ANNUAL NORMALIZED DIFFERENCE VEGETATION INDEX DYNAMICS AND CLIMATIC CONTROLS IN MYMENSINGH DISTRICT, BANGLADESH

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ABSTRACT

Understanding how vegetation greenness responds to climate variability at operational management scales is essential for climate smart land management in floodplain agro ecosystems. The study develops a reproducible, district level assessment of vegetation–climate coupling for Mymensingh, Bangladesh, by combining Landsat Collection 2 Level 2 surface reflectance–derived Normalized Difference Vegetation Index (NDVI) (annual means, 2000–2021) with station based Bangladesh Meteorological Department records (mean annual temperature, total annual rainfall, mean annual relative humidity). Yearly NDVI mosaics were clipped to the administrative boundary, and district mean NDVI values were extracted using zonal statistics. Daily climate records were aggregated to annual metrics via Power Query, merged with the NDVI time series, and analysed using correlation and multiple linear regression in SPSS. Across 22 annual observations, mean NDVI averaged 0.0458 (SD = 0.1468) and exhibited interannual variability but no strong monotonic trend. Pairwise analysis indicated a moderate positive correlation between NDVI and mean annual temperature ($r = 0.539$, $p = 0.010$), while correlations with total annual rainfall ($r = -0.007$, $p = 0.975$) and relative humidity ($r = -0.352$, $p = 0.108$) were weak and non significant. A multiple regression including temperature, rainfall and humidity explained 42.2% of NDVI variance ($R^2 = 0.422$; adjusted $R^2 = 0.325$; $F(3,18) = 4.378$, $p = 0.018$), with mean temperature the only significant independent predictor ($B = 0.212$, $p = 0.009$). Results suggest that, at annual and district mean aggregation, temperature is the dominant linear predictor of NDVI in Mymensingh, while rainfall and humidity effects may be seasonal, lagged, non linear, or mediated by land use and irrigation Seasonal and land cover–stratified analyses, lag testing, and the use of alternative vegetation indices (e.g., EVI) are recommended to more comprehensively resolve vegetation–climate dynamics and to support local adaptation planning. Mymensingh District represents a climatically sensitive floodplain agro-ecosystem characterized by intensive agricultural activity, seasonal monsoon rainfall, and increasing anthropogenic pressure. The district plays a significant role in regional food production and is highly vulnerable to climate variability, making it an appropriate case for assessing vegetation–climate interactions at an operational management scale. Despite its importance, long-term district-level analyses of NDVI–climate relationships remain limited in this region.

Keywords: *NDVI, Vegetation dynamics, Climate variability, Temperature–vegetation relationship, Time series analysis*

1. INTRODUCTION

Vegetation dynamics are sensitive indicators of ecosystem responses to climatic variability and land use change, underpinning services such as carbon sequestration, crop productivity, and biodiversity support (Mehmood et al., 2024; Das & Sarkar, 2023). High resolution satellite time series integrated with station meteorological records provide the temporal fidelity and spatial specificity needed to untangle how vegetation greenness responds to interannual shifts in temperature, precipitation, and humidity (Rajesh et al., 2022; Guha & Govil, 2020). Regional studies highlight that vegetation–climate relationships are often spatially heterogeneous and modulated by land cover change and urbanization (Fattah & Morshed, 2021; Akhter & Afroz, 2024). In contrast, analyses that explicitly link NDVI trends to extreme climatic indices reveal important lagged and seasonal responses (Islam et al., 2021). Despite this body of work, district-scale, replicable assessments that combine Landsat-derived NDVI with station-based BMD records over multi-decadal windows remain limited for many floodplains and agroecological landscapes, constraining locally relevant climate-smart management and policy decisions (Bari et al., 2021; Mehmood et al., 2024).

This study fills that gap for Mymensingh district by quantifying long-term NDVI trends (2000–2021) and testing their statistical relationships with annual temperature, rainfall, and relative humidity using a reproducible workflow based on Landsat Collection 2 Level 2 surface reflectance products and daily BMD observations (Roy et al., 2020; Das & Sarkar, 2023). The approach isolates the study area via district boundary clipping, extracts robust annual greenness metrics using zonal statistics, and aligns remote sensing and meteorological time series through careful temporal aggregation and dataset merging methods that are effective in recent vegetation–climate studies (Mehmood et al., 2024; Rajesh et al., 2022).

Our objectives are:

- Produce a reproducible annual NDVI time series for Mymensingh using standardized Landsat processing (Collection 2 Level 2) and zonal extraction.
- Derive consistent annual climate metrics (mean temperature, total rainfall, mean relative humidity) from daily BMD records using Power Query aggregation.
- Quantify the strength, direction, and significance of correlations and predictive relationships between NDVI and the selected climatic drivers using correlation and regression analysis in SPSS, and present graphical diagnostics to interpret seasonal and interannual patterns.

The methodological choices emphasize reproducibility, minimal pre-processing bias, and direct applicability for local land management and climate adaptation planning, following best practices established in recent NDVI–climate literature (Mehmood et al., 2024; Fattah & Morshed, 2021).

2. METHODOLOGY

2.1 Study area and period

The analysis focused on Mymensingh District is located in north-central Bangladesh between approximately 24°15′ and 25°12′ N latitude and 90°04′ and 90°49′ E longitude, for the period 2000–2021. The temporal window was chosen to capture two decades of Landsat observations and corresponding daily meteorological records to evaluate interannual vegetation dynamics and their links to climate (Das & Sarkar, 2023; Akhter & Afroz, 2024).

2.2 Data acquisition

Satellite data: Yearly Landsat Collection 2 Level 2 surface reflectance scenes were downloaded from the USGS archive for all available acquisition dates covering Mymensingh (Roy et al., 2020; Mehmood et al., 2024).

Meteorological data: Daily station observations (temperature, rainfall, relative humidity) for 2000–2021 were obtained from the Bangladesh Meteorological Department (BMD) for the station(s) representing the district (Islam et al., 2021; Bari et al., 2021).

2.3 Remote sensing pre-processing and NDVI generation

Atmospherically corrected surface reflectance products (Landsat Collection 2 Level 2) were used to minimize preprocessing bias and ensure inter-scene comparability (Roy et al., 2020; Mehmood et al., 2024). For each yearly scene, NDVI was computed using the standard index formula: NDVI = (NIR − RED) / (NIR + RED) using the Landsat NIR and Red bands (Guha & Govil, 2020; Rajesh et al., 2022). Cloud and cloud shadow screening was applied using the Collection 2 QA band and visual inspection to exclude contaminated pixels from annual composites (Das & Sarkar, 2023). All raster processing (band arithmetic, masking, and QA filtering) was performed in ArcGIS Pro to maintain a reproducible geoprocessing workflow (Mehmood et al., 2024).

2.4 Spatial clipping and annual aggregation

Each NDVI raster was clipped to the official Mymensingh district boundary shapefile to restrict analysis to the administrative extent of interest (Akhter & Afroz, 2024). The Zonal Statistics as Table tool (ArcGIS Pro) was applied to each clipped yearly NDVI raster to extract the district-level mean NDVI for that year; the mean was selected as the primary metric to represent average greenness while retaining sensitivity to interannual change (Das & Sarkar, 2023; Rajesh et al., 2022). Yearly zonal statistics outputs were exported as .dbf files and combined into a single Excel workbook to form the NDVI annual time series (Mehmood et al., 2024)

2.5 Climate data processing and aggregation

Daily BMD records for temperature, rainfall, and relative humidity were quality checked for missing/erroneous values and homogenized where necessary (Islam et al., 2021). Using Power Query in Excel, daily records were converted to annual metrics: mean annual temperature, total annual rainfall, and mean annual relative humidity. Aggregation followed standard arithmetic averaging and summation rules, and flagged years with excessive missing data for sensitivity analyses (Bari et al., 2021; Islam et al., 2021). Metadata documenting station IDs, periods of record, and any gap-filling or flagging decisions were recorded alongside the aggregated series to ensure transparency and reproducibility (Mehmood et al., 2024)

2.6 Data integration

NDVI annual values and annual climate metrics were merged in Excel using the common field "Year" to create a combined annual dataset spanning 2000–2021 (Mehmood et al., 2024). Before analysis, the merged dataset was inspected for temporal mismatches, duplicate rows, and outliers; where appropriate, outliers were annotated and retained for sensitivity testing rather than automatically excluded (Akhter & Afroz, 2024).

2.7 Statistical analysis

All statistical evaluations were performed in SPSS. Descriptive statistics and visual diagnostics (time series plots, histograms, and scatterplots) were produced to inspect trends and distributional assumptions (Das & Sarkar, 2023).

Trend detection: Nonparametric Mann–Kendall trend tests and Sen's slope estimates were used to quantify monotonic trends in NDVI and climate variables where distributional assumptions were not satisfied (Das & Sarkar, 2023; Mehmood et al., 2024).

Relationship testing: Pearson (or Spearman, where appropriate) correlation analyses quantified pairwise associations between annual NDVI and each climate variable (rainfall, mean temperature, mean relative humidity), including assessment of lagged correlations (e.g., one year lag) informed by previous findings on lagged vegetation responses (Islam et al., 2021; Rajesh et al., 2022).

Regression modelling: Linear regression models were fitted with mean annual NDVI as the dependent variable and climate metrics as predictors. Model diagnostics (residual analysis, multicollinearity checks using VIF, and adjusted R2) were used to evaluate explanatory power and model validity.

Where linear assumptions were violated, transformations or non-parametric regression approaches were considered (Mehmood et al., 2024; Guha & Govil, 2020).

Sensitivity and robustness: Alternative NDVI aggregations (median, percentile composites) and exclusion of years with significant data gaps were used to test result robustness; key statistical results were reported with confidence intervals and p-values (Das & Sarkar, 2023).

2.8 Quality control, reproducibility, and data archiving

All processing steps, parameter settings for ArcGIS tools, Power Query scripts, and SPSS syntax were documented and archived to enable reproducibility (Mehmood et al., 2024). Versioned datasets (raw Landsat IDs, clipped NDVI raster, yearly zonal tables, aggregated climate files, and the merged annual dataset) were kept with clear metadata describing provenance and any preprocessing decisions (Akhter & Afroz, 2024). The methodological choices use of Collection 2 surface reflectance, annual aggregation, zonal statistics, and station-based climate aggregation, were aligned with best practices in recent NDVI–climate studies to ensure comparability with regional literature (Roy et al., 2020; Das & Sarkar, 2023).

3. RESULTS AND DISCUSSIONS

3.1 Descriptive statistics

Twenty-two annual observations (2000–2021) were available for district-level mean NDVI and the three climate variables (Table 1). Mean annual NDVI was low but positive (mean = 0.0458, SD = 0.1468), with values spanning −0.0925 to 0.3051. Mean annual temperature averaged 29.981 °C (SD = 0.396; range = 29.290–30.867 °C). Total annual rainfall averaged 2132.18 mm (SD = 360.43; range = 1479–2842 mm). Mean annual relative humidity averaged 82.143% (SD = 0.863; range = 80.742–84.099%).

Table 1: Descriptive statistics (2000–2021, n = 22)

Parameters	Mean	Standard Deviation	Minimum	Maximum
MEAN NDVI	0.0458	0.1468	−0.0925	0.3051
Avg_Temp (°C)	29.981	0.396	29.290	30.867
Total_Rain (mm)	2132.18	360.43	1479	2842
Avg_RH (%)	82.143	0.863	80.742	84.099

3.2 Pairwise associations (correlation analysis)

Pearson correlation coefficients quantify linear pairwise relationships between annual mean NDVI and the climate variables (Figure 1).

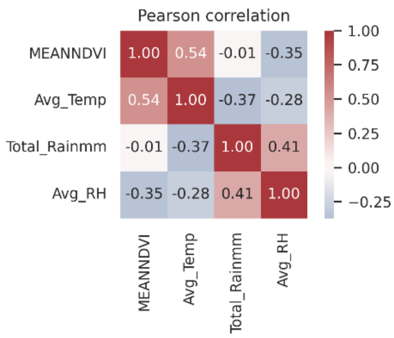


Figure 1: Pearson correlation

NDVI vs Average Temperature: r = +0.539, p = 0.010, NDVI vs Total Annual Rainfall: r = −0.007, p = 0.975, NDVI vs Average Relative Humidity: r = −0.352, p = 0.108.

Mean annual temperature shows a moderate, statistically significant positive association with district mean NDVI. Rainfall shows essentially no linear association with NDVI in the annual aggregated series. Relative humidity exhibits a moderate negative association with NDVI that does not reach conventional significance (p = 0.108). Scatterplots with fitted markers are shown in Figure 2. a (NDVI × temperature), Figure 2.b (NDVI × rainfall), and Figure 2.c (NDVI × relative humidity).

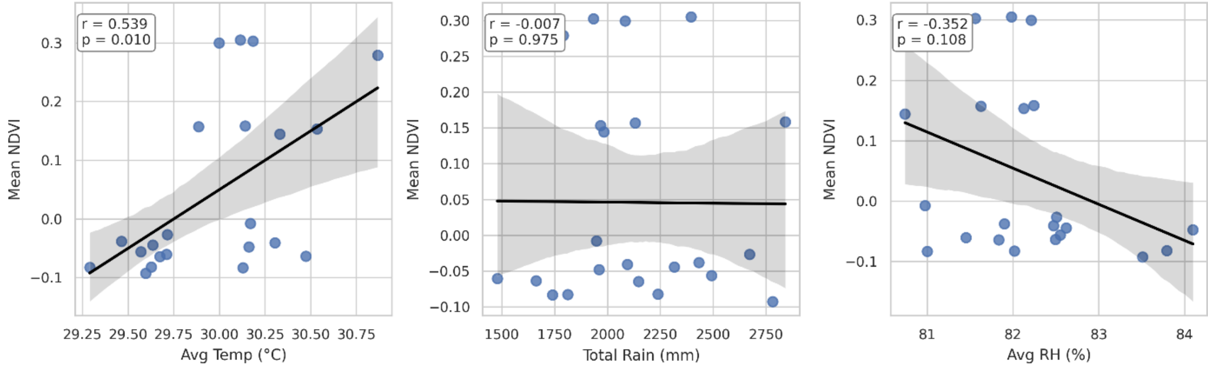


Figure 2. Mean NDVI relationships with (a) for the average temperature, (b) for the total rainfall, and (c) for the average relative humidity.

3.3 Temporal trends

Visual inspection of the annual time series (Figure 3) shows interannual variability in NDVI accompanied by modest variation in temperature, larger interannual swings in rainfall, and very small changes in mean relative humidity across the study period. No monotonic trend tests are reported here, but summary values indicate that climate variability and NDVI (figure 4) fluctuations both occur at interannual scales rather than as large linear trends over the 22-year window.

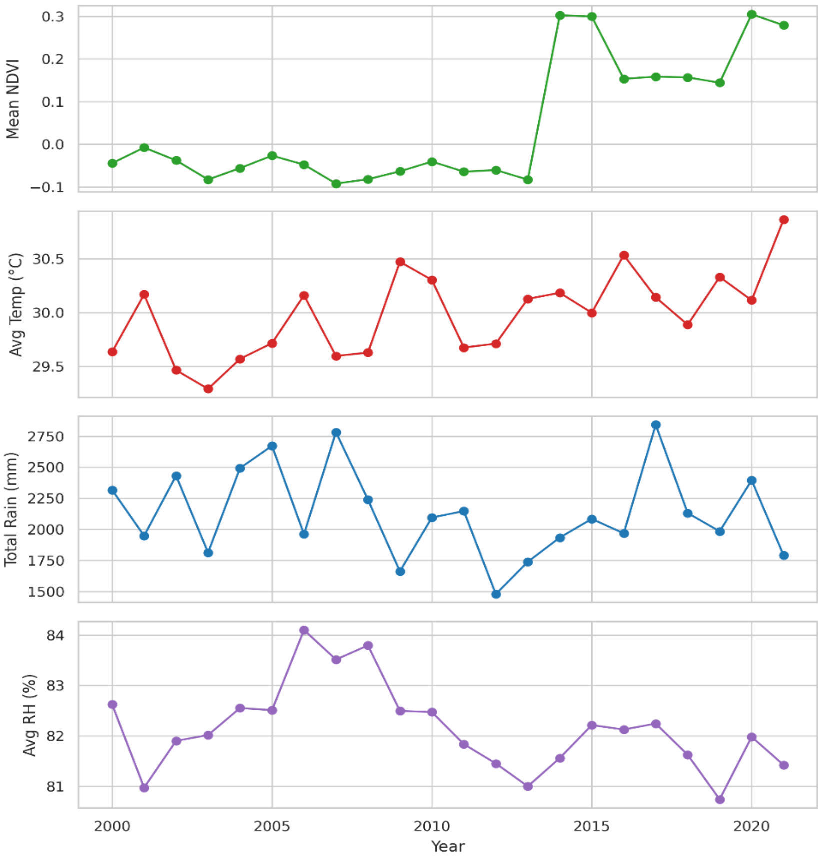
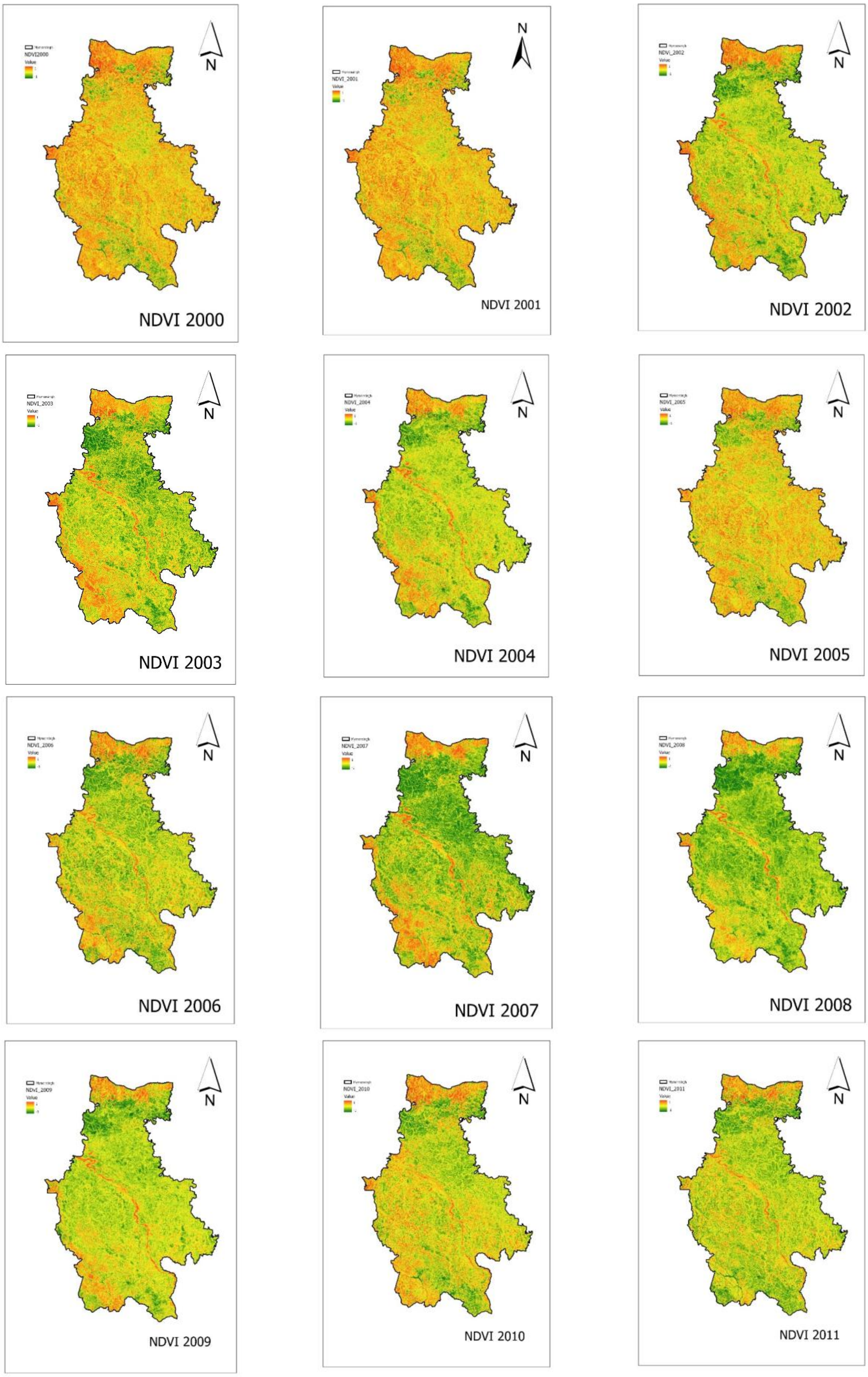


Figure 3: Annual time series for mean NDVI, mean temperature (°C), total rainfall (mm), and mean relative humidity (%) for Mymensingh district, 2000–2021.


NDVI 2000
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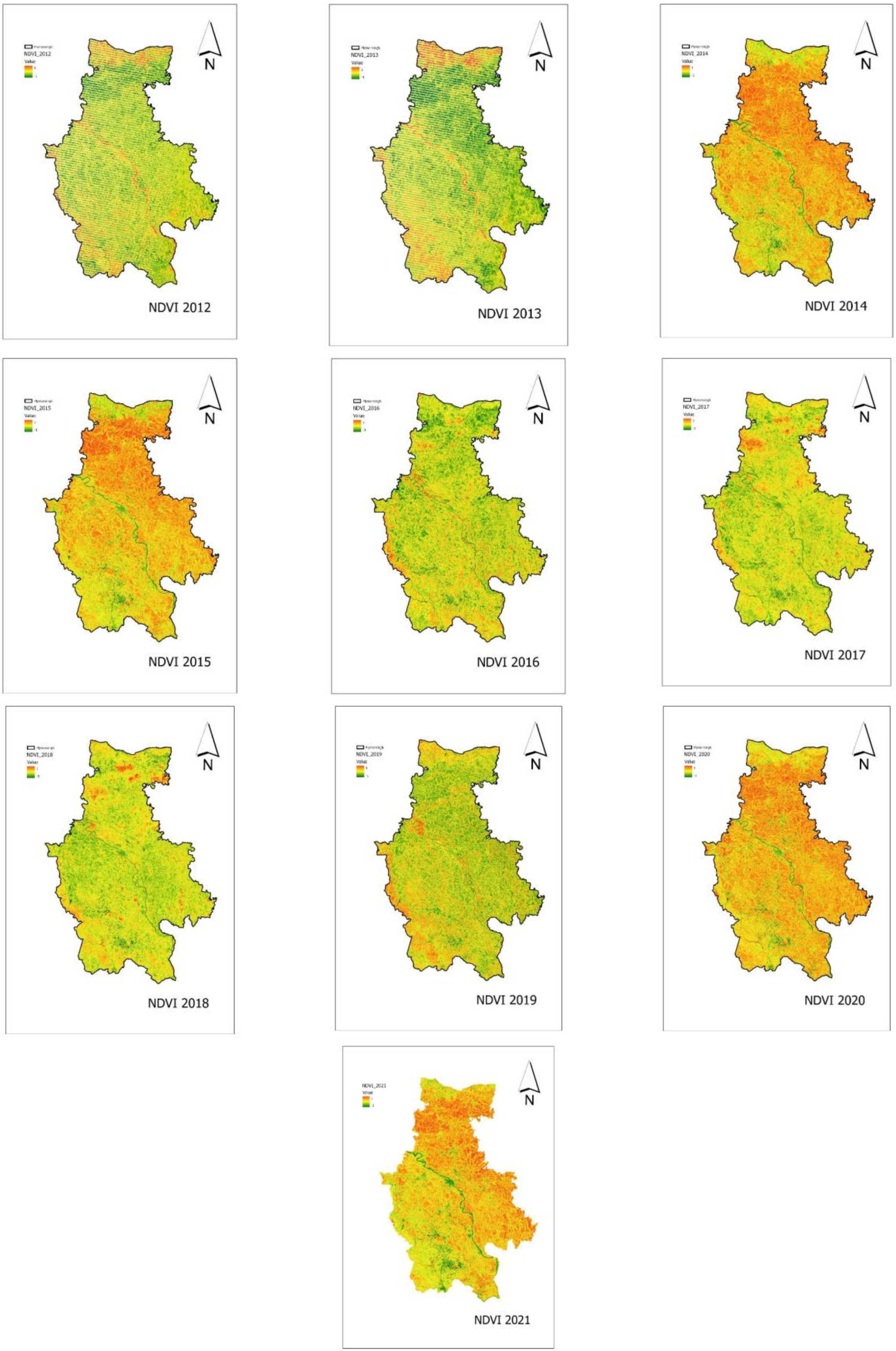

Figure 4: Year-wise NDVI map of study area

3.4 Multivariate model (multiple linear regression)

A multiple linear regression model with MEAN NDVI as the dependent variable and Avg_Temp, Total_Rain, and Avg_RH as simultaneous predictors was fitted to the 22 annual observations.

Model fit: $R = 0.650$; $R^2 = 0.422$; Adjusted $R^2 = 0.325$, indicating the predictors together explain ~42.2% of the variance in mean NDVI (adjusted for three predictors, ~32.5%). Overall model significance: ANOVA $F(3,18) = 4.378$, $p = 0.018$.
Unstandardized coefficients and inferential statistics:
Intercept: $B = -2.012$ ($SE = 3.770$), $p = 0.600$.
Avg_Temp: $B = 0.212$ ($SE = 0.072$), standardized $\beta \approx 0.572$, $t = 2.930$, $p = 0.009$.
Total_Rain: $B \approx 0.000$ ($SE \approx 0.000$), standardized $\beta \approx 0.339$, $t = 1.652$, $p = 0.116$.
Avg_RH: $B = -0.056$ ($SE = 0.034$), standardized $\beta \approx -0.329$, $t = -1.657$, $p = 0.115$.
Interpretation: After accounting for total rainfall and relative humidity, mean annual temperature remains the only statistically significant predictor of district mean NDVI (positive effect). Rainfall and relative humidity do not show significant independent contributions in the multivariate context, although their standardized coefficients suggest potential moderate effects (positive for rainfall, negative for relative humidity) that are not statistically robust given sample size and variability.

The model's adjusted R^2 (0.325) and significant overall F indicate meaningful explanatory power, but the sample size is modest ($n = 22$) for a three-predictor model, so inference should be cautious. Key diagnostic checks recommended before final inference: residual normality and homoscedasticity, influence diagnostics (Cook's D, leverage), and multicollinearity (VIF). These diagnostics were not included in the SPSS printout summary provided here and should be computed to confirm stability. Given the absence of a significant bivariate relationship between NDVI and rainfall and the significance of temperature in both bivariate and multivariate tests, results suggest temperature is the dominant linear annual predictor in this dataset for Mymensingh, while rainfall and humidity effects may be nonlinear, seasonal, lagged, or spatially heterogeneous and therefore not captured by annual district mean aggregation.

The district scale analysis for Mymensingh (2000–2021) indicates that annual mean NDVI fluctuated interannually but showed a moderate, significant positive relationship with mean annual temperature and no significant bivariate association with total annual rainfall or relative humidity. In a multivariate model including rainfall and humidity, temperature remained the only significant predictor, with the three predictors together explaining ~42% of NDVI variance (adjusted $R^2 \approx 0.33$). These results suggest that, at an annual and district mean aggregation, temperature variations explain more of the observed NDVI variability than total annual precipitation or mean RH.

Positive temperature–NDVI relationships have been reported in other regional and subregional studies. Mehmood et al. (2024) and the related Pakistan province analyses found upward NDVI trends linked to slight decreases in some climate variables and highlighted temperature as an important driver under certain contexts, consistent with our finding that warmer years are associated with higher mean NDVI in Mymensingh. Das & Sarkar (2023) and Bari et al. (2021) emphasise that the choice of greenness index and temporal aggregation affects sensitivity to hydroclimatic drivers; Das & Sarkar found stronger hydroclimatic coupling for EVI than NDVI, which may help explain why district mean NDVI in our annual aggregation showed limited sensitivity to rainfall. Several Bangladesh-specific studies point to strong spatial heterogeneity in vegetation–climate coupling: Fattah & Morshed (2021) report that urban expansion and land cover change substantially modulate vegetative responses and can weaken direct climate signals at administrative scales, while Akhter & Afroz (2024) attribute NDVI trends largely to land cover change rather than direct climate trends. These findings indicate that land use dynamics or urbanization may attenuate or confound the rainfall–NDVI link in our district-level annual series. Islam et al. (2021) demonstrated that extreme precipitation and temperature indices have seasonally lagged impacts on NDVI; their work suggests that annual aggregation can mask lagged or season-specific responses, which may explain the non-significant rainfall result in our annual model, despite ecological expectations that precipitation drives productivity in monsoon-dominated systems. Studies focused on LST–NDVI and finer urban contexts (Roy et al., 2020; Guha & Govil, 2020) show inverse or complex LST–NDVI relationships at urban or subpixel scales; our positive temperature association at the district scale likely reflects dominant cropping, irrigation, or phenological processes rather than urban heat island effects.

At the annual district mean scale in Mymensingh over 2000–2021, mean temperature emerges as the dominant linear predictor of NDVI, while rainfall and humidity do not explain significant independent variance. This pattern aligns with several regional studies that emphasize scale, index choice, and land use change as crucial moderators of vegetation–climate relationships. To translate these findings into robust ecological inference and policy guidance, follow-up analyses should unpack seasonal timing, spatial heterogeneity, and human management that mediate the NDVI response to hydroclimatic variability (Mehmood et al., 2024; Das & Sarkar, 2023; Islam et al., 2021).

4. CONCLUSIONS

This district-level analysis for Mymensingh (2000–2021) demonstrates that annual mean NDVI exhibits interannual variability but no strong monotonic trend, and that mean annual temperature is the dominant linear predictor of NDVI at the annual, district mean scale. The multivariate model, including temperature, total rainfall, and relative humidity, explained a substantial proportion of interannual NDVI variance ($R^2 = 0.422$; adjusted $R^2 = 0.325$), with temperature the only statistically significant independent predictor. The absence of a significant positive rainfall–NDVI relationship in the annual aggregated series suggests that total annual precipitation alone does not capture the hydrological controls most relevant to vegetation greenness in Mymensingh. Possible explanations include seasonality and intra-seasonal rainfall timing, irrigation and groundwater buffering, land use change and urbanization, and index limitations (NDVI saturation and soil background effects). Relative humidity showed a negative but non-significant association, indicating limited direct explanatory power at the annual aggregation level. Methodologically, the combined use of Landsat Collection 2 Level 2 surface reflectance, district-scale zonal statistics, and station-based climate aggregation produced a reproducible framework suitable for operational monitoring, but inference is constrained by annual aggregation, single station climate representation, and a modest sample size ($n = 22$). These constraints caution against strong causal claims and motivate complementary analyses. Future work should (1) disaggregate analyses seasonally and by land cover class, (2) test lagged and nonlinear predictor formulations, (3) compare NDVI with alternative greenness indices (EVI, percentile composites), and (4) incorporate irrigation, cropping pattern, and land use change data to separate climatic from anthropogenic drivers. Such extensions will strengthen the ecological interpretation and enhance the utility of findings for climate-smart land management and adaptation planning in Mymensingh and comparable floodplain agro ecosystems.

Declaration of Use of AI: AI is not used in this manuscript.

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