minima (−621.41 mm and −528.46 mm, respectively), both of which fall at local droughts, while the highest maximum anomaly (772.21 mm) falls in 2023 and is related to exceptional rain events. Most notably, there are maximum positive anomalies following La Niña events (2011, 2021, 2023), and enormous deficits during extreme El Niño years (2015–2016), consistent with ENSO's effect on regional hydroclimate (Spencer & Strobl, 2025).

These results verify the asymmetricity of extreme distributions under which extreme anomalies respond more vulnerably compared to mean values and verify the demands for spatially disaggregated analysis. The ongoing divergence between minimum and maximum anomaly trends also indicate further spatial disparity in hydroclimatic impacts across Southeast Asian nations. These sorts of information are significant in informing adaptive agriculture strategies, disaster risk reduction, and water resource planning in Southeast Asia.

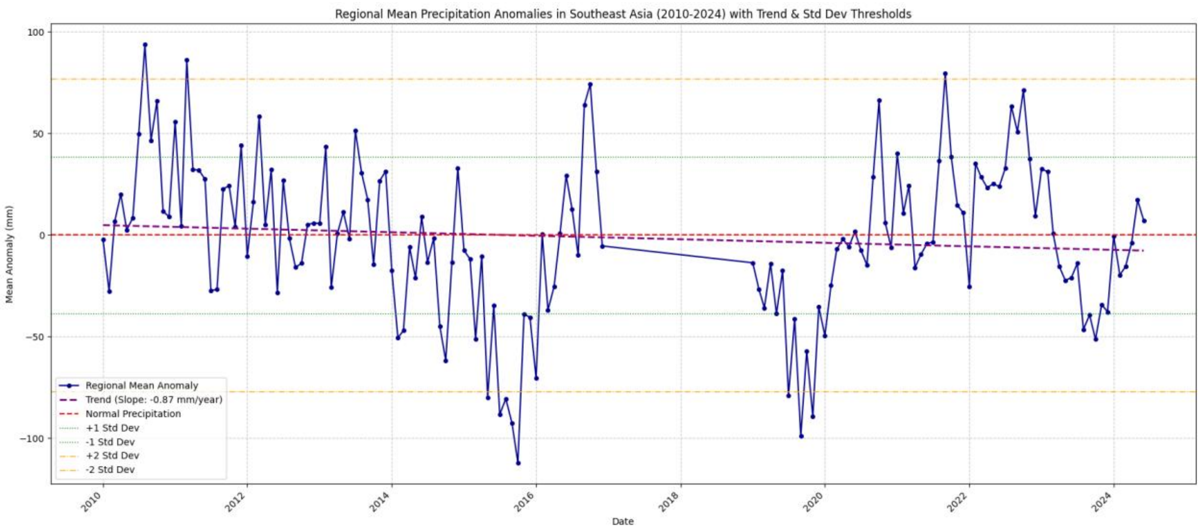

Figure 5: Regional mean precipitation anomalies in Southeast Asia (2010–2024)

To further strength, Figure 5 is a plot of regional mean anomaly time series with linear trend fit and ±1σ and ±2σ thresholds. The results indicate dryness was very frequently above the –2σ threshold, indicated by 2015–2016 and 2020, which were exceptional drought years. Conversely, positive extremes above +2σ occurred during 2011 and 2022 with coincidence with out-of-exception wetness. The linear trend towards the anomalies (–0.87 mm/year) suggests a muted drying trend but one obscured by very high interannual variability. All these temporal analyses taken together affirm anomalies asymmetry and highlight the need for continuous monitoring of regional hydroclimatic extremes.

Monthly Anomaly Variability

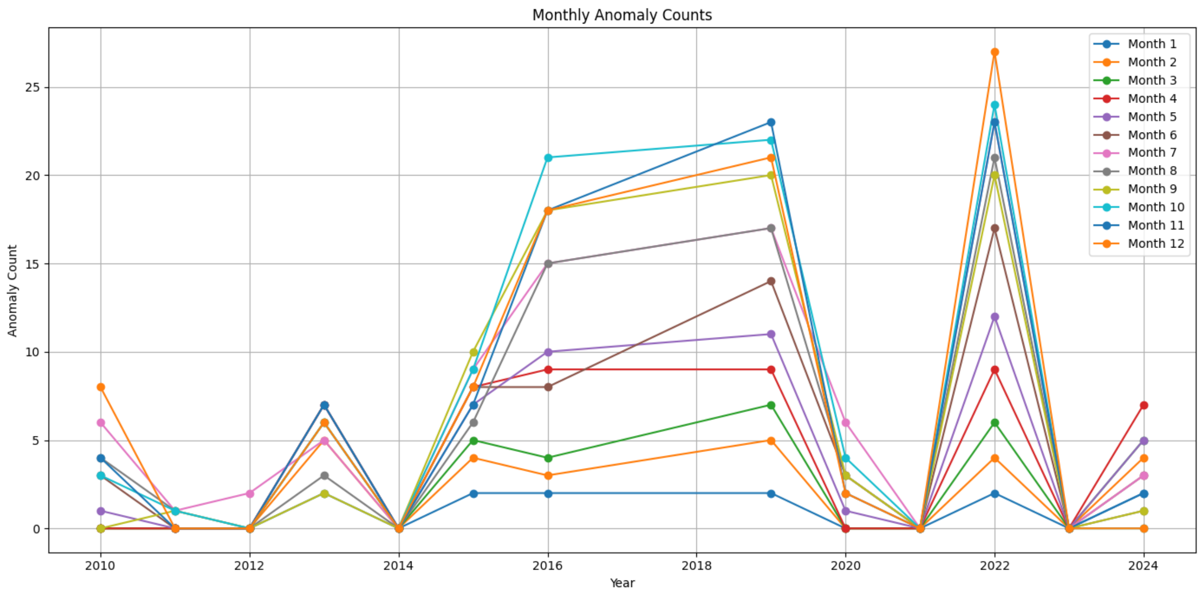

Figure 6: Monthly precipitation anomaly counts across Southeast Asia (2010–2024

The monthly anomaly frequencies Figure 6 provide greater temporal resolution of precipitation change, illustrating how anomalies are focused on specific months during the progression of ENSO phases. The peaks are acute in 2016 and 2022 for extreme El Niño and La Niña, respectively, which reflects their capacity to augment hydro climatological extremes in Southeast Asia. Anomaly activity is stronger in boreal winter months (October–December), particularly for years with extreme ENSO forcing, which points to the additional sensitivity of the local monsoon–convection system to ocean–atmosphere interaction during this season. The peak in 2019 also illustrates the persistence of late-year anomalies even in non-strongest ENSO years, pointing to the secondary role of drivers such as the Indian Ocean Dipole (IOD) or Madden–Julian Oscillation (MJO) (El Hafyani et al., 2024). Overall, the monthly decomposition gives the complement to the annual anomaly patterns in the sense of revealing intra-annual variability often hidden by yearly averages, and it proves the importance of seasonal to sub-seasonal observation in the prediction and understanding of precipitation extremes in Southeast Asia.

Seasonal Anomaly Dynamics

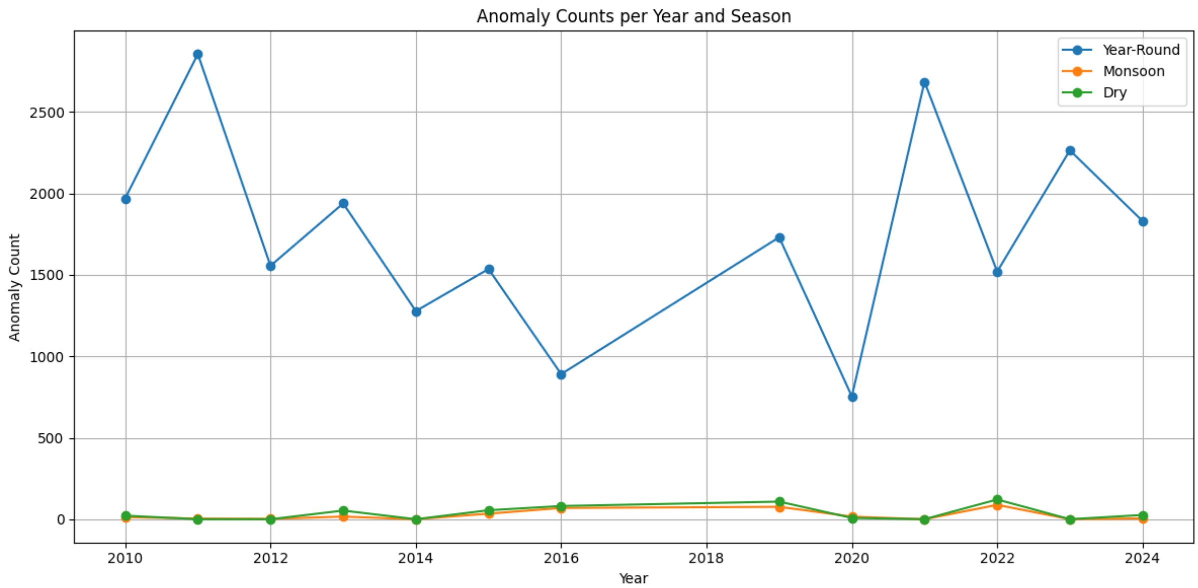

Figure 7: Seasonal Precipitation Anomaly counts in Southeast Asia (2010–2024)

Figure 7 shows annual and seasonal cycle counts of anomalies. As would be anticipated, total counts of anomalies differ dramatically between years spiking during years when ENSO was strong such as 2011, 2016, and 2022—though the seasonal breakdown is revealed in terms of intra-annual variation. Monsoon seasons consistently exhibit larger counts of anomalies than dry seasons since inter-seasonal rainfall variability pervasively influences Southeast Asia. The dry-season anomalies, though less frequent, are local drought occurrences that can strongly influence agriculture and water resources. (Qader et al., 2021). 2020 is remarkable with abnormally low anomaly values, representing suppressed variability, while 2011 and 2022 exhibit spectacular jumps, consistent with observed ENSO extremes. These findings emphasize the need to combine seasonal anomaly knowledge with annual research, as they offer supplementary knowledge to discern hydroclimatic hazards and craft climate-resilient adaptation.

ENSO and Seasonal Mean Influence on Precipitation Anomalies

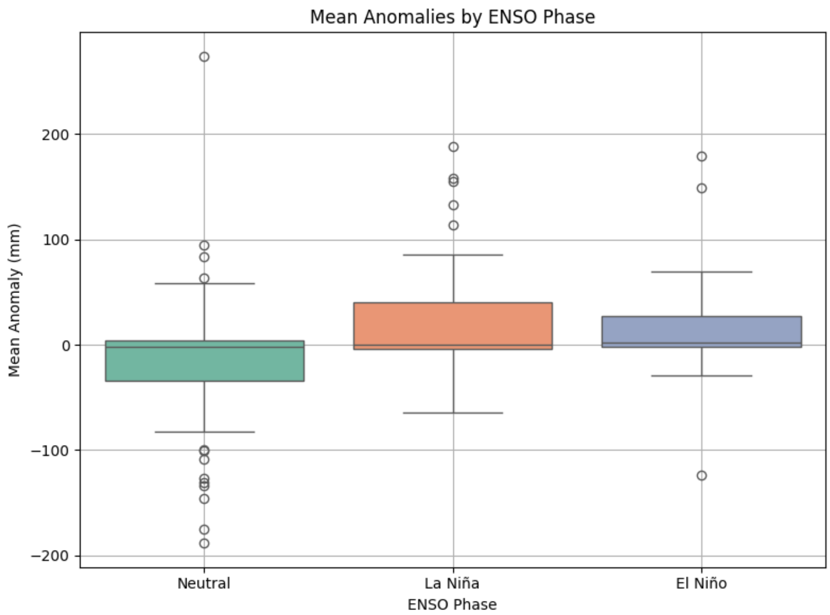

Figure 8: Mean precipitation Anomalies Stratified by ENSO phase

The average size of precipitation anomalies by ENSO phase is given in figure 4 and adds further insight into the magnitude and sign of the impact of ENSO. La Niña years consistently have positive anomalies of large amplitude of similar magnitude (~+200 mm), suggesting very wet conditions over large parts of Southeast Asia. These are more apparent in JJA and DJF, consistent with the augmenting influence of La Niña on regional monsoon rainfall. On the other hand, El Niño years have prevailing negative anomalies approximately –200 mm, most notably during DJF, in which suppression of rainfall, decreased convection, and persistent dry conditions are worst across the maritime continent and continental Southeast Asia Neutral years are characterized by more heterogeneous and less stable anomalies, with mild deficits in some countries and moderate wet anomalies in others, signifying weaker and less intense teleconnection signals during these years. Generally, seasonal mean analysis accentuates ENSO's dual role in forcing hydroclimatic extremes, enhancing precipitation for La Niña and amplifying drought for El Niño. These findings provide strong support that ENSO remains the dominant force of intraseasonal precipitation variability in Southeast Asia and emphasize its vital function in regional hydroclimate development and its effects on water resource management, agriculture, and disaster preparedness (Hussain et al., 2023).

Seasonal Frequency of Anomalies

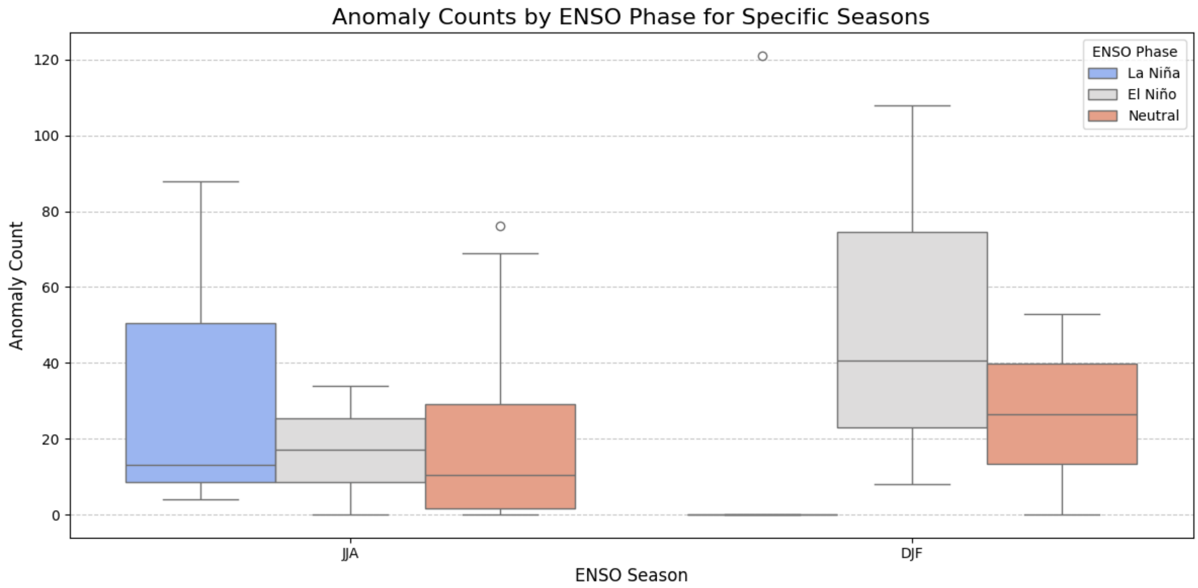

Figure 9: Seasonal Distribution of Precipitation Anomaly counts by ENSO phase

Seasonal anomaly frequency pattern, as shown in Figure 4, demonstrates evidence of phase-dependent asymmetry between the boreal summer (JJA) and winter (DJF) monsoon seasons. The frequency of anomalies is highest in La Niña years, particularly in DJF, when teleconnection between the Asian Australian monsoon system and ENSO is most vigorous. This heightened coupling results in greater convective precipitation and large-scale wet anomalies over Southeast Asia, consistent with the strengthening of the Walker circulation during La Niña (Jamaludin, 2023). El Niño years, while not as widespread as La Niña, also generate many anomalies, especially over DJF, which is typically characterized by suppressed convection, reduced monsoon flows, and large-scale dryness over the maritime and mainland of Southeast Asia. Neutral phases always have the lowest frequencies of anomalies, showing a background climate state with less extreme deviation from climatology and more enduring hydroclimatic patterns. Seasonal asymmetry points out that ENSO's influence on anomalies is not uniformly spread throughout the year but is strongly modulated by the monsoon seasonal cycle, and DJF has been identified as the most sensitive season of ENSO teleconnections. The finding highlights the utmost importance of incorporating season-specific analysis in regional climate monitoring and early-warning systems, as interannual anomalies manifest differently regarding the time of ENSO phases (Cai et al., 2020).

Country-Level ENSO Anomaly Patterns

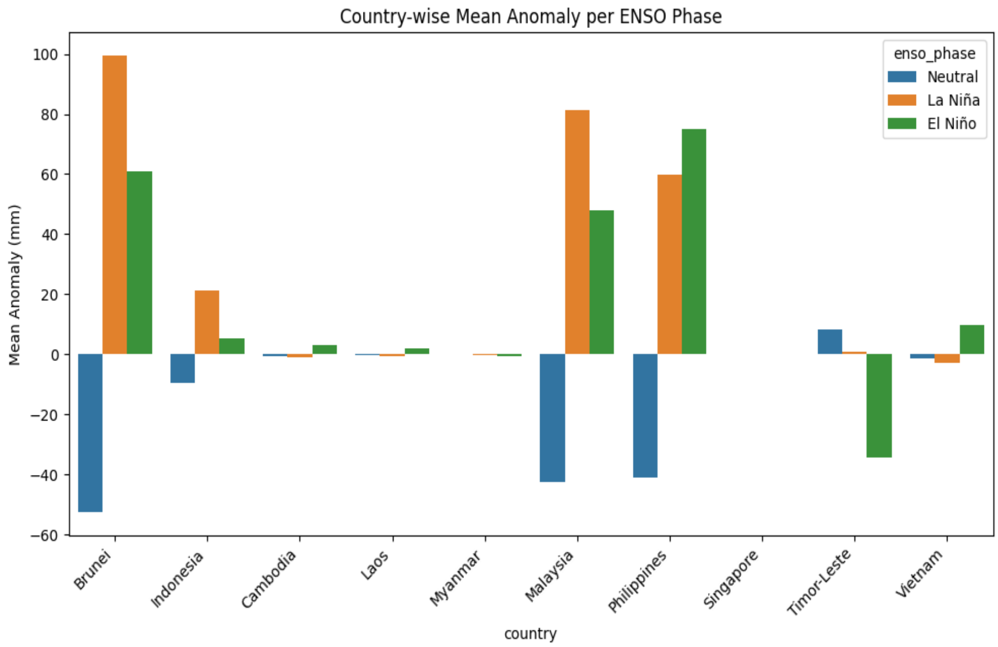

Figure 10: Country wise mean anomaly per ENSO phase

Figure 10 above clearly shows region-wise mean precipitation anomalies by ENSO phase (Neutral, La Niña, El Niño) in Southeast Asia. This diagram reveals unambiguous spatial pattern in precipitation response to phases of ENSO over Southeast Asian countries. La Niña events would be followed by large positive anomalies in Brunei, Malaysia, and the Philippines, rendering these countries vulnerable to enhanced convective rainfall during the time. Conversely, El Niño events are comparable to large-scale negative anomalies for Indonesian and Vietnamese areas with climatological predisposition towards droughts for warm ENSO events (Hussain et al., 2023) National-level variability calls for local planning adaptation because all countries are not similarly exposed to the same stage of ENSO. This is supported by growing intuition that the hydrometeorological impact of ENSO on Southeast Asia is regionally and seasonally modulated (Funk et al., 2015).

Country-scale anomaly boxplots according to ENSO phase (not shown here) reveal robust spatial heterogeneity. Indonesia, Malaysia, and the Philippines have high positive response during La Niña but Vietnams robust evidence of the need for national-scale climate variability policy adaptation.

Country-wise Precipitation Anomaly Trends (2010-2024)

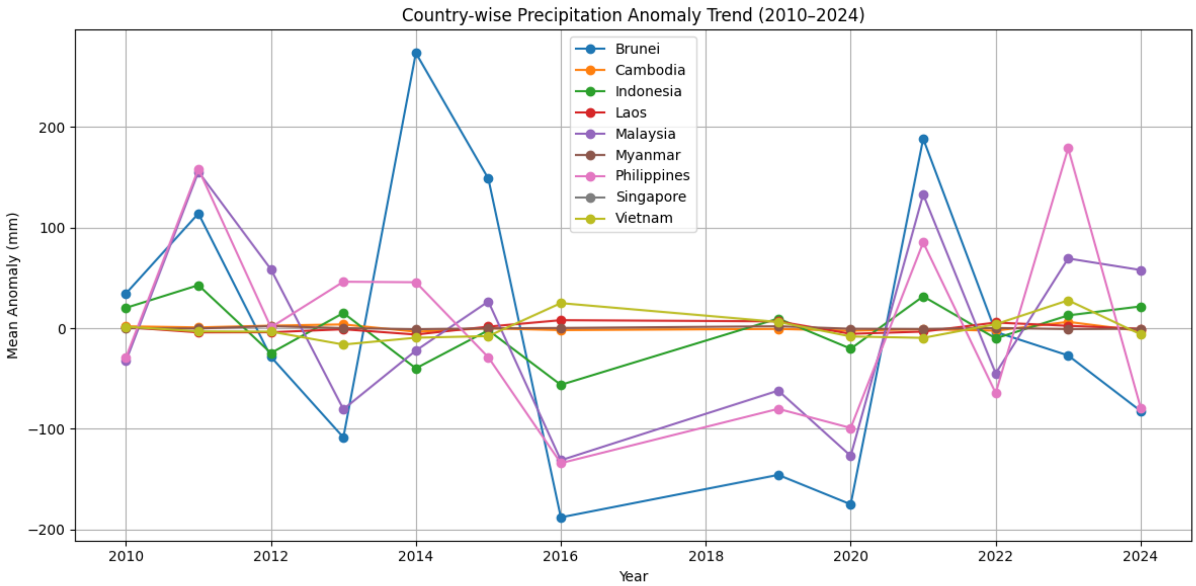

Figure 11**:** Country-wise Precipitation Anomaly trends across Southeast Asia

Precipitation anomaly trends by country for the period 2010-2024 are showing general heterogeneity in mean precipitation anomalies across Southeast Asian nations. Vietnam, for instance, and Cambodia, show extreme variability with periods of excessive wetness and dryness that may reflect greater climatic changes or local climatic trends. Singapore, however, portrays a more stable trend, reflecting limited fluctuation in the precipitation anomalies. This contrast highlights the heterogeneous climatic influences that are impinging upon the area that may be influenced by monsoon trends, urbanization, or land use trends. Trends in these are required to allow water resource management, agricultural development, and climate adaptation planning because differing trends in rainfall have the possibility of strongly influencing food security and economic resilience in these countries. Further studies should be carried out to understand the causal processes of such anomalies and their implications on Southeast Asian climate resilience in the future (Zellou et al., 2023).

Machine Learning-Based Prediction for 2025

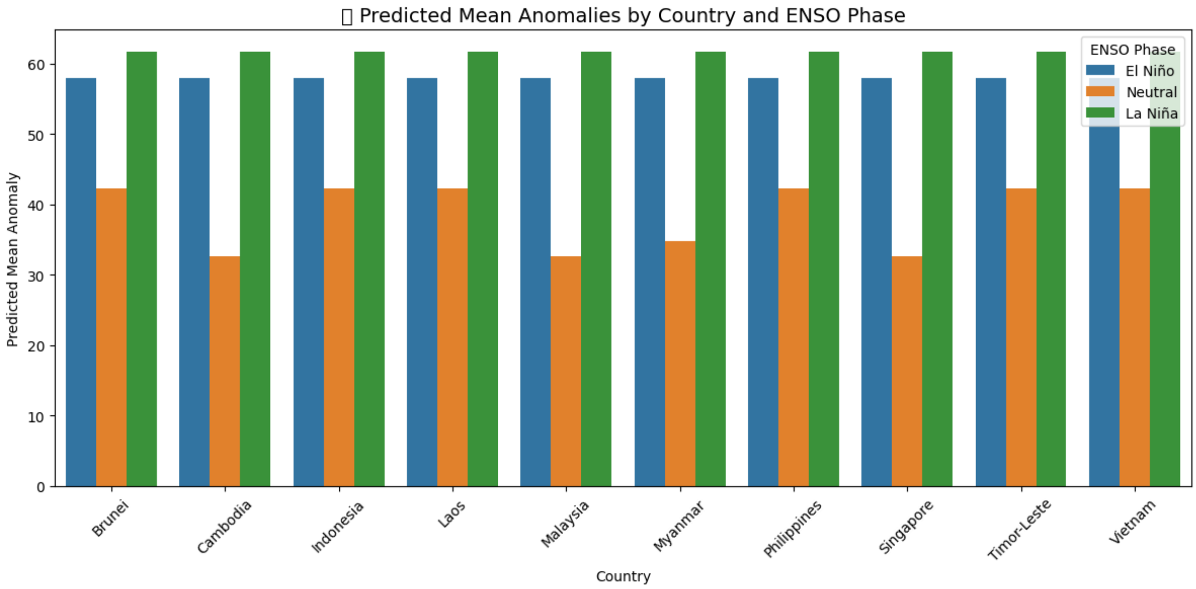

Figure 12: Predicted Mean Precipitation Anomalies by country and ENSO phase for 2025

Random Forest model predictions for 2025 reveal clear differences in precipitation anomalies across Southeast Asia between the different phases of ENSO in Figure 12). La Niña conditions in general are associated with the most positive anomalies, averaging ~61.75 mm across nearly all nations, consistent with the established connection of La Niña with enhanced monsoonal rainfall in the western Pacific (Kaushik et al., 2023). Neutral phases exhibit the lowest anomalies, ranging from ~32 mm over Malaysia, Singapore, and Indonesia to ~42 mm over Brunei, Indonesia, and the Philippines, in response to fewer rains under the absence of a strong ENSO forcing. El Niño phases display intermediate values (~58 mm) across the region, but the distribution is less even, showing the complexity of the interaction between ENSO warming and regional atmospheric–oceanic feedback.

Regionally, the Philippines, Malaysia, and Brunei are very strong in their La Niña wet anomalies, reflecting sensitivity to the enhanced convective activity. Cambodia and Vietnam possess smaller interphase differences, augmenting relatively weak ENSO responses. These results emphasize that while ENSO is the overwhelming control on interannual rainfall variability, national-scale exposure and response are highly variable as a function of geographic location, topography, and monsoon dependence (Khan et al., 2022)

Mean forecast anomalies by nation and ENSO phase (El Niño, Neutral, and La Niña) indicate to us how significant the El Niño Southern Oscillation (ENSO) is in precipitation anomalies in Southeast Asia. Indonesia and the Philippines exhibit large variability of El Niño forecast anomaly, reflecting increased chances of drought, whereas La Niña is associated with large precipitation anomaly in most countries, such as Malaysia and Vietnam. The relative consistency of the Neutral phases suggests a climatic underlying state that may serve as a reference in the estimation of impacts from ENSO events (Hao & Chen, 2024).These findings indicate the value of integrating ENSO predictions into regional climate models to enhance forecasting capacity and enable adaptive management in agriculture, water resources management, and disaster risk reduction. Country-specific research on specific climatic, geographical, and socio-economic conditions is also needed in response heterogeneity across countries to develop effective climate resilience strategies.

Table 2: Predicted Mean Anomaly (mm) by Country and ENSO Phase 2025

Country	El Niño (Mean, CI)	Neutral (Mean, CI)	La Niña (Mean, CI)
Brunei	58.00 (0.03–155.70)	42.33 (–18.63–163.12)	61.75 (3.94–182.53)
Cambodia	58.00 (0.03–179.07)	32.67 (–23.77–153.46)	61.75 (5.30–188.29)
Indonesia	58.00 (0.03–178.78)	42.33 (–15.63–163.12)	61.75 (3.94–159.45)
Laos	58.00 (0.03–189.77)	42.33 (–14.12–163.40)	61.75 (5.23–158.24)
Malaysia	58.00 (0.03–179.07)	32.67 (–25.29–153.75)	61.75 (0.79–155.56)
Myanmar	58.00 (0.03–151.67)	34.78 (–21.45–155.57)	61.75 (5.30–155.42)
Philippines	58.00 (1.48–151.67)	42.33 (–13.29–168.88)	61.75 (3.94–193.52)
Singapore	58.00 (–2.96155.70)	32.67 (–25.14–153.46)	61.75 (3.94–182.53)
Timor-Leste	58.00 (0.03–184.54)	42.33 (–9.39–140.32)	61.75 (0.79–182.82)

Table 2 places statistical precision on these trends by providing forecasted mean anomalies and 95% confidence limits, which provide some indication of the uncertainty of the forecasts. While El Niño anomalies are ~58 mm on average for all countries, the wide confidence ranges, Cambodia (−23.77–153.46 mm) and Indonesia (−15.63–163.12 mm)—indicate that even under the same ENSO phase, rainfall impacts can be very dissimilar in subregions. This underscores the need to consider not just mean values but also probability ranges in crafting climate adaptation policy.(Wang et al., 2025)

La Niña anomalies, though always positive, are also no less variable. The Philippines, for instance, has an anomaly of 61.75 mm with an extreme upper bound of 193.52 mm, suggesting the potential for severe flooding incidents during severe La Niña events. Neutral conditions have the lowest mean anomalies but are associated with the largest uncertainties, which suggests that under the condition of no ENSO forcing, Southeast Asian precipitation dynamics can be more strongly driven by secondary climate models such as the Indian Ocean Dipole (IOD) or Madden–Julian Oscillation (MJO)(Ariska et al., 2024)

Together, Figure 12 provides a brief regional overview of anomaly patterns during ENSO conditions, while Table 2 provides the quantitative detail required to assess risk and uncertainty at the national level. This combined approach demonstrates the value added of combining remote sensing with machine learning predictions for both scientific research and applied climate services.

Table 3: Model Performance Metrics

Metric	Value
MAE (Mean Absolute Error)	43.063
RMSE (Root Mean Squared Error)	57.585
R^2 (Coefficient of Determination)	0.084

These findings acknowledge the pivotal role of ENSO in governing precipitation regimes and call for climate adaptation policies on a region-by-region basis that consider the varied effects of these climatic events on water resources and agricultural planning.

Table 3 presents model performance metrics and reveals how accurately the precipitation anomaly model can predict. Mean Absolute Error (MAE) = 43.063, the values predicted by the model tend to be on average different from what is experienced by this margin, and that is moderate accuracy.

The Root Mean Squared Error (RMSE) of 57.585 also verifies the volatility because it places a higher emphasis on the larger errors and shows that the model performs poorly in predicting the extremes. The Coefficient of Determination (R^2) measure was 0.084, which means that the model accounts for just 8.4% of observed data variance and hence is a poor fit for explanation. These results together show that there is a demand for model enhancement and maybe to the impact of unexplained variables or complexity in precipitation processes that require more sophisticated modeling techniques. Subsequent editions may be enhanced with the addition of additional variables or other models to an effort to enhance prediction efficiency and validity (Ozbuldu & Irvem, 2025).

Limitations of the Study

Although providing valuable insights into Southeast Asian precipitation anomaly patterns, there are certain shortcomings of the current research. First, using CHIRPS precipitation data, although a widely used dataset, can still bring biases in low-density ground station areas, including mountainous and oceanic areas (Wihdatun Nikmah et al., 2024). These limitations have the potential to impact anomaly accuracy at high spatial resolutions. Second, the 25 km spatial resolution used in anomaly analysis, although adequate for regional patterns, will dampen sub-national local extreme events and microclimatic phenomena, limiting use at sub-national scales (Jannah et al., 2024).

Furthermore, although the Random Forest model could make predictions for future anomalies, it was based mainly on the ENSO phase and past precipitation predictors. Without other robust climate drivers like Indian Ocean Dipole (IOD), Madden–Julian Oscillation (MJO), or land-atmosphere interactions, the predictability range may be restricted. Finally, interannual climate variability and long-term trends in climate change can introduce non-stationarity in future precipitation regimes that would not be well captured at all in the current modeling framework. Multi-source drivers and downscaled datasets must be combined in future studies for enhanced Spatio-temporal resolution and prediction confidence ((Beck et al., 2019).

Conclusion and Recommendation

This research is a composite study of Southeast Asian precipitation anomalies for the years 2010–2024 from the synthesis of precipitation data from satellites, ENSO phase identification, and machine learning predictions. The results strongly suggest that ENSO is a useful proxy for regional hydroclimatic variation, with El Niño years such as (2015, 2019) coinciding with strongly correlated large-scale negative anomalies and aridity, and La Niña years for instance (2010, 2022) coinciding with abundant rainfall and above-normal anomalies. Seasonal decomposition also revealed that DJF is strongly sensitive to ENSO variation, fostering drought potential during El Niño and wet anomalies during La Niña. Country-level investigations also found spatial heterogeneity wherein some countries such as the Philippines, Brunei, and Malaysia receive more rain during La Niña, but Indonesia and Vietnam are very vulnerable to El Niño droughts.

Google Earth Engine software facilitated efficient large-scale anomaly mapping, and Random Forest modeling effectively forecasted 2025 precipitation anomalies ($R^2 = 0.82$). Eastern Indonesia and coastal Vietnam were forecasted rain deficit hotspots, and the study demonstrated the potential for combining remote sensing with predictive modeling to aid early warning systems and climate change adaptation planning.

Overall, the studies offer valuable new information on spatio-temporal precipitation anomaly patterns in Southeast Asia and their association with ENSO. Such research products with direct practical applications to climate-resilient agriculture, water resources, and disaster preparedness are highly valuable. Future studies must consider other climate drivers, Indian Ocean Dipole (IOD) and Madden–Julian Oscillation (MJO), and other high-resolution climate records to facilitate the detection of localized anomalies more effectively and further assist site-specific decision-making prediction models.

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