

Long-term vegetation–thermal coupling and environmental resilience in a mining-affected tropical forest landscape

Sk Mujibar Rahaman

mujibar08@gmail.com

National Atlas and Thematic Mapping Organisation

Masjuda Khatun

ICAR-National Bureau of Soil Survey & Land Use Planning, Regional Centre

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Abstract

Tropical forest ecosystems play a role in climate regulation, biodiversity conservation, and ecosystem services, while climatic variability can alter vegetation and thermal conditions. This study investigates the spatiotemporal dynamics and interrelationships of vegetation, land surface temperature (LST), and rainfall in the Saranda Forest Division, Jharkhand, India, during 1995–2025. Landsat Collection 2 Level-2 imagery for 1995, 2005, 2015, and 2025 and CHIRPS rainfall data were processed using Google Earth Engine. NDVI, LST, and annual rainfall were derived and harmonized to a common 30-m analytical grid. A pixel-wise database containing 1.1 million observations was analysed in Python using descriptive statistics, Pearson correlation, and linear regression. Mean NDVI declined from 0.606 in 1995 to 0.494 in 2005, then recovered to 0.619 in 2015 and 0.668 in 2025. Mean LST increased from 21.65°C in 1995 to 34.81°C in 2005 before declining to 29.81°C and 26.63°C in 2015 and 2025, respectively. Mean annual rainfall increased from 1147.80 to 1760.15 mm. The NDVI–LST relationship remained consistently negative ($r = -0.600$ to -0.754), whereas relationships involving annual rainfall were weak and temporally inconsistent. These findings indicate stronger and more persistent vegetation–thermal coupling than rainfall associations. The study provides a baseline for environmental monitoring and sustainable forest management.

Introduction

Climate change has emerged as one of the most significant environmental challenges of the twenty-first century, influencing terrestrial ecosystems through alterations in temperature regimes, precipitation patterns, and the frequency of extreme climatic events. These changes have profound implications for forest ecosystems, which regulate biodiversity, carbon sequestration, hydrological processes, and regional climate while supporting the livelihoods of millions of people (IPCC, 2023). Understanding long-term environmental dynamics within forested landscapes is therefore essential for developing sustainable management strategies and strengthening ecosystem resilience under changing climatic conditions.

Vegetation is a sensitive indicator of environmental change because its growth, productivity, and physiological condition respond directly to climatic variability. The Normalized Difference Vegetation Index (NDVI), derived from multispectral satellite observations, has become one of the most widely used indicators for monitoring vegetation health, biomass, and ecosystem productivity over large spatial and temporal scales (Tucker, 1979; Pettorelli et al., 2005). Simultaneously, Land Surface Temperature (LST) provides valuable information on the thermal characteristics of the Earth's surface and reflects the interactions among land cover, vegetation, soil moisture, and atmospheric conditions (Li et al., 2013). Rainfall, as a primary climatic driver, regulates vegetation growth, soil moisture availability, and evapotranspiration, thereby strongly influencing ecosystem functioning and landscape dynamics (Trenberth, 2011). The integrated assessment of NDVI, LST, and rainfall offers a comprehensive framework for understanding climate-driven environmental processes and ecosystem responses.

Advances in Earth observation technologies have revolutionized environmental monitoring by enabling consistent, long-term observations at regional and global scales. The Landsat satellite program, with a continuous archive spanning more than five decades, provides an unparalleled resource for analysing vegetation dynamics and land surface temperature. Likewise, the Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS) dataset combines satellite observations with in-situ measurements to deliver reliable rainfall estimates suitable for climate and environmental studies (Funk et al., 2015). The integration of these freely available datasets within cloud-based platforms such as Google Earth Engine facilitates efficient, reproducible, and large-scale geospatial analyses (Gorelick et al., 2017).

Saranda Forest Division represents an ecologically important tropical deciduous forest landscape in eastern India. Dominated by extensive sal (*Shorea robusta*) forests, the region supports rich biodiversity, provides essential ecosystem services, and plays an important role in regional ecological stability. At the same time, Saranda is recognized for its substantial iron ore resources, making it a landscape where ecological conservation and mineral-based economic development coexist. In such multifunctional landscapes, continuous environmental monitoring is crucial for understanding long-term ecological changes and supporting evidence-based planning for sustainable forest management.

Integrated assessments of vegetation dynamics, land surface temperature and rainfall across multiple decades remain comparatively limited for the Saranda Forest Division. Most previous studies have focused on individual environmental variables or shorter time periods, leaving a gap in understanding the long-term interactions among climatic drivers and ecosystem responses. A multi-decadal geospatial assessment can therefore provide valuable insights into environmental dynamics and contribute to improved climate adaptation and sustainable resource management.

Against this background, the present study investigates climate-driven environmental dynamics in Saranda Forest Division using multi-temporal Landsat imagery and CHIRPS rainfall data. Specifically, the study analyses the spatio-temporal variations in vegetation, land surface temperature, and rainfall between 1995 and 2025 and examines their interrelationships. The findings are expected to provide a scientific basis for environmental monitoring, climate resilience, and sustainable forest landscape management in one of India's most important forest ecosystems.

Materials and Methods

Study Area

The study was conducted in the Saranda Forest Division of West Singhbhum district, Jharkhand, India. Saranda represents a predominantly forested landscape characterized by dense vegetation, heterogeneous terrain, and spatially distributed anthropogenic pressures, including iron-ore mining. The combination of substantial forest cover, terrain variability, and mining-related land-use pressures makes the area an appropriate setting for examining interactions among vegetation condition, land surface

temperature (LST), and rainfall over time. Understanding these relationships is particularly relevant for evaluating environmental dynamics in a landscape where forest conservation and resource development coexist. The geographical location and extent of the study area are shown in Fig. 1.

Data Sources and Pre-processing

The analysis integrated satellite-derived observations of vegetation and land surface temperature (LST) with gridded precipitation data to examine the environmental relationships within the Saranda Forest Division. Landsat Collection 2 Level-2 products were used because they provide atmospherically corrected surface reflectance and surface-temperature products suitable for quantitative land-surface analysis. Surface-reflectance digital numbers (DN_s) were converted to physical reflectance using the USGS scaling equation, $SR = DN_s \times 0.0000275 - 0.2$, while the surface-temperature product was converted from DN to Kelvin using $ST = DN_s \times 0.00341802 + 149.0$; LST was subsequently expressed in degrees Celsius by subtracting 273.15. The four reference years—1995, 2005, 2015 and 2025—were selected to provide approximately decadal snapshots of environmental conditions. Landsat 5 Thematic Mapper (TM) was used for 1995 and 2005, Landsat 8 Thermal Infrared Sensor (TIRS) for 2015, and Landsat 9 Infrared Sensor-2 (TIRS-2) for 2025. These sensor selections are temporally appropriate because Landsat 5 surface-temperature products are available from 1984–2012, Landsat 8 from 2013 onward and Landsat 9 from 2022 onward. All Landsat processing was performed in Google Earth Engine (GEE), a cloud-based platform designed for large-scale geospatial analysis (Gorelick et al., 2017). For each reference year, the relevant Landsat Collection 2 Level-2 image collection was filtered by the Saranda Forest Division boundary and the corresponding annual time period. The QA_PIXEL band was used to exclude cloud-, cloud-shadow- and other quality-flagged pixels from the analysis. The appropriate Collection 2 scaling factors were then applied to the surface-reflectance and surface-temperature bands. The remaining observations were combined using a median reducer to generate a representative within-year composite and reduce the influence of residual clouds and anomalous observations. NDVI was subsequently derived from the atmospherically corrected red and near-infrared surface-reflectance bands, while the Level-2 surface-temperature product was converted to degrees Celsius for LST analysis. For precipitation, the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) daily dataset was used. CHIRPS combines satellite-derived precipitation information with in-situ station observations and provides approximately 0.05° (~ 5 km) gridded rainfall data from 1981 onward, making it suitable for long-term environmental and rainfall-variability analyses (Funk et al., 2015). Daily CHIRPS precipitation observations were summed for each calendar year to derive annual rainfall (mm) for 1995, 2005, 2015 and 2025, after which the resulting annual rainfall surfaces were spatially restricted to the Saranda Forest Division boundary. Thus, all three environmental variables—NDVI, LST and annual rainfall—were prepared for the same four reference years and subsequently brought into a common spatial framework for pixel-level statistical analysis.

Environmental Variable Derivation

Three environmental variables—Normalized Difference Vegetation Index (NDVI), land surface temperature (LST), and annual rainfall—were derived for each of the four reference years (1995, 2005, 2015 and 2025). NDVI was used as an indicator of vegetation greenness and condition based on the contrasting response of vegetation in the red and near-infrared portions of the electromagnetic spectrum. The index follows the formulation originally introduced for vegetation monitoring by Tucker (1979) and was calculated as:

$$\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}}$$

For Landsat 5 TM, SR_B4 and SR_B3 were used as the near-infrared (NIR) and red bands, respectively, whereas SR_B5 and SR_B4 were used for Landsat 8 OLI and Landsat 9 OLI-2. The sensor-specific band configuration therefore differed while the mathematical formulation remained consistent across the four reference years. Higher positive NDVI values generally represent greater vegetation abundance and photosynthetic activity, whereas low or negative values may indicate sparse vegetation, exposed surfaces or water. LST was obtained directly from the Landsat Collection 2 Level-2 Surface Temperature (ST) product, rather than being independently retrieved from top-of-atmosphere thermal radiance. The ST_B6 band was used for Landsat 5, while ST_B10 was used for Landsat 8 and Landsat 9. The Collection 2 ST digital numbers were converted to temperature in Kelvin using the USGS-provided scaling relationship:

$$\text{ST(K)} = (\text{DN} \times 0.00341802) + 149.0$$

and subsequently converted to degrees Celsius as:

$$\text{LST(C)} = \text{ST(K)} - 273.15$$

The resulting LST surfaces represent the spatial distribution of land-surface thermal conditions within the forest division. Landsat-derived NDVI and LST are widely used together for examining vegetation–temperature interactions because vegetation abundance and surface thermal conditions are often closely associated. Annual rainfall was derived from the daily Climate Hazards Center InfraRed Precipitation with Station data (CHIRPS) dataset. CHIRPS combines satellite-based precipitation estimates with in-situ station observations and provides rainfall information at approximately 0.05° spatial resolution, with data available from 1981 onward. For each reference year, the daily precipitation observations falling within the corresponding calendar year were summed to obtain annual cumulative rainfall:

$$P_{\text{annual}} = \sum_{i=1}^n P_i$$

where P_i represents precipitation on day i , and n represents the number of days in the respective calendar year. The resulting rainfall values were expressed in millimetres (mm). The native spatial resolution of CHIRPS is substantially coarser than that of Landsat.

Spatial Harmonization and Pixel Database

Because the environmental datasets had different native spatial resolutions, all layers were clipped to the Saranda Forest Division boundary and aligned to a common 30-m analytical grid corresponding to the Landsat spatial resolution. The datasets were projected to WGS 84 / UTM Zone 45N (EPSG:32645), and bilinear resampling was applied to the continuous variables to obtain spatially consistent layers.

The four annual layers of NDVI, LST and rainfall (1995, 2005, 2015 and 2025) were integrated to form a 12-variable spatial database. A pixel-wise point dataset was then generated, with each point containing the corresponding values of all 12 variables at the same analytical location. Approximately 1.1 million pixel observations were obtained. The resulting point database was used for subsequent statistical analysis in Python/Google Colab, enabling pixel-level assessment of the relationships among vegetation, LST and annual rainfall.

Statistical Analysis

Statistical analysis was performed in Python using Google Colab based on the pixel-wise environmental database. Descriptive statistics, including minimum, maximum, mean and standard deviation, were calculated for NDVI, LST and annual rainfall for each reference year. Temporal variability was evaluated by comparing the spatial mean values for 1995, 2005, 2015 and 2025, with the resulting patterns presented as line graphs.

The interrelationships among NDVI–LST, NDVI–rainfall and LST–rainfall were assessed separately for each year using Pearson’s correlation coefficient (r). Simple linear regression and scatterplots were used to visualize the direction and strength of these relationships, while R^2 was used to describe the variance associated with the fitted linear relationships. Correlation matrices and regression plots were examined collectively to identify temporal changes in the environmental relationships.

Given the very large number of pixel observations (approximately 1.1 million), greater emphasis was placed on the magnitude and direction of r , R^2 , temporal consistency and environmental interpretation rather than statistical significance alone. Although the complete pixel database contained approximately 1.1 million observations, 50,000 spatial observations per year were used for the correlation and regression analyses to facilitate computationally efficient statistical processing.

The overall methodological workflow, from data acquisition and pre-processing through environmental-variable derivation, spatial harmonization, pixel-database generation, and statistical analysis, is summarized in Fig. 2.

Results

Spatial and Temporal Variation of LST

The spatial distribution of land surface temperature (LST) revealed substantial variation across the Saranda Forest Division during the four reference years (Fig. 3). The mean LST was $21.64 \pm 2.08^{\circ}\text{C}$ in 1995, increasing sharply to $34.81 \pm 3.21^{\circ}\text{C}$ in 2005. It subsequently declined to $29.80 \pm 2.79^{\circ}\text{C}$ in 2015 and $26.63 \pm 1.91^{\circ}\text{C}$ in 2025. The corresponding LST ranges were $16.03\text{--}35.32^{\circ}\text{C}$, $21.88\text{--}50.88^{\circ}\text{C}$, $23.60\text{--}42.31^{\circ}\text{C}$, and $21.25\text{--}36.90^{\circ}\text{C}$, respectively.

The temporal pattern therefore indicates a pronounced increase in surface temperature between 1995 and 2005, followed by a progressive decline during the subsequent two periods. Despite this decline after 2005, the mean LST in 2025 remained 4.99°C (23.04%) higher than that of 1995. Spatially, higher LST values were generally distributed in relatively warmer parts of the division, while comparatively lower temperatures were associated with areas showing greater vegetation cover (Fig. 3).

Spatial and Temporal Variation of NDVI

NDVI exhibited considerable spatial heterogeneity across the forest division and showed a non-linear temporal pattern (Fig. 4). The mean NDVI decreased from 0.606 ± 0.113 in 1995 to 0.494 ± 0.093 in 2005, representing an 18.53% decline. This was followed by a substantial recovery to 0.619 ± 0.118 in 2015 and 0.669 ± 0.111 in 2025. Thus, the highest mean NDVI occurred in 2025, whereas the lowest occurred in 2005.

The NDVI ranges were -0.241 to 0.798 in 1995, -0.331 to 0.755 in 2005, -0.185 to 0.838 in 2015, and -0.197 to 0.841 in 2025. The spatial distribution indicates that higher NDVI values were concentrated across areas of relatively dense vegetation, while lower values occurred locally in less-vegetated or non-vegetated areas (Fig. 4). Over the entire 1995–2025 period, mean NDVI increased by 0.062 (10.25%), although this overall increase was preceded by a marked decline during 1995–2005.

Spatial and Temporal Variation of Annual Rainfall

Annual rainfall showed an overall increasing pattern during the study period, with considerable spatial variability across the forest division (Fig. 5). The mean annual rainfall increased from $1,147.69 \pm 48.36$ mm in 1995 to $1,228.67 \pm 31.35$ mm in 2005 and $1,237.07 \pm 54.99$ mm in 2015. A much larger increase occurred in 2025, when mean annual rainfall reached $1,759.99 \pm 50.29$ mm.

The corresponding rainfall ranges were $1,050.57\text{--}1,257.54$ mm in 1995, $1,159.32\text{--}1,293.53$ mm in 2005, $1,102.24\text{--}1,349.94$ mm in 2015 and $1,606.90\text{--}1,860.35$ mm in 2025. The mean annual rainfall consequently increased by 612.31 mm (53.35%) between 1995 and 2025. The largest increase occurred between 2015 and 2025, when mean rainfall increased by approximately 522.92 mm (42.27%) (Fig. 5).

Table 1
Temporal variation and overall change in environmental variables

Variable	1995	2005	2015	2025	Change, 1995–2025	Change (%)
NDVI	0.606 ± 0.113	0.494 ± 0.093	0.619 ± 0.118	0.669 ± 0.111	+ 0.062	+ 10.25
LST (°C)	21.64 ± 2.08	34.81 ± 3.21	29.80 ± 2.79	26.63 ± 1.91	+ 4.99	+ 23.04
Annual rainfall (mm)	1147.69 ± 48.36	1228.67 ± 31.35	1237.07 ± 54.99	1759.99 ± 50.29	+ 612.31	+ 53.35
<i>Note: Values represent spatial mean ± standard deviation. Change represents the difference between the 2025 and 1995 spatial means.</i>						

Relationships among NDVI, LST and Rainfall

The correlation analysis revealed a clear contrast between the relatively strong and temporally consistent relationship between NDVI and LST and the comparatively weak relationships involving rainfall (Fig. 6).

The NDVI–LST relationship was consistently negative and strong throughout the study period. Pearson's correlation coefficient (r) was -0.630 in 1995, -0.600 in 2005, -0.754 in 2015, and -0.739 in 2025. The corresponding R^2 values were 0.397, 0.360, 0.568 and 0.546, respectively. Thus, the strongest inverse association occurred in 2015, followed closely by 2025. The fitted regression relationships consistently showed an inverse linear association between NDVI and LST (Fig. 7), indicating a persistent negative vegetation–thermal association across the forest division.

In contrast, the NDVI–rainfall relationship was very weak in all four years. The correlation was negative in 1995 ($r = -0.162$), positive in 2005 ($r = 0.185$), nearly zero in 2015 ($r = -0.022$), and weakly negative in 2025 ($r = -0.048$). The corresponding R^2 values remained very low, ranging from 0.0005 to 0.034. The regression plots similarly showed only weak relationships between annual rainfall and NDVI (Fig. 7).

The LST–rainfall relationship varied considerably among the reference years. A very weak positive association was observed in 1995 ($r = 0.187$; $R^2 = 0.035$), followed by a weak negative association in 2005 ($r = -0.393$; $R^2 = 0.155$). The relationship changed to a weak positive association in 2015 ($r = 0.261$; $R^2 = 0.068$) and became very weakly positive by 2025 ($r = 0.090$; $R^2 = 0.008$). These results indicate that, unlike the relatively stable NDVI–LST relationship, the association between rainfall and LST was temporally inconsistent.

Overall Temporal Pattern

The combined temporal profiles provide an integrated view of environmental variability within the Saranda Forest Division (Fig. 8). LST showed the strongest inter-decadal fluctuation, with a sharp

maximum in 2005 followed by successive declines in 2015 and 2025. NDVI followed a contrasting pattern, decreasing substantially between 1995 and 2005 and subsequently recovering to its highest mean value in 2025. Annual rainfall, meanwhile, displayed a clear overall increase, particularly during 2015–2025.

The contrasting temporal behaviour of the three variables indicates that changes in vegetation, surface temperature and rainfall were not synchronous. Nevertheless, the consistently strong negative NDVI–LST correlations across all four reference years indicate a persistent spatial association between vegetation condition and surface thermal behaviour. Conversely, the weak and temporally variable relationships between rainfall and the other two variables suggest that annual rainfall alone was not strongly associated with the spatial variability of NDVI or LST during the selected reference years.

Given the large number of spatial observations used for correlation analysis, the interpretation emphasizes the magnitude and direction of the correlation coefficients, the associated R^2 values and their temporal consistency, rather than statistical significance alone. This provides a more meaningful assessment of the environmental relationships represented by the spatially distributed observations.

Discussion

The integrated analysis of NDVI, LST and annual rainfall reveals that the environmental dynamics of the Saranda Forest Division are characterized by substantial temporal variability and strong vegetation–thermal coupling, while the association of vegetation with annual rainfall is comparatively weak and inconsistent. The most prominent feature is the persistent inverse relationship between NDVI and LST across all four reference years. Pearson's correlation coefficients ranged from -0.600 in 2005 to -0.754 in 2015, with corresponding R^2 values of 0.360 – 0.568 . This indicates that areas with relatively higher vegetation greenness generally experienced lower land-surface temperatures. Such behaviour is consistent with the established physical relationship between vegetation cover and surface thermal conditions, whereby vegetation can reduce surface heating through shading and evapotranspiration (Weng et al., 2004). Similar negative NDVI–LST relationships have also been reported in Indian environments. Guha and Govil (2021), for example, found a strong negative association between NDVI and LST in Raipur, while their later seasonal analysis demonstrated that the strength of this relationship varies considerably with season and land-cover type (Guha & Govil, 2022). Similar investigations in the Lower Son River Basin of India have also examined the spatial relationship among LULC, NDVI and LST, demonstrating the usefulness of integrated remote-sensing approaches for interpreting vegetation–thermal interactions (Singh et al., 2024). The present findings are also consistent with Garai et al. (2022), who reported an inverse NDVI–LST relationship across eastern India, although the strength of the association varied according to the environmental context and temporal conditions. The stronger and persistent relationship observed in Saranda suggests that vegetation–thermal coupling remains particularly pronounced within this predominantly forested landscape.

The strength and persistence of the NDVI–LST relationship in Saranda are particularly noteworthy because the study area is predominantly forested rather than an intensively urbanized landscape. The correlation became strongest in 2015 ($r = -0.754$) and remained strong in 2025 ($r = -0.739$), suggesting that vegetation condition was strongly associated with spatial thermal variability. This finding broadly agrees with observations from other Indian landscapes, although the magnitude of the relationship differs according to environmental setting. For instance, Sharma et al. (2022) reported a negative NDVI–LST relationship in Gautam Buddh Nagar, while Guha and Govil (2022) found stronger negative relationships over vegetated surfaces than over barren or built-up areas. The relatively high R^2 values obtained for Saranda in 2015 and 2025 therefore indicate that vegetation condition explains a substantial component of the spatial variation in LST, although it should not be interpreted as evidence that NDVI alone determines surface temperature.

The temporal behaviour of NDVI provides further evidence of changing vegetation conditions. Mean NDVI declined from approximately 0.606 in 1995 to 0.494 in 2005, followed by a recovery to 0.619 in 2015 and 0.669 in 2025. Thus, despite the pronounced reduction during 1995–2005, the subsequent increase resulted in a 2025 mean NDVI higher than that observed in 1995. This overall greening tendency is broadly consistent with findings from central Indian forests. Singh et al. (2021), using MODIS NDVI and CHIRPS rainfall, reported predominantly greening conditions across central Indian forests and concluded that many forest ecosystems demonstrated considerable resilience to rainfall variability. Their study also showed that vegetation vigour differed substantially among climatic epochs, emphasizing that forest vegetation does not necessarily respond uniformly to rainfall changes. Similarly, Prasad et al. (2005) demonstrated that NDVI–rainfall relationships vary among Indian forest types and that time lags between precipitation and vegetation response can substantially influence the observed relationship.

The rainfall results show a markedly different pattern from the NDVI–LST relationship. Mean annual rainfall increased from approximately 1,148 mm in 1995 to 1,760 mm in 2025, representing an increase of about 53% over the study period. However, the pixel-level NDVI–rainfall correlations were weak: -0.162 in 1995, $+0.185$ in 2005, -0.022 in 2015 and -0.048 in 2025. The near-zero correlations in 2015 and 2025 indicate that annual cumulative rainfall alone provides limited explanation for the spatial variability of NDVI within the forest division. This does not necessarily imply that rainfall is ecologically unimportant. Rather, annual rainfall totals may not adequately represent the timing, intensity, duration and seasonal distribution of precipitation that influence forest productivity. Prasad et al. (2005) specifically demonstrated that the relationship between rainfall and forest NDVI can be strongly affected by temporal lags, while Singh et al. (2021) found that rainfall variability and vegetation response in central Indian forests were closely linked when rainfall anomalies and temporal behaviour were considered.

The weak NDVI–rainfall relationship observed here is also supported by broader Indian research. Rajesh et al. (2023) reported a strong negative NDVI–LST relationship over the monsoon core region of India but found that vegetation responses were more strongly associated with soil moisture and groundwater than with rainfall alone. Their results emphasize that precipitation may influence vegetation indirectly

through the availability of soil and subsurface water. Therefore, the weak annual NDVI–rainfall correlations in Saranda should be interpreted as evidence that annual rainfall totals alone are insufficient to explain spatial vegetation variability, rather than as evidence of an absence of climatic influence.

The LST–rainfall relationship was also temporally unstable, changing from positive in 1995 ($r = 0.187$) to negative in 2005 ($r = -0.393$), positive again in 2015 ($r = 0.261$) and weakly positive in 2025 ($r = 0.090$). The corresponding R^2 values were relatively low (0.008–0.155), indicating that rainfall explained only a small proportion of the spatial variation in LST. This variability suggests that surface temperature in Saranda is controlled by a combination of vegetation condition, moisture availability, terrain, surface characteristics and the timing of satellite observations rather than annual rainfall alone. Research from eastern India similarly indicates that vegetation dynamics can be influenced jointly by climatic and anthropogenic factors, with the relative contribution of these drivers varying spatially (Banerjee et al., 2024).

An important feature of the temporal results is the unusually high mean LST observed in 2005 (approximately 34.8°C) compared with 1995, 2015 and 2025. The subsequent decline in mean LST to approximately 29.8°C in 2015 and 26.6°C in 2025 means that the four observations should not be interpreted as a simple monotonic warming trend. Rather, they represent environmental conditions at four decadal reference points. This distinction is important because Landsat observations are instantaneous measurements and surface temperature is highly sensitive to acquisition date, season, atmospheric conditions, soil moisture and vegetation phenology. Studies examining LST–NDVI relationships have demonstrated substantial seasonal variability in both LST and the strength of their statistical association (Guha & Govil, 2022). Consequently, the large 2005 value should be interpreted in the context of the specific observations contributing to the annual composite rather than being treated as direct evidence of a long-term regional warming trajectory.

The positive association between LST and rainfall in 1995 and 2015, despite the physical expectation that moisture can reduce surface temperature, further illustrates the complexity of the relationship. Rainfall and LST do not necessarily respond synchronously at the annual scale. Rainfall may increase vegetation growth and soil moisture, which can subsequently affect evapotranspiration and surface temperature, but the response may occur with temporal lags. In addition, areas receiving greater rainfall may differ systematically in elevation, vegetation structure and terrain. The weak and changing LST–rainfall correlations therefore suggest that precipitation acts as one component of a coupled environmental system rather than as a direct determinant of surface temperature. This consideration is particularly important in Saranda, where forest dynamics are influenced not only by climatic variability but also by anthropogenic pressures and disturbance processes. Previous spatial assessment of the Saranda Forest Division has demonstrated substantial variation in forest-fire susceptibility associated with vegetation condition, moisture and landscape characteristics, highlighting the ecological sensitivity of the landscape (Rahaman et al., 2022).

A major strength of the study is its integrated multi-variable and pixel-based framework, combining Landsat-derived NDVI and LST with CHIRPS rainfall for four reference years. The common 30-m analytical framework and approximately 1.1 million pixel observations enabled detailed assessment of spatial environmental variability beyond division-wide averages. The combined use of Google Earth Engine and Python/Google Colab also provides a reproducible and scalable workflow that can be extended to additional years, environmental variables and forest landscapes.

The study is limited by the use of only four temporal snapshots and annual composites, which restricts assessment of continuous trends and seasonal variability. In addition, CHIRPS has a much coarser native resolution than Landsat; resampling therefore provides spatial alignment but does not increase the actual rainfall information content. Pearson correlation and simple regression also indicate association rather than causation, and the influence of terrain, soil moisture, vegetation structure and anthropogenic activities cannot be separated using the present framework. Future studies should therefore incorporate continuous and seasonally matched time series, validated rainfall observations, soil moisture, evapotranspiration, topography, fire and mining-related variables, together with multivariate or spatial modelling approaches, to better distinguish climatic and anthropogenic controls on vegetation and thermal dynamics.

Conclusion

This study provides a spatially explicit assessment of environmental dynamics in the Saranda Forest Division by integrating Landsat-derived NDVI and LST with CHIRPS annual rainfall for 1995, 2005, 2015 and 2025. The results demonstrate pronounced temporal variability in vegetation and surface thermal conditions, alongside a substantial increase in annual rainfall. Most importantly, the consistently strong negative NDVI–LST relationship across all four reference years indicates a persistent vegetation–thermal coupling, whereas the weak and temporally inconsistent relationships involving annual rainfall suggest that precipitation totals alone cannot explain the observed spatial variability in vegetation and surface temperature.

The study establishes a pixel-level geospatial baseline for understanding environmental interactions within a forest landscape where ecological conservation and resource development coexist. The integration of GEE-based remote sensing with large-scale Python statistical analysis provides a transferable framework for assessing environmental dynamics in other forested and resource-sensitive regions. The persistent vegetation–temperature coupling identified across three decades highlights vegetation condition as a key spatial dimension of thermal behaviour in the Saranda landscape. This study provides a reproducible baseline against which future climate variability, ecological change and sustainable landscape-management strategies in Saranda can be quantitatively evaluated.

Declarations

Authorship Contribution

Sk Mujibar Rahaman: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Supervision, Visualization, Writing – original draft, Writing – review & editing.

Masjuda Khatun: Formal analysis, Software, Visualization, Writing – review & editing.

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Data Availability Statement

The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request. Landsat Collection 2 Level-2 data are publicly available from the U.S. Geological Survey (USGS) at <https://www.usgs.gov/landsat-missions/landsat-collection-2-level-2-science-products>. The Landsat 4–5 Thematic Mapper Collection 2 Level-2 dataset is available at <https://doi.org/10.5066/P9IAXOVV>, and the Landsat 8–9 Operational Land Imager/Thermal Infrared Sensor Collection 2 Level-2 dataset is available at <https://doi.org/10.5066/P9OGBGM6>. CHIRPS v2.0 daily precipitation data are publicly available from the Climate Hazards Center, University of California, Santa Barbara, at <https://data.chc.ucsb.edu/products/CHIRPS-2.0/> and through the Google Earth Engine Data Catalog at https://developers.google.com/earth-engine/datasets/catalog/UCSB-CHG_CHIRPS_DAILY

Declaration of Competing Interests

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.

Ethical Statement

This study did not involve human participants, animal experiments, or clinical trials; therefore, ethical approval and informed consent were not required.

Clinical trial number

Not applicable.

Consent to publish

Not applicable.

Consent to participate

Not applicable.

Author Contribution

Authorship Contribution Sk Mujibar Rahaman: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Supervision, Visualization, Writing – original draft, Writing – review & editing. Masjuda Khatun: Formal analysis, Software, Visualization, Writing – review & editing.

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The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request. Landsat Collection 2 Level-2 data are publicly available from the U.S. Geological Survey (USGS) at <https://www.usgs.gov/landsat-missions/landsat-collection-2-level-2-science-products>. The Landsat 4–5 Thematic Mapper Collection 2 Level-2 dataset is available at <https://doi.org/10.5066/P9IAXOVV>, and the Landsat 8–9 Operational Land Imager/Thermal Infrared Sensor Collection 2 Level-2 dataset is available at <https://doi.org/10.5066/P9OGBGM6>. CHIRPS v2.0 daily precipitation data are publicly available from the Climate Hazards Center, University of California, Santa Barbara, at <https://data.chc.ucsb.edu/products/CHIRPS-2.0/> and through the Google Earth Engine Data Catalog at https://developers.google.com/earth-engine/datasets/catalog/UCSB-CHG_CHIRPS_DAILY

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Figures

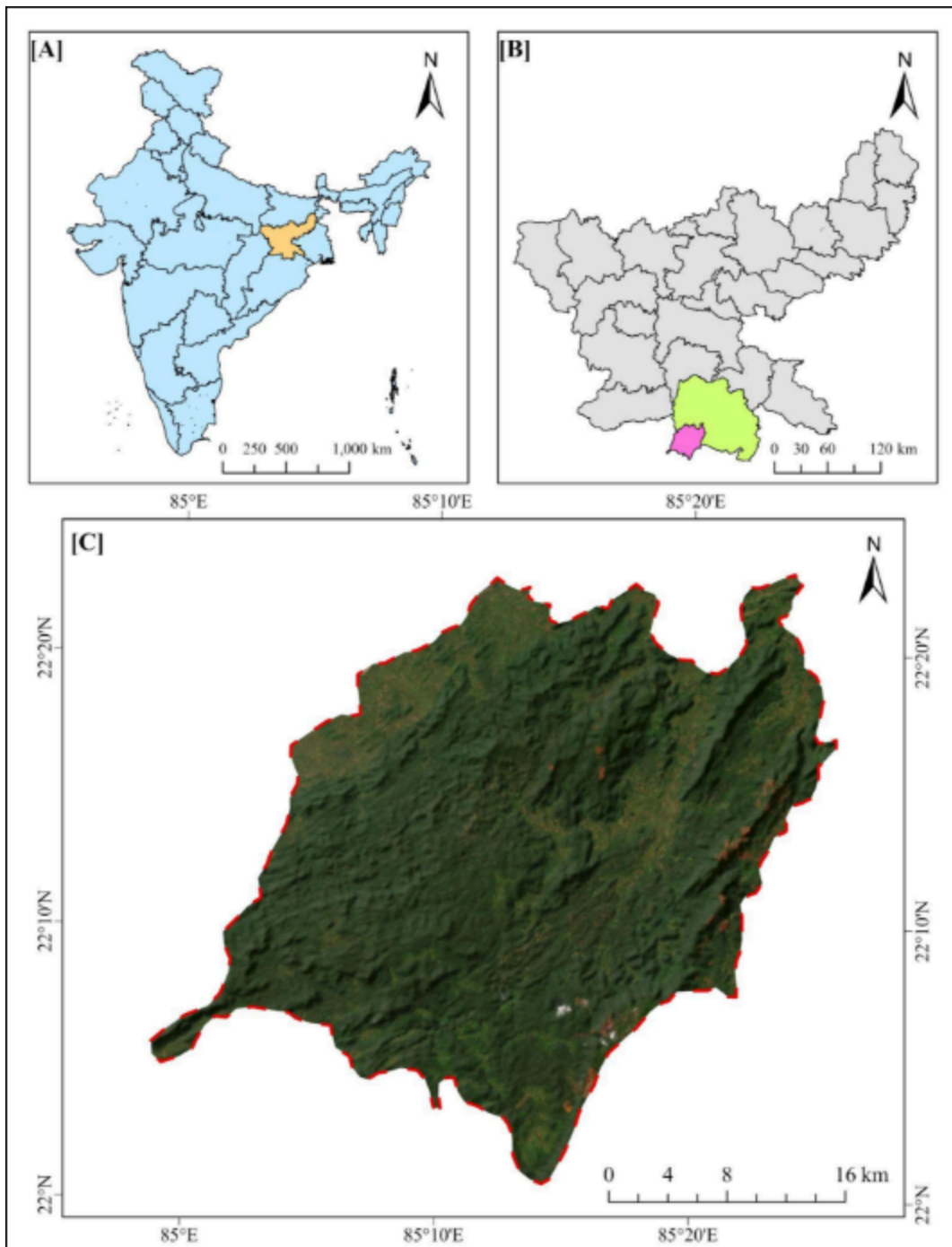


Figure 1

Location of Saranda Forest Division, West Singhbhum district, Jharkhand, India. (A) Location of Jharkhand in India; (B) location of West Singhbhum district and the Saranda Forest Division within Jharkhand; and (C) detailed view of the Saranda Forest Division showing its forested landscape and boundary.

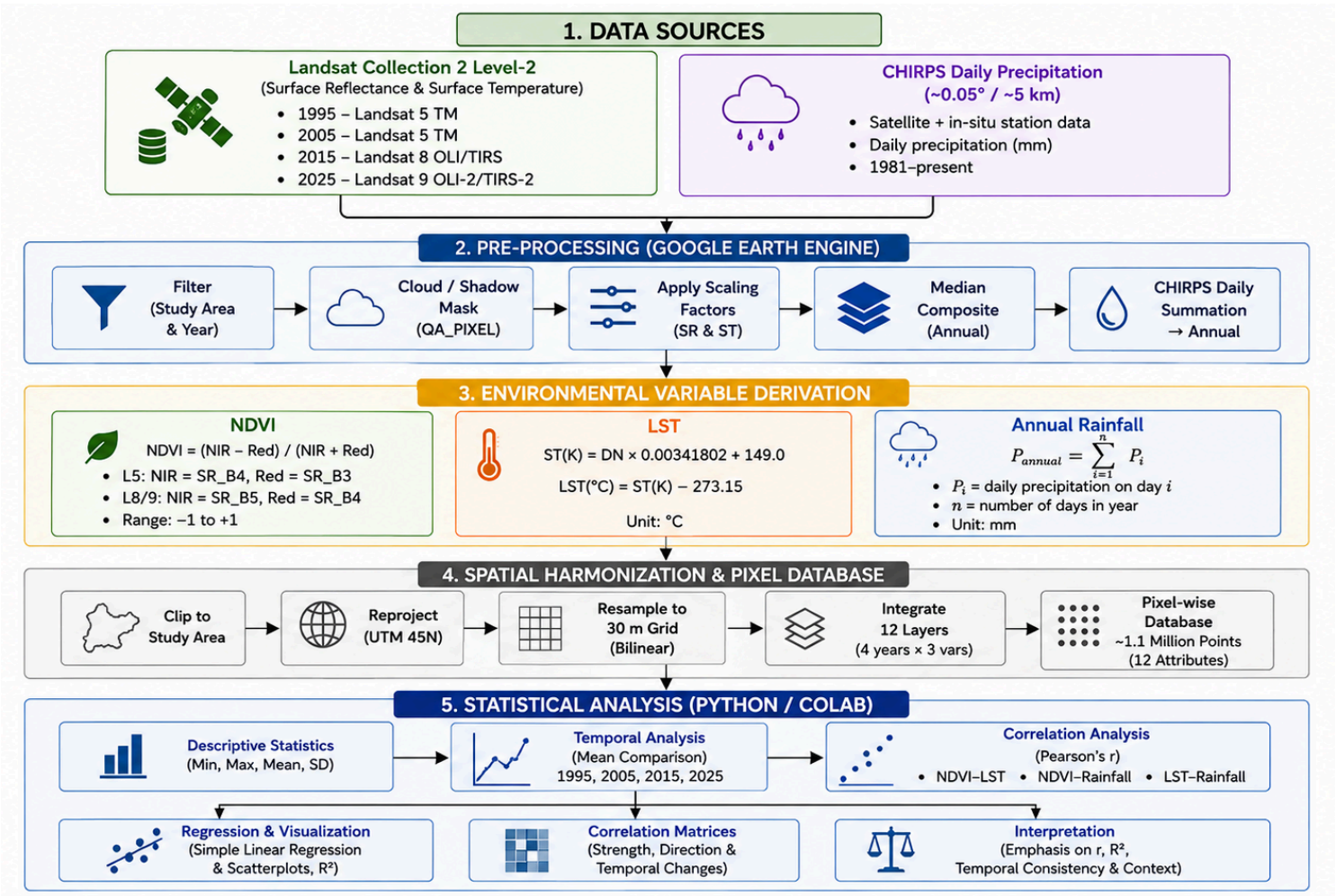


Figure 2

Methodological workflow adopted for the assessment of temporal variability and interrelationships among NDVI, land surface temperature (LST), and annual rainfall in the Saranda Forest Division during 1995, 2005, 2015, and 2025.

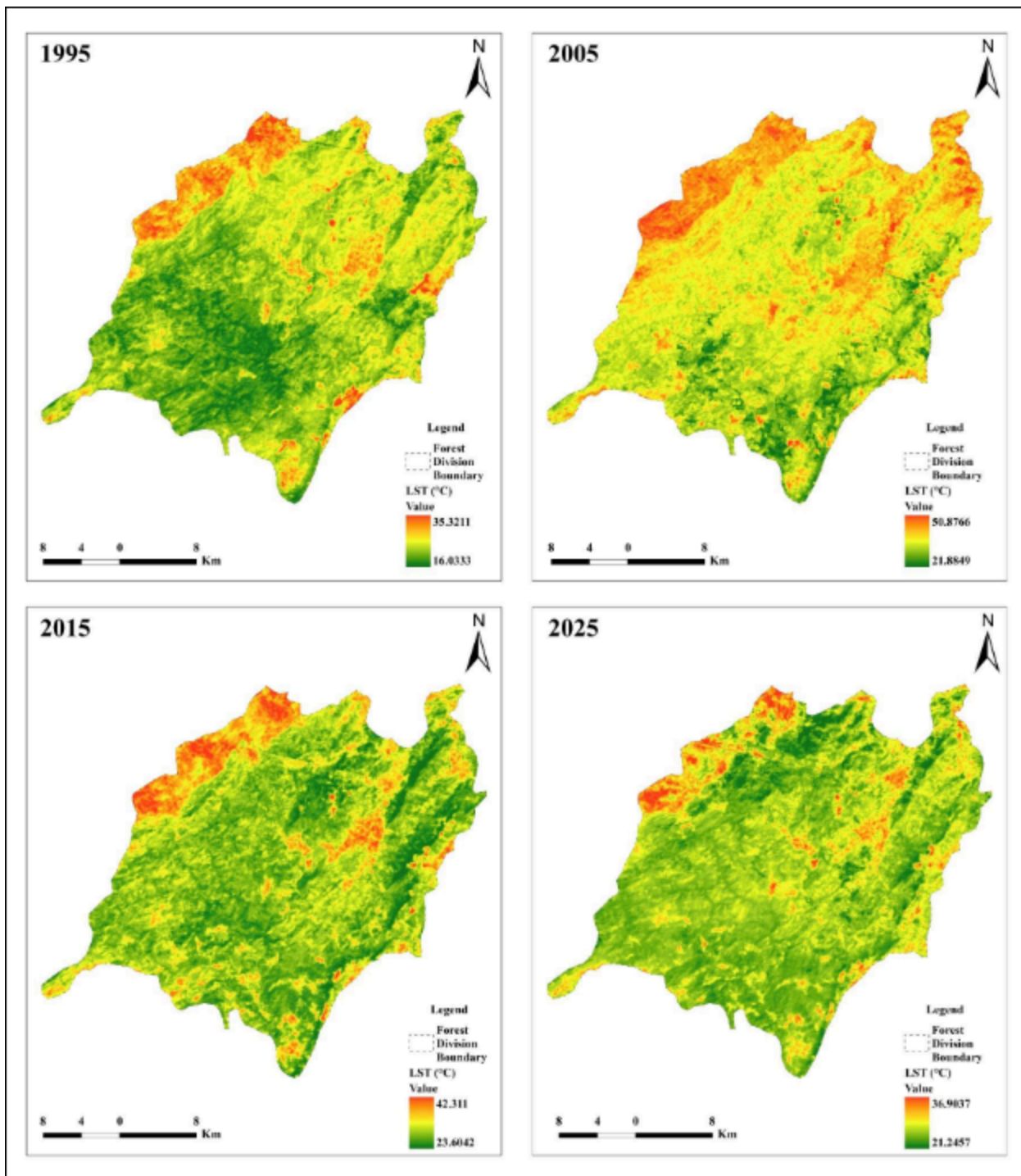


Figure 3

Spatial distribution of land surface temperature (LST) across the Saranda Forest Division for 1995, 2005, 2015 and 2025.

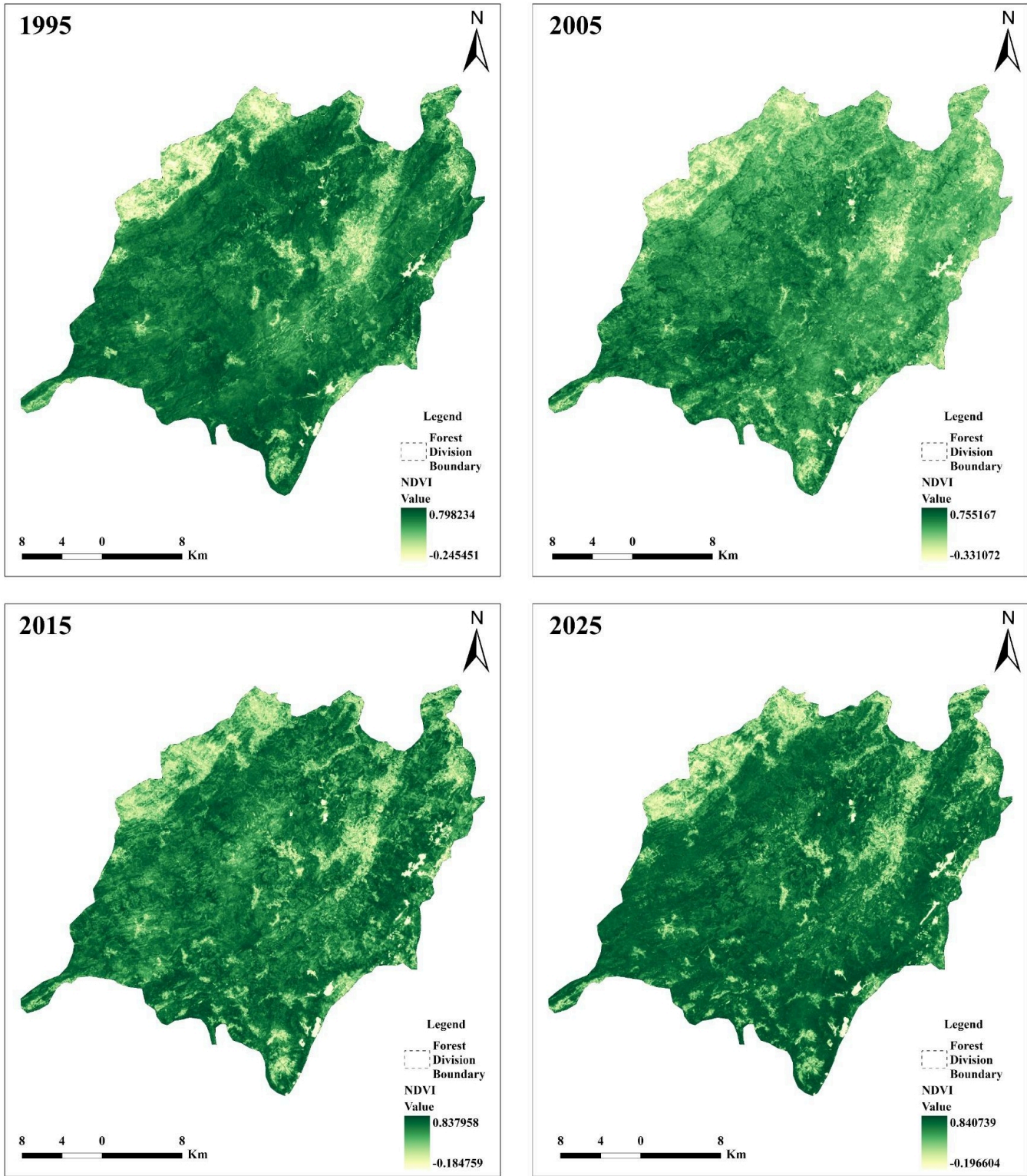


Figure 4

Spatial distribution of Normalized Difference Vegetation Index (NDVI) across the Saranda Forest Division for 1995, 2005, 2015 and 2025.

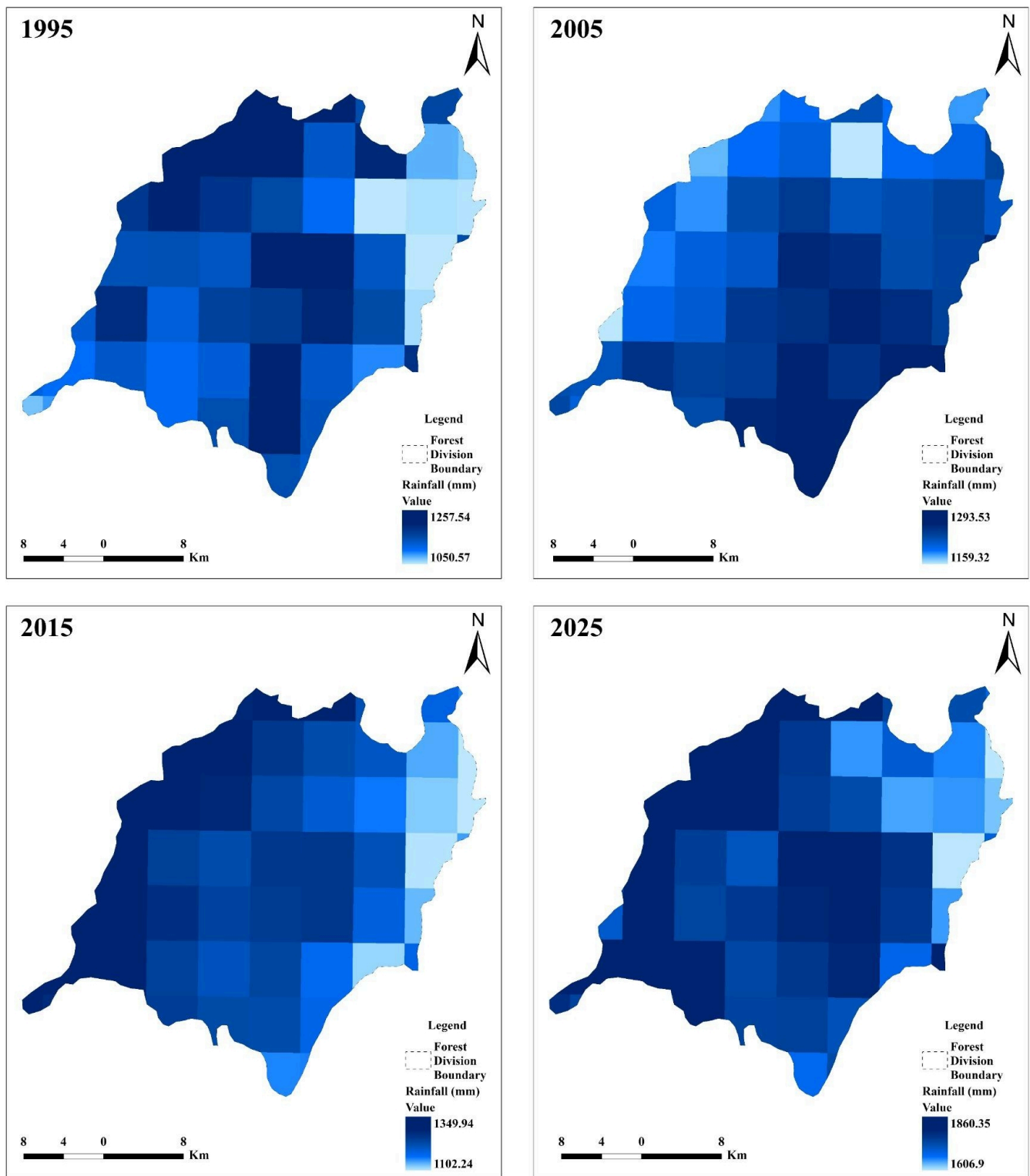


Figure 5

Spatial distribution of annual rainfall across the Saranda Forest Division for 1995, 2005, 2015 and 2025.

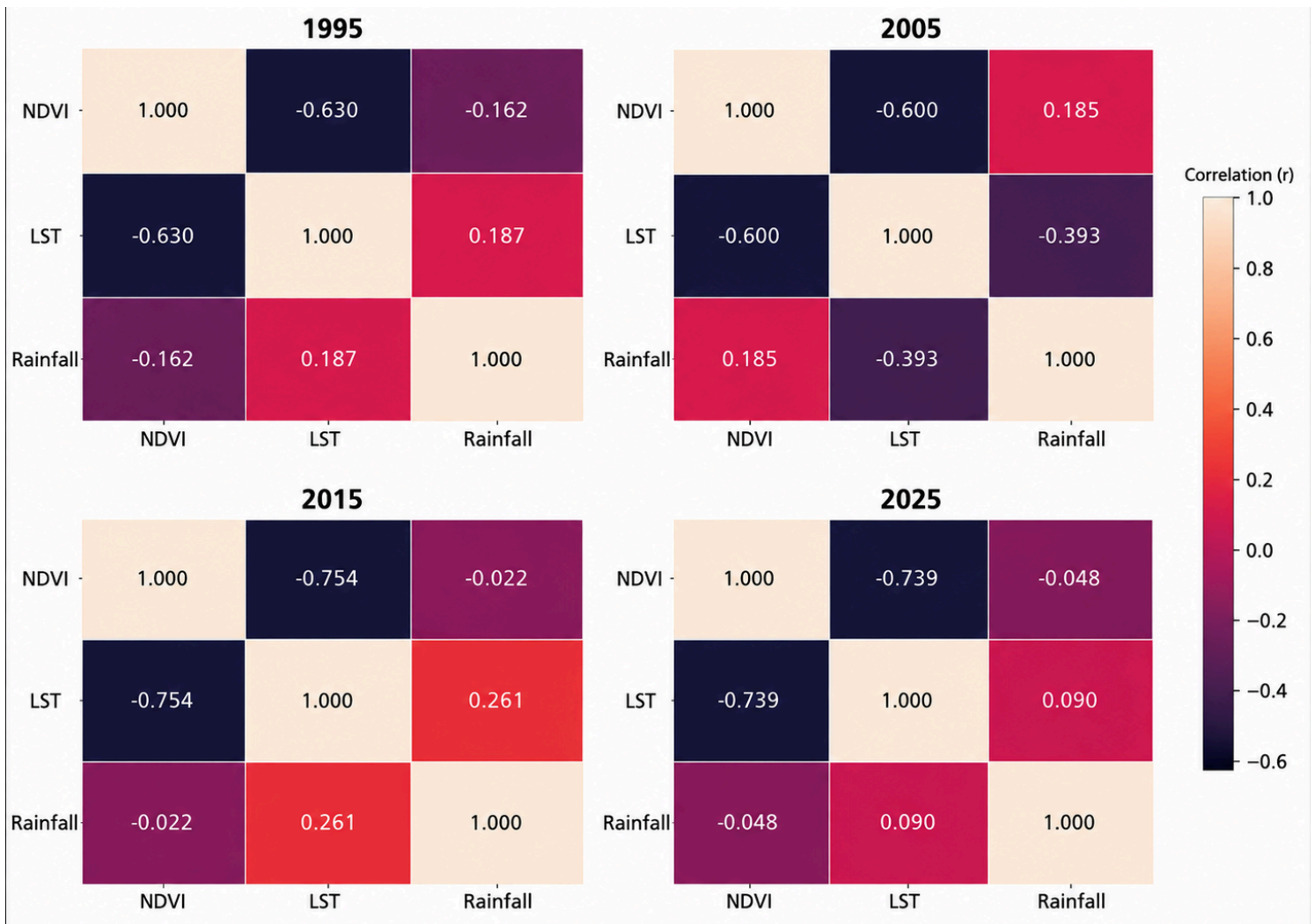


Figure 6

Pearson correlation matrices showing the relationships among NDVI, LST and annual rainfall for the four reference years in the Saranda Forest Division.

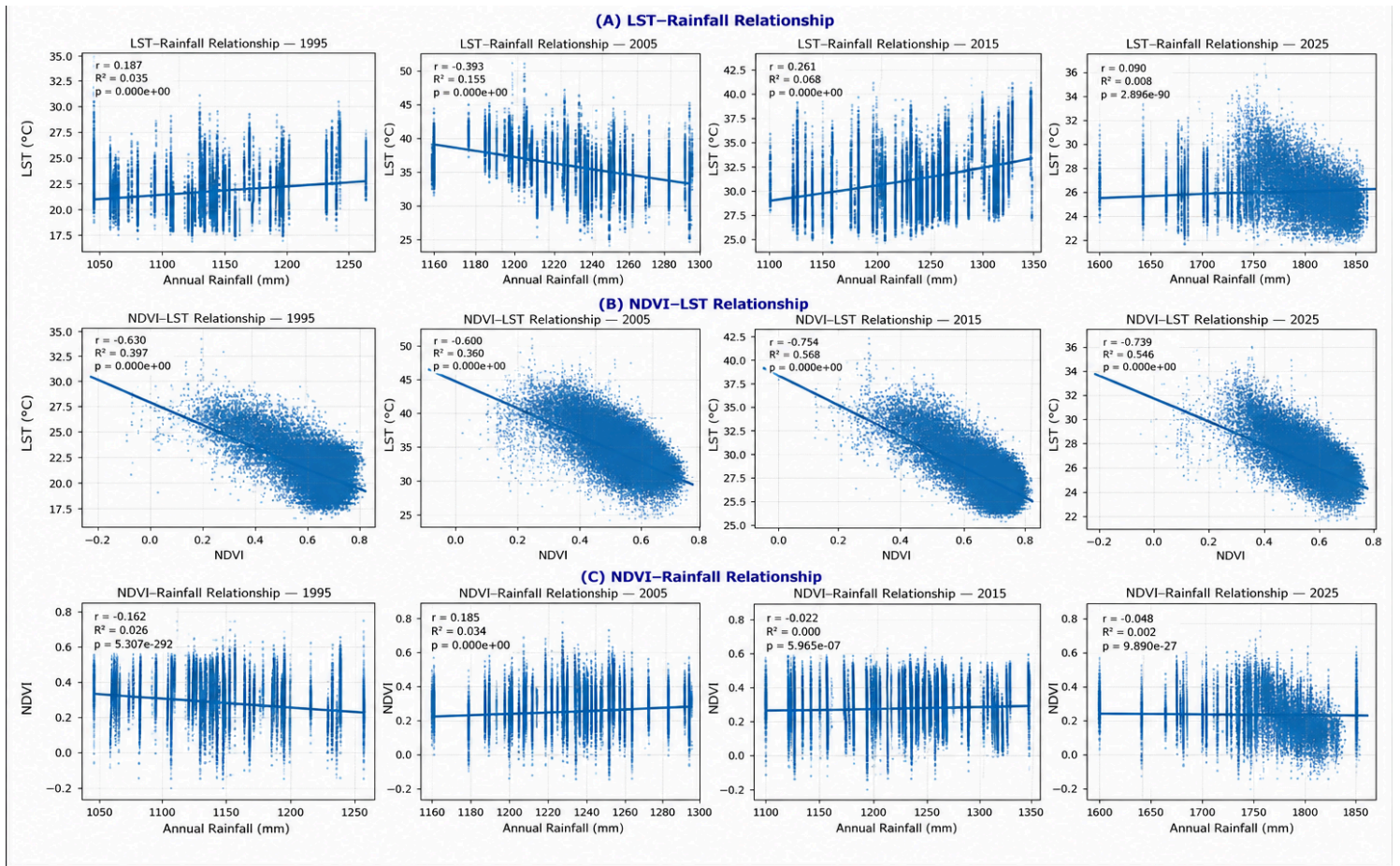


Figure 7

Pixel-level scatterplots and linear regression relationships for NDVI-LST, LST-rainfall and NDVI-rainfall across the Saranda Forest Division during 1995, 2005, 2015 and 2025.

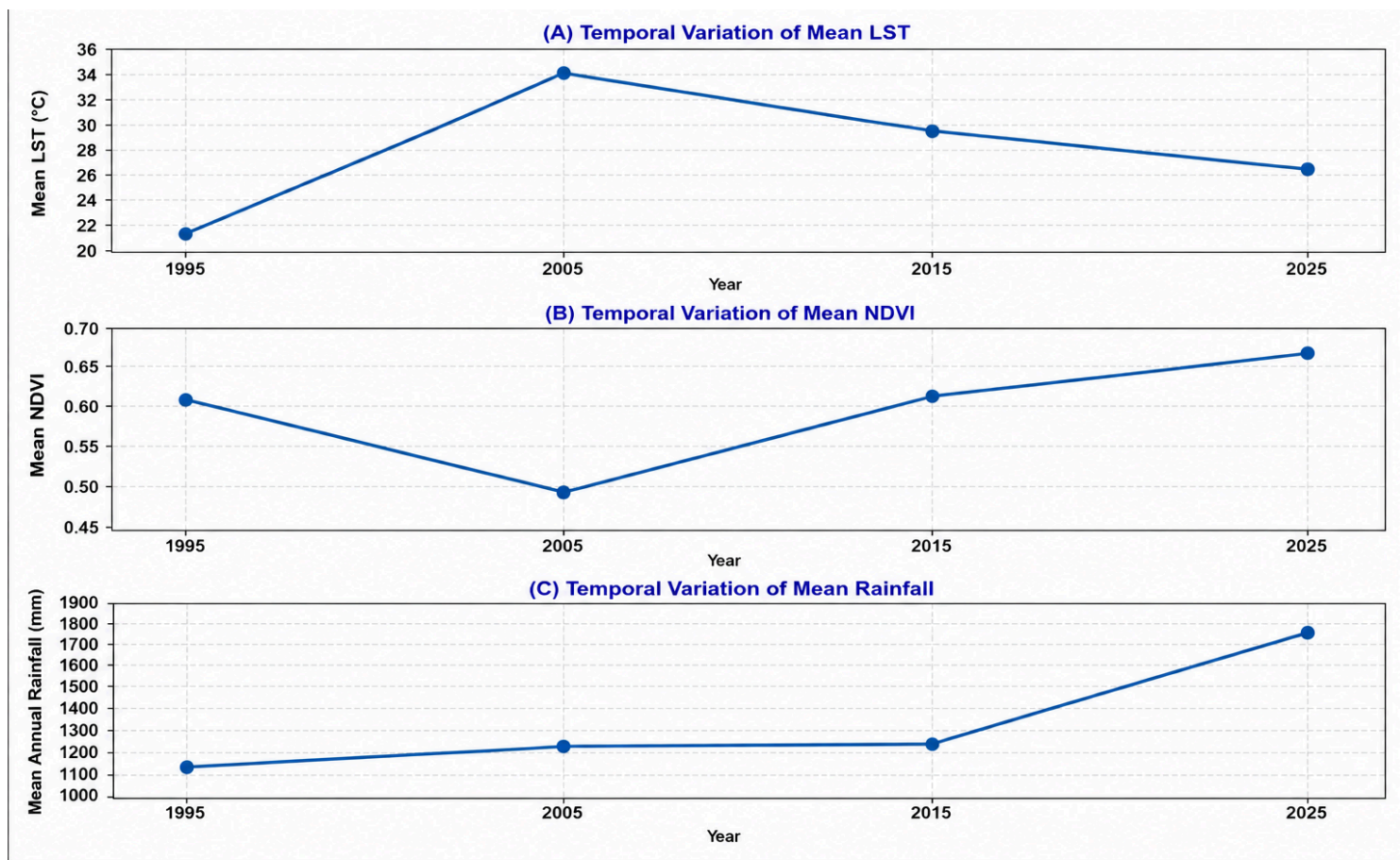


Figure 8

Temporal variation in the spatial mean values of (A) LST, (B) NDVI and (C) annual rainfall across the Saranda Forest Division during 1995, 2005, 2015 and 2025.