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Climate vulnerability assessment of vegetation under rainfall variability in Andhra Pradesh using Satellite time series data (2015-2025)

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Abstract

Vegetation patterns change with climate conditions. Rainfall variability is especially important in regions that depend on the monsoon. This study examines how rainfall changes affect vegetation across the state of Andhra Pradesh, India, from 2015 to 2025. Satellite data were used to study both vegetation condition and rainfall distribution. Vegetation status was analysed using the MODIS Normalized Difference Vegetation Index (NDVI) dataset. Rainfall information was obtained from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) dataset. All data processing and analysis were carried out on the Google Earth Engine platform.

Annual NDVI composites were prepared to study patterns of vegetation greenness. Changes in rainfall and rainfall anomalies were examined to identify climate fluctuations across the region. Long-term vegetation trends were analysed using linear regression, the Mann-Kendall non-parametric test, and Sen's slope estimation. Vegetation health was evaluated through the Vegetation Condition Index. Pearson correlation analysis was also applied to explore the link between rainfall and vegetation greenness. Finally, a Climate Vulnerability Index was created by combining vegetation trends, rainfall trends, and vegetation condition indicators.

The results show moderate spatial differences in rainfall across Andhra Pradesh. Coastal districts receive more rainfall than the semi-arid districts of the Rayalaseema region. NDVI values range from 0.445 to 0.529, which suggests a moderate level of vegetation cover in the state. Trend analysis shows an overall increase in vegetation, with a Mann-Kendall τ value of 0.363 and a Sen's slope of 0.00657 per year. The NDVI-rainfall correlation indicates that vegetation growth is generally linked to rainfall availability. However, the strength of this relationship differs among districts.

Vegetation Condition Index values varied between 0.43 and 0.57, which suggests moderate vegetation health. The Climate Vulnerability Index results indicate that some districts in the northern and coastal parts of Andhra Pradesh are relatively more sensitive to climate variability. In contrast, several districts in the Rayalaseema region and southern parts of the state show lower levels of vulnerability.

The findings show that changes in rainfall play a key role in controlling vegetation patterns across the region. Combining satellite-based vegetation monitoring with climate analysis offers a practical way to study ecosystem resilience. This approach can also support climate adaptation planning in semi-arid agricultural areas of Andhra Pradesh, India.

Keywords: Climate vulnerability index, CHIRPS, NDVI, vegetation condition index, Mann-Kendall, Sen slope estimator

1. Introduction

The global climate is shifting rapidly, with increasing temperatures and erratic rainfall patterns disrupting terrestrial ecosystems ^[1]. Among these, vegetation serves as a vital indicator of environmental health, acting as a primary carbon sink and a regulator of hydrological cycles ^[2]. However, in semi-arid and tropical regions like Andhra Pradesh, India, the stability of these green covers is increasingly threatened by high rainfall variability ^[3]. Since nearly 60% of Indian agriculture remains rain-dependent, understanding how vegetation responds to these climatic shifts is essential for regional food security and ecological resilience ^[4, 5]. Andhra Pradesh presents a complex landscape where seasonal monsoons dictate the phenological cycles of both natural forests and vast agricultural tracts ^[1]. In recent years, the frequency of extreme weather events, including prolonged dry spells and unseasonal heavy downpours, has intensified ^[1, 6].

These fluctuations lead to significant vegetation stress, often resulting in land degradation and loss of biomass ^[7]. For instance, districts such as Anantapur frequently face severe moisture deficits, which directly impact the photosynthetic activity and greenness of the local flora ^[7].

Remote sensing has emerged as a transformative tool for monitoring these dynamics across large spatial scales ^[4]. Satellite-derived indices, particularly the Normalized Difference Vegetation Index (NDVI), allow researchers to quantify vegetation health by measuring the contrast between near-infrared and red light reflectance ^[8]. By utilizing long-term time series data from platforms like Landsat or Sentinel, it is possible to track how vegetation “greenness” correlates with precipitation patterns over a decade ^[8]. Modern geospatial frameworks now integrate these spectral indices with climate variables to delineate vulnerability hotspots ^[7].

Despite existing studies on regional climate impacts, there is a lack of high-resolution, long-term assessments focusing specifically on the last decade (2015-2025) in Andhra Pradesh. This period is particularly significant as it encompasses a series of record-breaking heat years and shifting monsoon windows. This research aims to bridge this gap by conducting a comprehensive climate vulnerability assessment. We utilize a decade of satellite time series data to analyze the sensitivity of different vegetation types to rainfall fluctuations. The findings seek to provide a robust spatial framework for targeted land restoration and sustainable resource management in the state's most vulnerable ecosystems.

2. Literature Survey

The literature surrounding vegetation dynamics in Andhra Pradesh highlights a complex interplay between monsoon patterns and ecological health. Recent research indicates that while the state receives a significant portion of its annual rainfall during the Southwest monsoon, districts such as Anantapur and Chittoor remain chronically water-stressed, necessitating robust monitoring frameworks that go beyond simple precipitation totals ^[9]. Scholars have established the Normalized Difference Vegetation Index (NDVI) as a primary metric for quantifying biomass and photosynthetic activity across these semi-arid landscapes, proving its utility in distinguishing between natural forest cover and seasonal agricultural crops ^[10]. To improve the accuracy of drought detection, integrated systems now utilize a combination of NDVI, the Normalized Difference Water Index (NDWI), and the Vegetation Condition Index (VCI) for real-time assessments that reflect both chlorophyll content and leaf water potential ^[4].

National-scale studies have identified over 80 million hectares in India as highly vulnerable to rainfall-induced climate shifts, with the rain-shadow regions of Andhra Pradesh consistently appearing as high-risk zones in climate models ^[6]. District-level vulnerability indices further confirm that the state is among the most exposed to hydro-meteorological extremes, which directly impacts local livelihoods and regional food security ^[11]. Long-term

performance evaluations suggest that nearly 94% of the agricultural land in the region is susceptible to drought, emphasizing the need for high-resolution satellite monitoring to capture sub-district variations ^[12]. Furthermore, investigations into the lag effects of precipitation reveal a specific temporal delay between rainfall events and the subsequent greening of vegetation, a factor that is critical for developing early warning systems for crop failure ^[13].

The response of flora to extreme weather has also been a focal point, with evidence suggesting that maximum NDVI values offer a clearer picture of ecosystem recovery following heavy precipitation than mean averages, which can often smooth out critical stress events ^[14]. Validating these satellite observations against ground-based lysimeter data and soil moisture sensors remains a priority for ensuring the reliability of climate-vegetation models in tropical climates ^[15]. Global climatic drivers, such as El Niño and La Niña cycles, have been shown to cause significant inter-annual fluctuations in the state's vegetation vigor, often leading to “false springs” or delayed harvests ^[16].

These shifts are often exacerbated by land cover transformations in major river basins, which alter the local thermal environment and reduce the land's natural buffering capacity against heatwaves ^[17]. The application of the Standardized Precipitation Index (SPI) alongside spectral data has allowed researchers to delineate zones of high ecological resilience, providing a blueprint for where to focus reforestation efforts ^[18]. Advancements in impact-based forecasting are now being integrated into state-level policies to mitigate the risks posed by erratic rainfall, transitioning from reactive to proactive disaster management ^[19]. However, identifying desertification hotspots remains a challenge, particularly in the Rayalaseema region where soil erosion and moisture deficits lead to permanent vegetation decline ^[20]. Consequently, experts advocate for localized adaptation strategies informed by long-term geospatial time series to ensure sustainable land management and the protection of biodiversity in the face of a changing climate ^[21].

3. Methodology

3.1 Study area

The study was conducted for the state of Andhra Pradesh (Figure 1) located in the southeastern part of India. The state lies between approximately 12°41'N to 19°54'N latitude and 76°46'E to 84°46'E longitude. Andhra Pradesh covers an area of about 162,975 square kilometers and includes 26 administrative districts. The region is characterized by a diverse physiography that includes fertile river deltas, the discontinuous mountain ranges of the Eastern Ghats, and the semi-arid peneplains of the Deccan Plateau. Bordered by the Bay of Bengal to the east, the state possesses the second-longest coastline in India at roughly 974 km, which significantly influences its atmospheric moisture and vulnerability to tropical cyclonic activity.

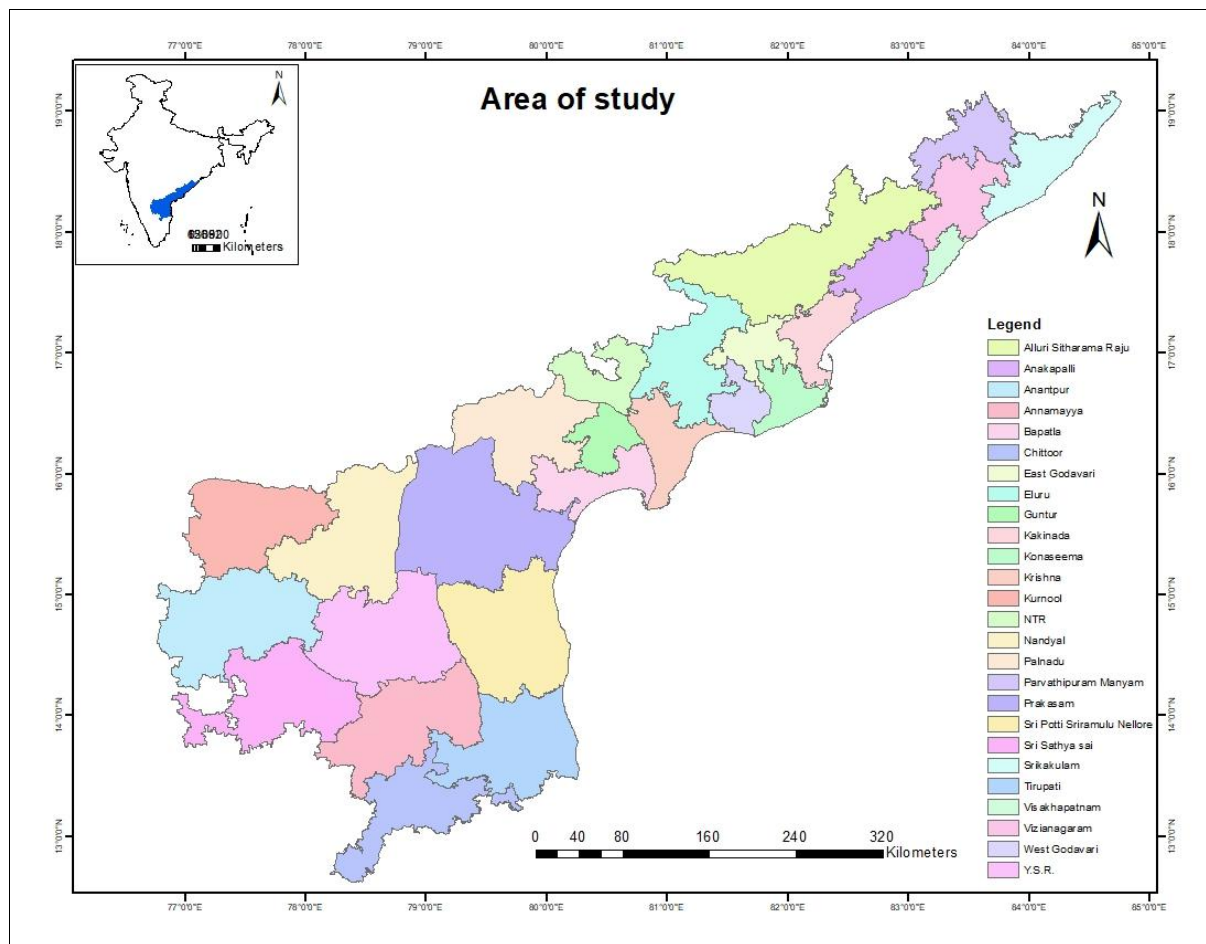


Fig 1: Outline map of the Study Area

Climatically, Andhra Pradesh experiences a tropical environment primarily governed by the monsoonal cycle. The state is broadly categorized into distinct regions: Coastal Andhra, which features fertile alluvial plains, and Rayalaseema, characterized by rocky terrain and higher elevations. Average annual rainfall typically ranges from 600 mm in the western rain-shadow areas to over 1200 mm in the northern coastal districts. Precipitation is largely concentrated during the Southwest monsoon (June-September) and the Northeast monsoon (October-December), with the latter contributing significantly to the moisture regime of the southern coastal belt.

The state is further delineated into six major Agro-Climatic Zones based on soil types, rainfall distribution, and cropping patterns: the North Coastal Zone, the Godavari Zone, the Krishna Zone, the Southern Zone, the Scarce Rainfall Zone (Rayalaseema), and the High-Altitude Tribal Areas [12]. The “Scarce Rainfall Zone” is of particular ecological concern, as it frequently records a low length of growing period (LGP) of only 70-90 days compared to 210-240 days in the delta plains [12]. Temperatures peak during the summer months, often exceeding 42 °C, while winter minimums

generally remain between 15 °C and 25 °C [22]. This intricate mosaic of climatic and topographical features makes Andhra Pradesh an ideal laboratory for studying the sensitivity of vegetation to rainfall variability.

Agriculture is the dominant land use in the region, and vegetation growth is largely dependent on rainfall availability and irrigation resources. Therefore, analysing the relationship between rainfall variability and vegetation dynamics is important for understanding ecosystem stability and climate vulnerability.

The administrative boundary of Andhra Pradesh was used as the spatial boundary for all analyses.

3.2 Data sources

This study uses satellite remote sensing datasets and precipitation data available through cloud based geospatial platforms.

NDVI dataset: Vegetation dynamics were analysed using the MODIS Normalized Difference Vegetation Index (NDVI) product. Dataset details are given in Table 1.

Table 1. Satellite datasets used in the study

Dataset	Sensor	Resolution	Temporal resolution	Source
MOD13Q1 NDVI	MODIS	250 m	16 days	NASA
CHIRPS rainfall	Satellite + gauge	5 km	Daily / monthly	Climate Hazards Center

The MOD13Q1 product provides NDVI values that represent vegetation greenness and photosynthetic activity.

Rainfall dataset: Rainfall data were obtained from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) dataset. CHIRPS integrates satellite

observations with station measurements and provides reliable rainfall estimates for climate studies.

3.3 Data preprocessing

All satellite datasets were processed using Google Earth Engine, which enables large scale geospatial analysis using cloud computing.

The following preprocessing steps were applied:

1. Import administrative boundary of Andhra Pradesh.
2. Filter MODIS NDVI images for the period 2015 to 2025.
3. Apply quality filtering to remove low quality pixels.
4. Calculate annual mean NDVI values.
5. Import CHIRPS rainfall dataset for the same time period.
6. Compute annual rainfall totals.
7. Clip datasets to the Andhra Pradesh boundary.

Annual composite images were generated to reduce seasonal noise and provide a stable representation of vegetation conditions.

3.4 NDVI calculation

Vegetation greenness was measured using the Normalized Difference Vegetation Index (NDVI). NDVI is calculated using reflectance values from the red and near infrared bands of satellite imagery.

The NDVI formula is:

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)} \quad (1)$$

Where NIR = reflectance in near infrared band, Red = reflectance in red band. NDVI values range between -1 and +1.

Table 2. Typical interpretation of NDVI values:

NDVI range	Vegetation condition
< 0	Water or barren land
0 - 0.2	Sparse vegetation
0.2 - 0.5	Moderate vegetation
> 0.5	Dense vegetation

In this study, NDVI values mostly ranged between 0.44 and 0.53, indicating moderate vegetation density across the state.

3.5 Trend analysis

Long term vegetation trends were evaluated using linear regression analysis.

For each pixel, NDVI values were fitted to a linear model:

$$Y = a + bt \quad (2)$$

Where Y = NDVI value, t = time, a = intercept and b = slope

The slope parameter represents the rate of vegetation change. Positive slope values indicate increasing vegetation greenness, while negative slopes indicate vegetation decline.

3.6 Mann-Kendall trend test

The Mann-Kendall test ^[23, 24] is a non-parametric statistical method used to detect monotonic trends in time series data.

The Mann-Kendall statistic S is calculated as:

$$S = \sum \sum sign(x_j - x_i) \text{ for all } j > i \quad (3)$$

Where x_i and x_j represent NDVI values at different time points.

The sign function is defined as

$$sign(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x = 0 \\ -1 & \text{if } x < 0 \end{cases} \quad (4)$$

The Kendall τ coefficient is computed as:

$$\tau = \frac{S}{[n(n-1)/2]} \quad (5)$$

Where n = number of observations

Table 3: Interpretation of τ values:

Tau value	Trend interpretation
$\tau > 0$	Increasing trend
$\tau < 0$	Decreasing trend
$\tau \approx 0$	No trend

In this study, the state level τ value was 0.363, indicating a moderate increasing trend in vegetation greenness.

3.7 Sen's slope estimator

Sen's slope estimator ^[24] was used to determine the magnitude of the vegetation trend.

Sen's slope is calculated as the median of all pairwise slopes:

$$Q_i = \frac{(j - x_i)}{(j - i)} \quad (6)$$

Where x_i and x_j are NDVI values at time i and j. The median of all Q_i values give the Sen slope estimate. Positive Sen slope values indicate increasing vegetation conditions.

The state level Sen slope obtained in this study is 0.00657, indicating that NDVI increased by approximately 0.0066 per year.

3.8 Vegetation Condition Index

Vegetation health was evaluated using the Vegetation Condition Index (VCI).

VCI measures vegetation stress relative to historical NDVI values.

The VCI formula is:

$$VCI = \frac{(NDVI - NDVI_{min})}{(NDVI_{max} - NDVI_{min})} \quad (7)$$

Where

$NDVI$ = current NDVI value

$NDVI_{min}$ = minimum NDVI observed

$NDVI_{max}$ = maximum NDVI observed

VCI values range between 0 and 1.

Table 4: Interpretation of VCI values

VCI value	Vegetation condition
< 0.3	Vegetation stress
0.3 - 0.5	Moderate condition
> 0.5	Healthy vegetation

In this study, VCI values ranged from 0.43 to 0.57, indicating moderate vegetation health across most districts.

3.9 Rainfall anomaly

Rainfall anomaly analysis was conducted to examine deviations from long term average rainfall.

The rainfall anomaly formula is:

$$RainfallAnomaly = \frac{P_i - \bar{P}}{\bar{P}} \quad (8)$$

Where

P_i = rainfall in year i , $\bar{P}$ = long term mean rainfall

Positive anomaly values indicate above average rainfall, while negative values indicate rainfall deficits.

3.10 Rainfall-vegetation correlation

The relationship between rainfall and vegetation greenness was examined using Pearson correlation analysis.

The Pearson correlation coefficient r is calculated as:

$$r_{XY} = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2 \sum_{i=1}^n (Y_i - \bar{Y})^2}} \quad (9)$$

Where X_i = rainfall values, Y_i = NDVI values

Positive r values indicate that higher rainfall corresponds to higher vegetation greenness.

3.11 Climate Vulnerability Index

The Climate Vulnerability Index was used to assess the combined influence of rainfall variability and vegetation trends. The CVI integrates multiple indicators including NDVI trend, rainfall trend and vegetation condition index

The index was normalized and combined using a weighted approach.

$$CVI = (W1 \times NDVI \text{ trend}) + (W2 \times rainfall \text{ trend}) + (W3 \times VCI) \quad (10)$$

Where

$W1$, $W2$, $W3$ represent weights assigned to each indicator. Higher CVI values indicate greater vulnerability to climate variability.

3.12 Algorithm workflow

Algorithm 1. Workflow for analysing rainfall variability and vegetation dynamics using satellite datasets and statistical trend analysis.

Algorithm: Analysis of Rainfall Variability and Vegetation Dynamics

- **Input:** MODIS NDVI dataset (2015-2025), CHIRPS rainfall dataset (2015-2025), Administrative boundary of Andhra Pradesh
- **Output:** NDVI trend maps, Rainfall trend maps, Vegetation Condition Index map, Rainfall anomaly map, NDVI-rainfall correlation map, Climate Vulnerability Index map, District level statistical tables

Pseudocode

Algorithm Rainfall_Vegetation_Analysis

1. Start
2. Import Andhra Pradesh boundary shapefile
3. Load MODIS NDVI dataset for years 2015-2025
4. Load CHIRPS rainfall dataset for years 2015-2025
5. Clip NDVI and rainfall datasets to study area boundary
6. For each year from 2015 to 2025
 - Compute annual NDVI mean
 - Compute annual rainfall total
7. End For
7. Generate NDVI time series for the study period
8. Generate rainfall time series for the study period
9. Perform linear regression on NDVI time series
 - Calculate NDVI slope for each pixel
10. Apply Mann-Kendall trend test
 - Compute Kendall tau statistic
 - Determine trend significance

11. Compute Sen slope estimator
 - Calculate median slope of NDVI change
12. Calculate Vegetation Condition Index
 - $VCI = (NDVI - NDVI_{min}) / (NDVI_{max} - NDVI_{min})$
13. Calculate rainfall anomaly
 - $Rainfall\ anomaly = (P_i - P_{mean}) / P_{mean}$
14. Calculate rainfall variability
 - $CV = (Standard\ deviation / Mean\ rainfall) \times 100$
15. Compute NDVI-rainfall correlation
 - Use Pearson correlation coefficient
16. Normalize NDVI trend, rainfall trend, and VCI values
17. Calculate Climate Vulnerability Index
 - CVI = weighted combination of NDVI trend, rainfall trend, and VCI
18. Extract district level statistics
 - Compute mean NDVI trend
 - Compute mean VCI
 - Compute CVI for each district
19. Generate thematic maps and statistical tables
20. End

4. Results and Discussion

4.1 Spatial distribution and variability of rainfall

Rainfall plays a critical role in controlling vegetation productivity in monsoon dominated regions such as Andhra Pradesh. The spatial distribution of average rainfall across the state during the study period is illustrated in Figure 2. The results show that rainfall is unevenly distributed across the region. Coastal districts and northern parts of the state generally receive higher rainfall compared to the semi-arid districts of Rayalaseema.

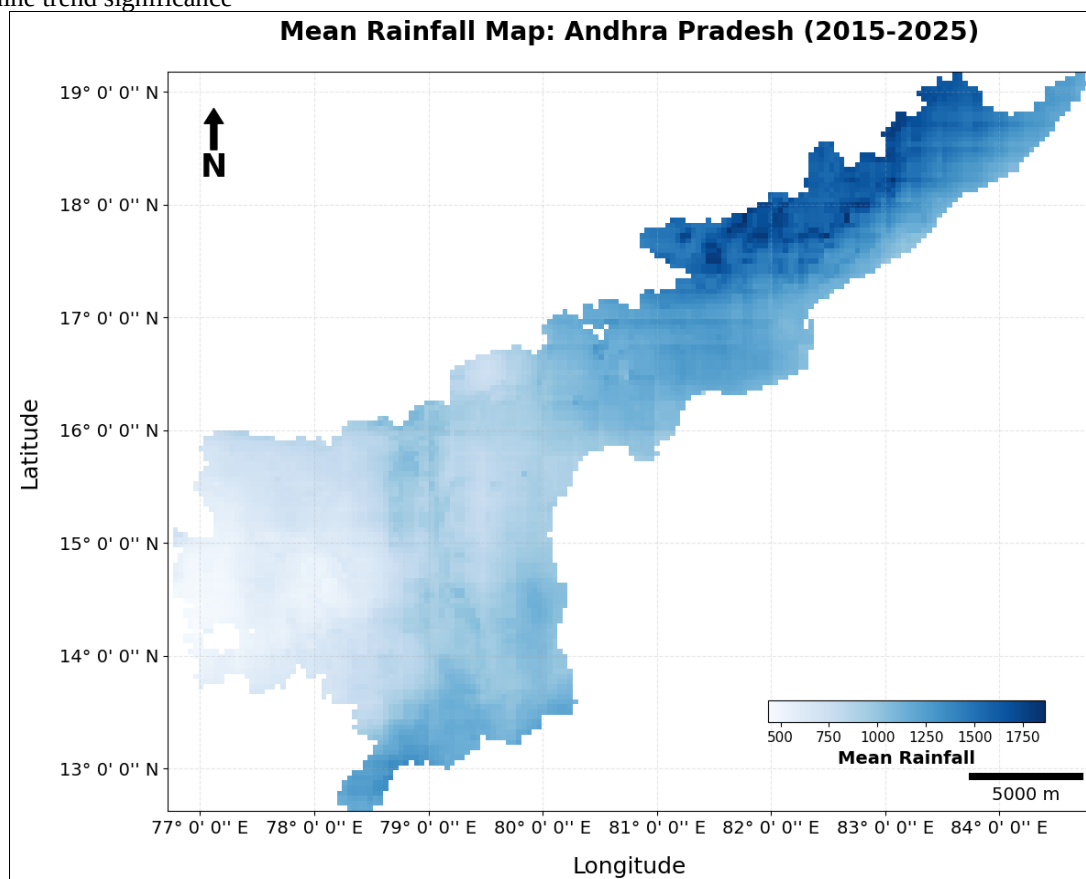


Fig 2: Spatial distribution of mean rainfall across Andhra Pradesh (2015-2025).

Temporal variability in rainfall was examined using the annual rainfall time series derived from the CHIRPS dataset. The results are shown in Figure 3. The time series indicates

considerable fluctuations in rainfall during the period 2015 to 2025.

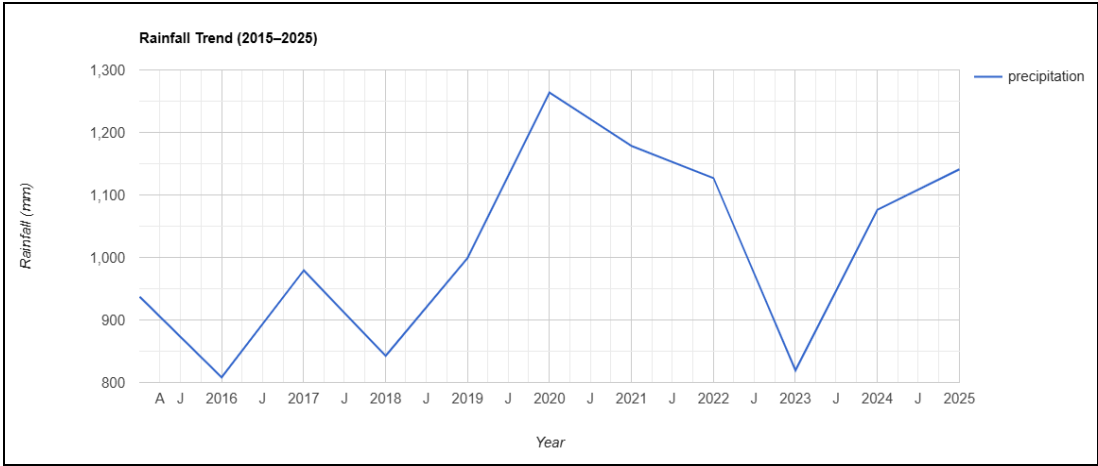


Figure 3. Annual rainfall variability across Andhra Pradesh from 2015 to 2025.

Annual rainfall ranged from approximately 810 mm to 1260 mm during the study period. The lowest rainfall occurred in 2016, when precipitation declined to nearly 810 mm, indicating a relatively dry year. Rainfall increased steadily after 2017 and reached a peak of approximately 1260 mm in 2020, which represents the wettest year in the study period. After this peak, rainfall gradually decreased during 2021 and 2022, followed by a sharp decline in 2023. Rainfall conditions improved again in 2024 and 2025, reaching about 1140 mm.

These variations highlight the irregular nature of rainfall patterns across the state. Such variability is typical of monsoon influenced climatic systems and can significantly affect vegetation growth, water availability, and agricultural productivity.

4.2 Vegetation dynamics and spatial patterns

Vegetation conditions were evaluated using MODIS derived NDVI data. The spatial distribution of average NDVI values across Andhra Pradesh is presented in Figure 4.

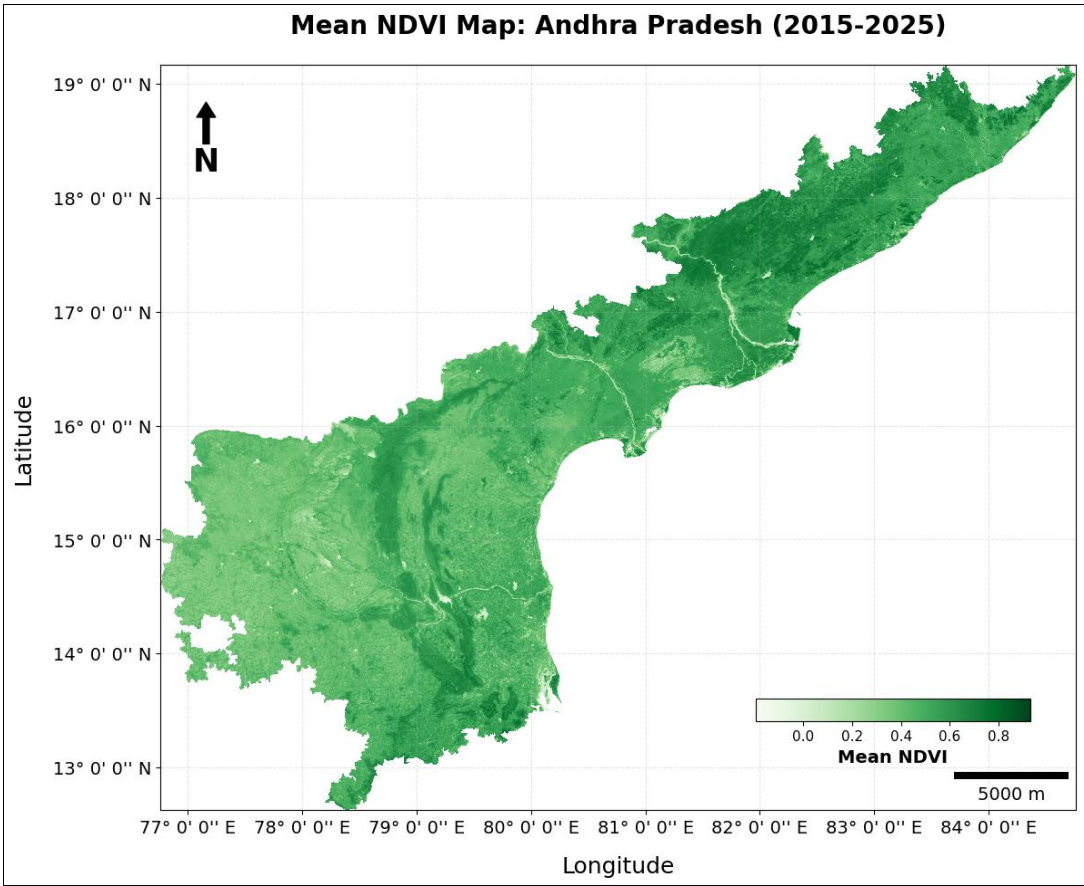


Fig 4: Mean NDVI distribution across Andhra Pradesh.

The NDVI map indicates moderate vegetation density across most districts of the state. Higher NDVI values are generally observed in coastal agricultural regions and central districts where cropping intensity and vegetation cover are relatively higher. In contrast, relatively lower

NDVI values are observed in parts of Rayalaseema where rainfall availability is comparatively lower.

Temporal changes in vegetation greenness were analysed using the NDVI time series shown in Figure 5. NDVI values varied between 0.445 and 0.529 during the study period.

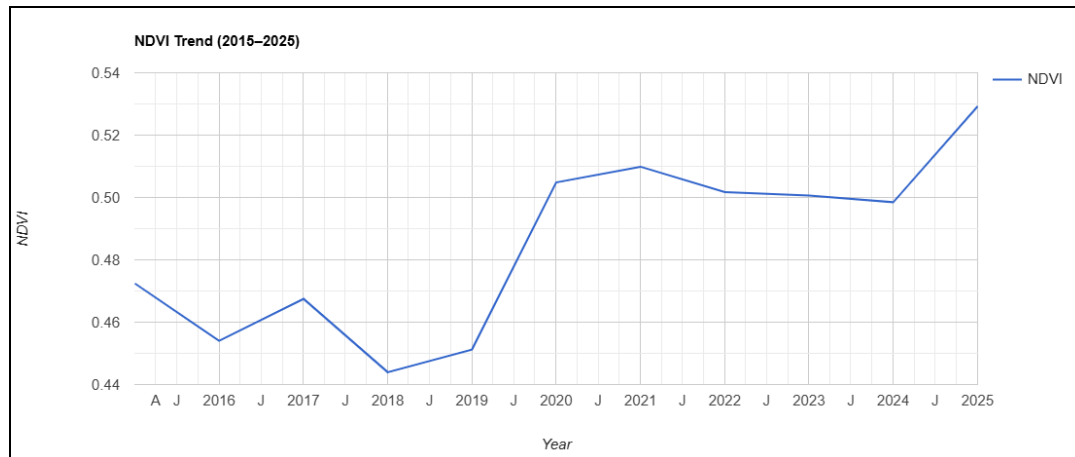


Fig 5: NDVI time series for Andhra Pradesh (2015-2025).

Vegetation greenness declined slightly during the early part of the study period, reaching its lowest value in 2018. After this period, NDVI values increased significantly and reached approximately 0.505 in 2020. This increase coincides with the higher rainfall observed during the same period.

Although NDVI experienced slight fluctuations between 2022 and 2024, vegetation conditions remained relatively stable. By 2025, NDVI increased to 0.529, which represents the highest vegetation greenness during the study period. The temporal patterns observed in NDVI suggest that vegetation growth across Andhra Pradesh responds strongly

to rainfall availability and seasonal climatic variability.

4.3 NDVI trend analysis

Long term vegetation trends were examined using linear regression, Mann-Kendall trend analysis, and Sen's slope estimation.

The spatial pattern of NDVI trends derived from linear regression is shown in Figure 6. The map indicates that most regions of Andhra Pradesh exhibit positive vegetation trends, suggesting gradual improvement in vegetation greenness over time.

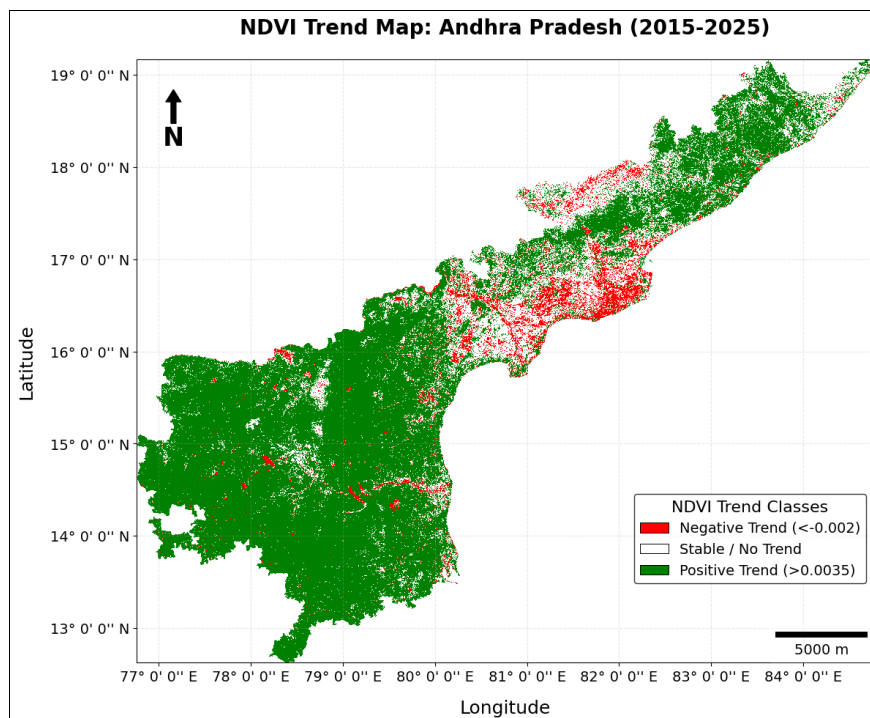


Fig 6: NDVI trend map derived from linear regression analysis.

The statistical significance of these trends was assessed using the Mann-Kendall test. The resulting spatial

distribution of the Mann-Kendall tau statistic is presented in Figure 7. Positive tau values dominate most parts of the

state, indicating increasing vegetation trends. The state level Mann-Kendall result produced a tau value of

0.363, indicating a moderate positive trend in vegetation greenness across Andhra Pradesh during the study period.

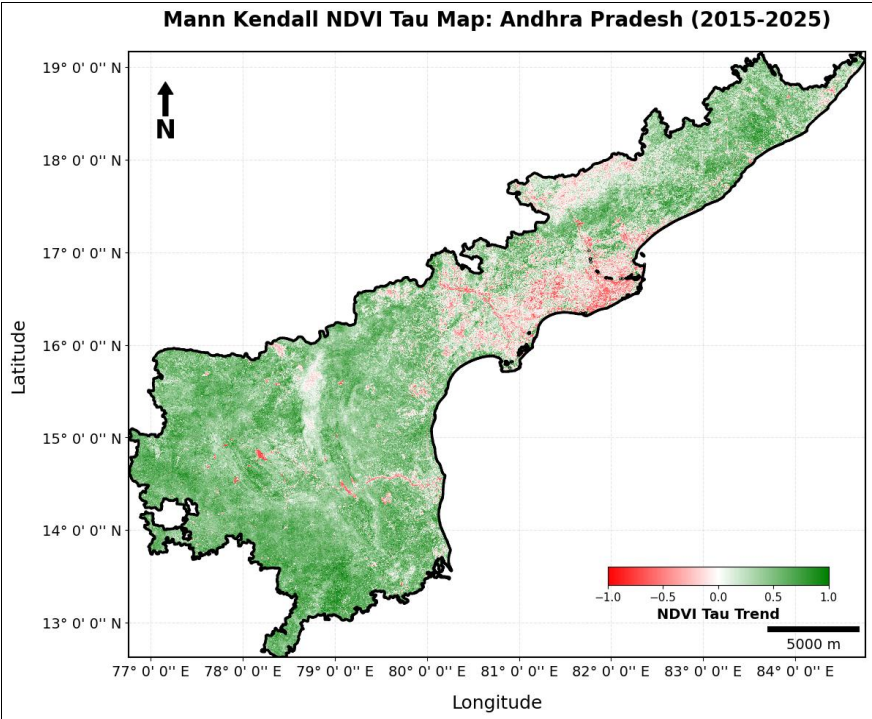


Fig 7: Mann-Kendall NDVI trend map.

The magnitude of vegetation change was estimated using Sen’s slope estimator. The Sen slope map is presented in Figure 8, which shows the rate of NDVI change across the

state. The state level Sen slope value of 0.00657 indicates that NDVI increased by approximately 0.0066 units per year between 2015 and 2025.

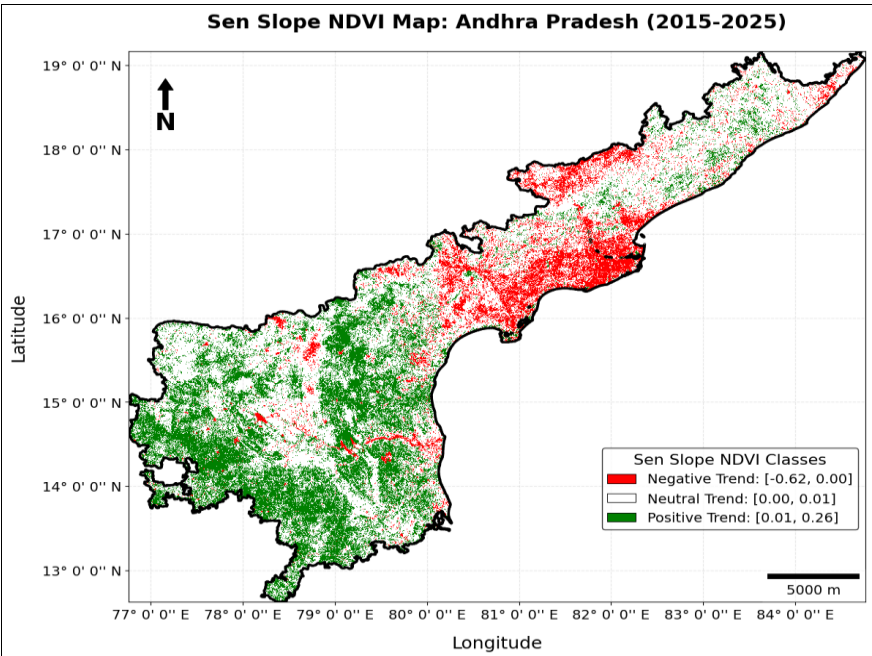


Fig 8: Sen slope map representing NDVI change rate.

Although the rate of increase is modest, the consistent positive trend suggests gradual improvement in vegetation conditions across several districts.

4.4 District level vegetation trends

District level analysis reveals considerable spatial variation in vegetation trends. Table 5 lists districts showing relatively strong positive vegetation trends based on Mann-

Kendall tau and Sen slope values.

Table 5: Districts with strongest positive vegetation trends

District	Mann Kendall Tau	Sen Slope
Chittoor	0.588	0.0102
Annamayya	0.524	0.0107
Sri Sathya Sai	0.513	0.0111
Anantapur	0.512	0.0104

Kurnool	0.496	0.0081
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These districts are mainly located in the Rayalaseema region, where vegetation growth appears to have improved during the study period. The improvement may be associated with irrigation expansion, agricultural intensification, and groundwater utilisation.

4.5 Rainfall trends and vegetation response

Rainfall trends derived from linear regression analysis are presented in Figure 9. The rainfall trend map indicates spatial variation in precipitation changes across the state. Some regions show increasing rainfall trends, while others exhibit weaker or slightly negative trends.

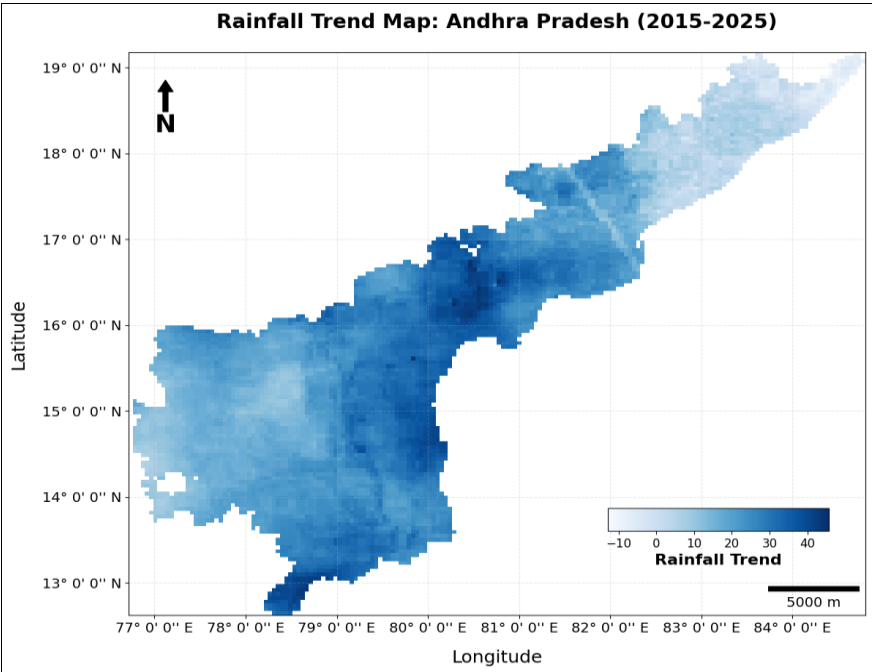


Fig 9: Rainfall trend map across Andhra Pradesh.

To examine the relationship between rainfall and vegetation growth, Pearson correlation analysis was performed. The

resulting NDVI rainfall correlation map is shown in Figure 10.

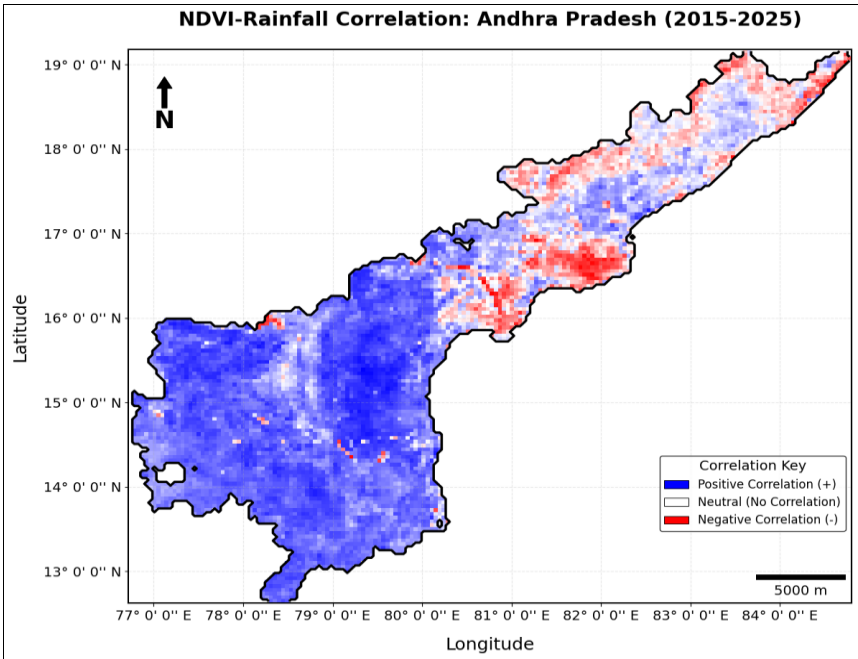


Fig 10: NDVI rainfall correlation map.

The results indicate that most regions of Andhra Pradesh exhibit positive correlation between rainfall and vegetation greenness, confirming that rainfall availability plays a key role in determining vegetation productivity. However, the strength of correlation varies spatially. Some

districts show moderate correlation values, indicating that vegetation growth may also be influenced by factors such as irrigation practices, cropping patterns, and land management strategies.

4.6 Vegetation condition assessment

Vegetation resilience was further analysed using the Vegetation Condition Index. The spatial distribution of mean VCI values is presented in Figure 11. VCI values across Andhra Pradesh range from approximately 0.43 to 0.57, indicating moderate vegetation health across the state. District level VCI values provide insights into the relative stability of vegetation conditions. Table 6 summarises selected districts with higher vegetation condition values.

Table 6: Districts with higher vegetation condition

District	VCI
Palnadu	0.574
Prakasam	0.548
Kurnool	0.542
Konaseema	0.534
Guntur	0.530

Higher VCI values indicate healthier vegetation conditions and stronger vegetation resilience to climatic variability.

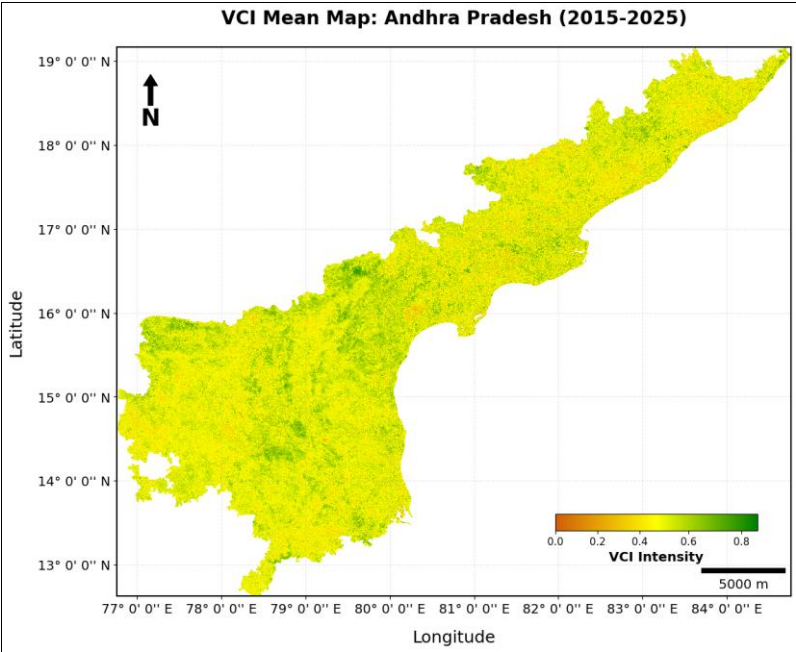


Fig 11: Vegetation Condition Index distribution across Andhra Pradesh.

4.7 Rainfall anomaly and variability

Rainfall anomaly analysis was conducted to identify

deviations from long term average rainfall. The spatial distribution of rainfall anomalies is presented in Figure 12.

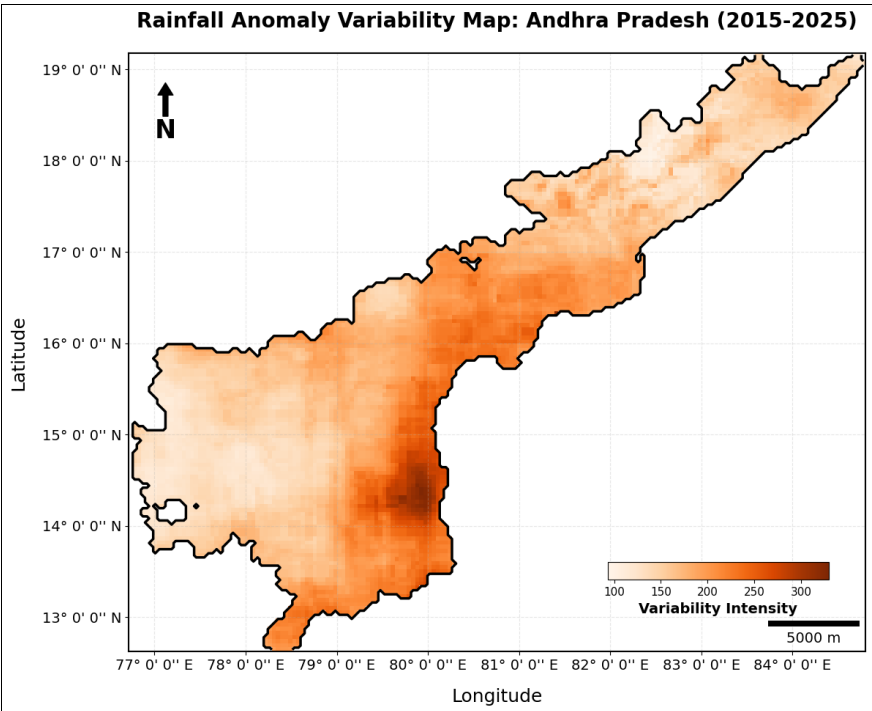


Fig 12: Rainfall anomaly distribution across Andhra Pradesh.

Positive anomaly values indicate areas receiving above average rainfall, whereas negative values represent rainfall

deficits. The results reveal considerable spatial variation in rainfall anomalies across the state.

Rainfall variability was further examined using the

coefficient of variation of annual rainfall. The resulting rainfall variability map is shown in Figure 13.

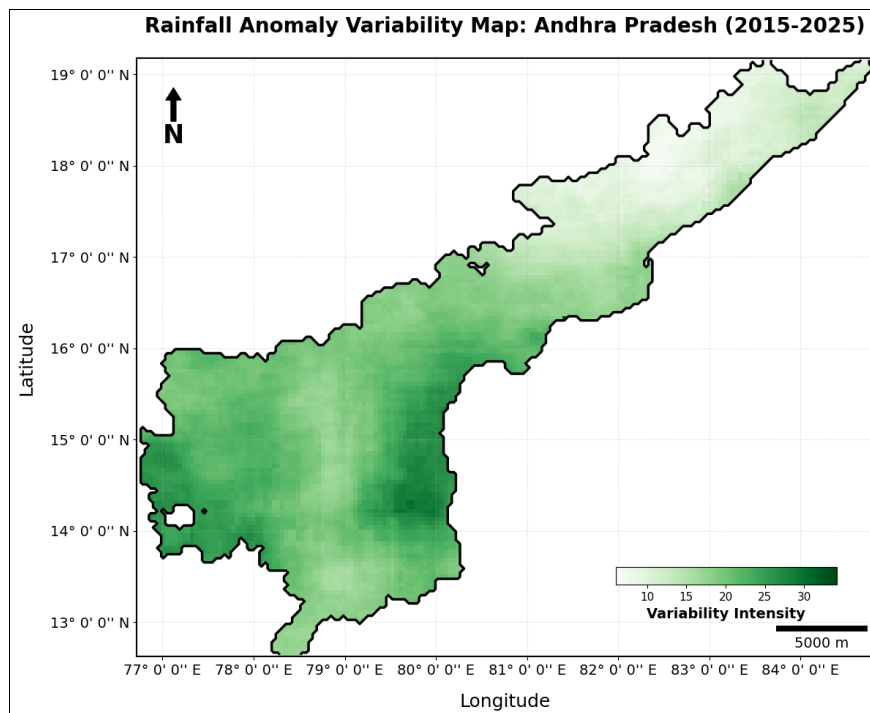


Fig 13: Rainfall variability map based on coefficient of variation.

Areas with higher variability values indicate regions where rainfall fluctuates significantly from year to year. Such variability can increase ecological stress and influence vegetation productivity.

4.8 Climate vulnerability assessment

The Climate Vulnerability Index integrates NDVI trends, rainfall trends, and vegetation condition to evaluate the vulnerability of vegetation systems to climate variability.

The spatial distribution of CVI values across Andhra Pradesh is presented in Figure 14. Regions with higher CVI values represent areas where vegetation systems are more vulnerable to climatic fluctuations. District level CVI values presented in Figure 15 were extracted to identify areas with relatively higher vulnerability and given in Table 7.

Table 7: Districts with relatively higher climate vulnerability

District	CVI	VCI
Konaseema	0.507	0.534
West Godavari	0.443	0.512
Kakinada	0.418	0.460
Krishna	0.412	0.477
Srikakulam	0.395	0.454

These districts are largely located in coastal or northern regions where rainfall variability and environmental factors may contribute to vegetation stress. Conversely, districts with lower vulnerability levels are shown in Table 8.

Table 8. Districts with lower climate vulnerability

District	CVI	VCI
Annamayya	0.056	0.515
Chittoor	0.059	0.479
Sri Sathya Sai	0.070	0.504
Prakasam	0.079	0.548
SPSR Nellore	0.091	0.509

These districts exhibit relatively stable vegetation conditions and stronger vegetation trends.

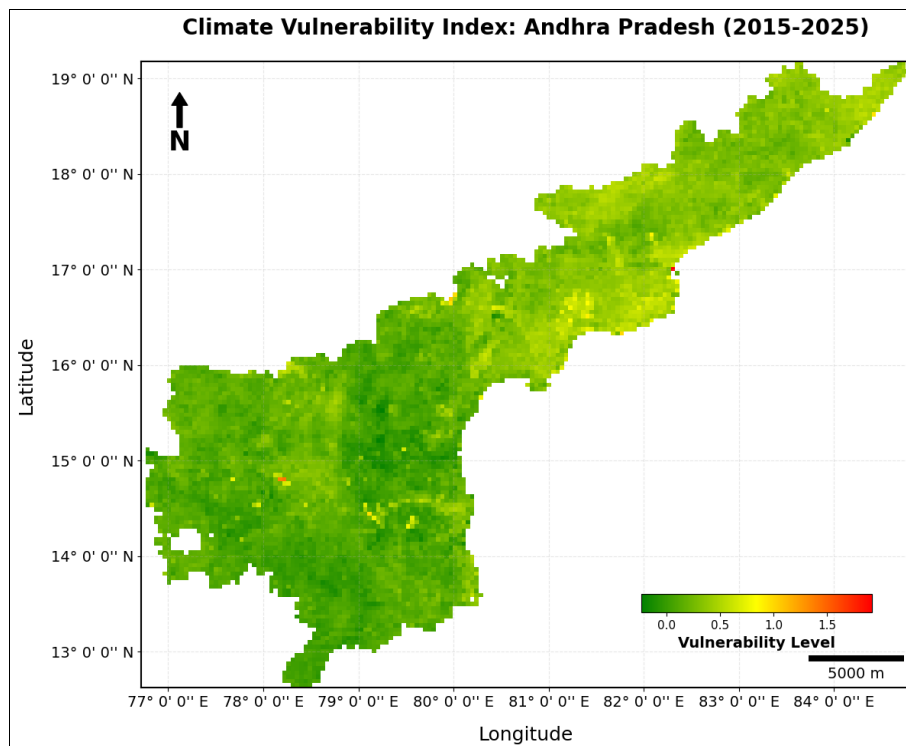


Fig 14: Climate Vulnerability Index map showing spatial distribution of vegetation vulnerability across Andhra Pradesh.

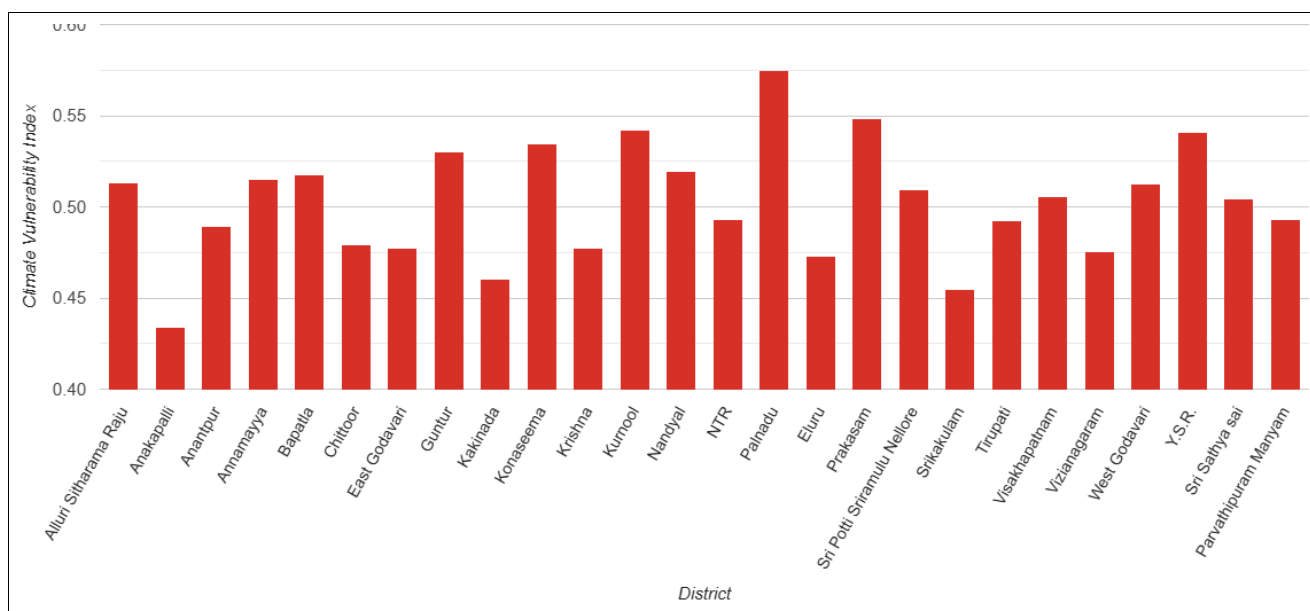


Fig 15: District Wise Climate Vulnerability Index

4.9 Implications for climate vulnerability and vegetation resilience

The results indicate that vegetation conditions across Andhra Pradesh have shown a moderate positive trend during the period 2015-2025, as indicated by the Mann-Kendall τ value of 0.363 and Sen slope estimate of 0.00657. Although rainfall variability remains significant, vegetation greenness has improved in several districts, suggesting possible influences from irrigation development, agricultural intensification, and land management practices. Although vegetation greenness shows a moderate positive trend at the state level, rainfall variability remains an important controlling factor. District level analysis reveals significant spatial heterogeneity in vegetation responses to climate variability.

Coastal districts tend to exhibit higher vulnerability due to

fluctuating rainfall patterns and climatic influences. In contrast, several inland districts show improved vegetation conditions and stronger NDVI trends, indicating greater resilience.

5. Conclusion

This study analysed the relationship between rainfall variability and vegetation dynamics across Andhra Pradesh during the period 2015 to 2025 using satellite remote sensing datasets and statistical trend analysis techniques. Vegetation patterns were examined using MODIS derived NDVI data, while rainfall variability was assessed using the CHIRPS precipitation dataset. The analysis was carried out using the Google Earth Engine platform, which enabled efficient processing of large scale geospatial datasets.

The spatial analysis revealed clear differences in rainfall

distribution across the state. Coastal and northern districts generally received higher rainfall compared to the interior semi arid districts of the Rayalaseema region. The rainfall time series analysis showed considerable interannual variability during the study period, with notable dry and wet years. Such variability has important implications for vegetation growth and agricultural productivity.

The analysis of NDVI data indicated moderate vegetation greenness across the state, with values ranging from 0.445 to 0.529. The NDVI time series revealed fluctuations in vegetation productivity, which corresponded broadly with rainfall variability patterns. Vegetation greenness increased after 2019, coinciding with higher rainfall during the same period.

Trend analysis provided further insights into long term vegetation dynamics. The Mann-Kendall test indicated a moderate positive trend in vegetation greenness across the state, with a tau value of 0.363. Similarly, the Sen slope estimate of 0.00657 suggests a gradual increase in NDVI over time. These findings indicate that vegetation conditions have generally improved during the study period, although the rate of change varies across districts.

The Vegetation Condition Index analysis showed moderate vegetation health across most districts, with values ranging from 0.43 to 0.57. District level analysis revealed spatial variation in vegetation resilience. Some districts showed stronger vegetation trends and higher vegetation condition values, suggesting relatively stable ecosystem conditions.

The Climate Vulnerability Index analysis identified districts that are relatively more sensitive to rainfall variability and vegetation stress. Northern and coastal districts showed comparatively higher vulnerability levels, while several districts in southern and interior regions exhibited lower vulnerability. These spatial differences highlight the importance of regional climatic and environmental factors in shaping vegetation responses.

The results demonstrate that rainfall variability plays an important role in influencing vegetation dynamics across Andhra Pradesh. However, the observed positive vegetation trends suggest that vegetation systems in several districts have shown resilience to climatic fluctuations during the study period. The integrated use of satellite-based vegetation indices, rainfall analysis, and statistical trend methods provides a useful framework for monitoring environmental changes and identifying climate vulnerable regions.

The findings of this study can support regional environmental monitoring, climate adaptation planning, and sustainable land management strategies. Future research could incorporate additional factors such as land use change, irrigation patterns, soil moisture, and temperature variability to provide a more comprehensive understanding of vegetation dynamics and climate impacts in the region.

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7. Disclosure of conflict of interest

The authors declare that there is no conflict of interest.

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