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RESEARCH ARTICLE

Quantifying the impact of land surface temperature on vegetation moisture for drought monitoring in Tamil Nadu

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Abstract

Drought significantly threatens agriculture, water resources, and ecosystems, particularly in Tamil Nadu, India. This study explores the link between Land Surface Temperature (LST) and the Normalized Difference Water Index (NDWI) to evaluate their effectiveness for drought monitoring across Tamil Nadu's districts from 2014 to 2023. Utilizing MODIS MOD11A2 for LST and MOD09A1 for NDWI, the analysis examines the influence of temperature variations on vegetation moisture levels. The Pearson correlation analysis identified substantial spatial differences, with strong correlations in districts such as Perambalur, Namakkal, and Dindigul (up to 0.91), suggesting higher temperatures are closely associated with reduced vegetation moisture content, heightening drought risk. Nonetheless, weaker correlations in regions like the Nilgiris and Tirunelveli suggest that temperature exerts a lesser influence on vegetation moisture in those areas. Further quantification was achieved through linear and polynomial regression models. The linear model explained 52.7% of NDWI variation due to LST (R-squared = 0.527) and was validated as the most robust model via cross-validation. While polynomial models accounted for slight non-linearities, they offered limited predictive improvement, confirming that a linear relationship generally describes the NDWI-LST dynamics adequately. The results indicate that LST is a valuable indicator for drought monitoring in strongly correlated areas. In contrast, additional variables like rainfall and soil moisture may be essential for accurate predictions in regions with weaker correlations. Overall, this study demonstrates the potential of remote sensing for drought monitoring and emphasizes the need to consider local environmental factors to refine predictive models across Tamil Nadu's diverse landscapes.

Keywords

drought monitoring; land surface temperature; Normalized Difference Water index (NDWI); correlation analysis; regression models

Introduction

Drought is a recurring environmental hazard that severely impacts agricultural productivity, ecosystems, and water resources. A prolonged environmental risk, drought has detrimental effects on ecosystems, water supplies, and agricultural production. Its repercussions extend beyond short-term crop failures; lower yields raise food costs and create shortages, endangering food security. Particularly vulnerable are rural areas, which frequently depend primarily on agriculture, as protracted droughts can lead to reduced revenue, forced migration, and worsened poverty. Drought also makes it challenging to manage water resources because it pressures natural and human systems, frequently leading to disputes over supply and long-term groundwater depletion.

With the increasing frequency and intensity of droughts due to climate change, the need for accurate and timely drought detection and monitoring methods has become more critical than ever (1). With its ability to provide continuous, large-scale coverage, remote sensing data offers significant advantages over traditional drought monitoring methods like on-ground measurements or manual assessments. While conventional methods are labor-intensive and limited in scope, remote sensing enables rapid, consistent, and comprehensive monitoring of large and remote areas. This allows for timely assessments and early detection of drought conditions, making it a more efficient and effective tool for large-scale drought management. Among the commonly used indices, the NDWI and LST are key indicators, with NDWI reflecting vegetation water content and LST representing surface temperature (2).

In this study, NDWI data is derived from the MODIS MOD09A1 product, while LST data is sourced from the MODIS MOD11A2 product. These indices provide valuable insights into vegetation health and surface dryness, which are essential for understanding drought conditions.This study's correlation analysis is performed to quantify the strength and direction of the relationship between NDWI and LST across various districts from 2014 to 2023. This step is crucial because it helps determine how temperature changes affect vegetation moisture content. A strong negative correlation would suggest that higher temperatures lead to reduced vegetation moisture, potentially signaling drought. Correlation analysis provides a foundational understanding of how these two variables interact, identifying regions where temperature-induced drought is more pronounced. Building on this, regression analysis is employed to model the relationship between NDWI and LST, going beyond correlation to quantify the impact of LST on NDWI. The study seeks to predict NDWI values based on LST by fitting linear and polynomial regression models. The linear model assesses whether a straightforward, proportional relationship exists, while the polynomial models explore more complex, non-linear interactions between temperature and vegetation moisture. These models undergo cross-validation to confirm their generalisability to unseen data, yielding robust conclusions regarding the link between LST and NDWI.

The use of both correlation and regression in this study is essential. Correlation reveals the strength of the relationship, helping to identify areas most affected by temperature changes (3), while regression quantifies this relationship and provides a predictive framework (4). This dual approach enhances the understanding of how thermal stress influences vegetation water content and enables the development of reliable models for drought monitoring. The results of this study will contribute to improving drought prediction systems, particularly in regions where LST and NDWI can serve as early indicators of drought conditions.

Materials and Methods

Study area

The study focuses on the southern Indian state of Tamil Nadu (Fig. 1), which is particularly susceptible to agricultural and meteorological droughts because of its primarily tropical environment. Tamil Nadu has high average temperatures all year round, usually between 25° C and 35°C. During the summer, especially from March to June, peak temperatures frequently reach 40°C. Additionally, there are significant differences in humidity levels. Inland places can have humidity as low as 50%, whereas coastal areas often have humidity levels around 70%. The state experiences unique seasonal fluctuations impacted by the northeast (October to December) and southwest (June to September) monsoons. Most of the state's yearly rainfall falls during the northeast monsoon, benefiting the eastern and coastal regions. On the other hand, the southwest monsoons produce mild rain, mainly in the northern and western areas of the state. It is crucial to adequately monitor and manage drought risks in this diversified climatic setting because Tamil Nadu is more susceptible to droughts due to seasonal variations in precipitation and temperature, intense heat waves, and dry spells.

For this study, remote sensing data from 2014 to 2023 was collected for all districts in Tamil Nadu. MODIS satellite data products were used to extract key drought indicators. Specifically, NDWI data was derived from the MOD09A1 (8-day composite surface reflectance) product, which provides the necessary bands (NIR and SWIR) to calculate vegetation water content. Land surface temperature data was obtained from the MOD11A2 (8-day LST and emissivity) product, providing surface temperature information at a spatial resolution of 1 km. The MODIS datasets were chosen for their high temporal resolution and reliable coverage of the study region, enabling continuous monitoring of drought conditions.

Data pre-processing

The MODIS NDWI and LST data were pre-processed to ensure temporal and spatial alignment. NDWI was calculated using the near-infrared (NIR) and shortwave infrared (SWIR) bands from the MOD09A1 product with the formula

$$NDWI = NIR+SWIR / NIR-SWIR \quad \text{(Eqn.1)}$$

The LST values from the MOD11A2 product were used directly after applying the necessary quality flags to filter out invalid data. Both datasets were aggregated to match the study period, ensuring temporal and spatial resolution consistency. Normalized difference water index and LST values were extracted for each district in Tamil

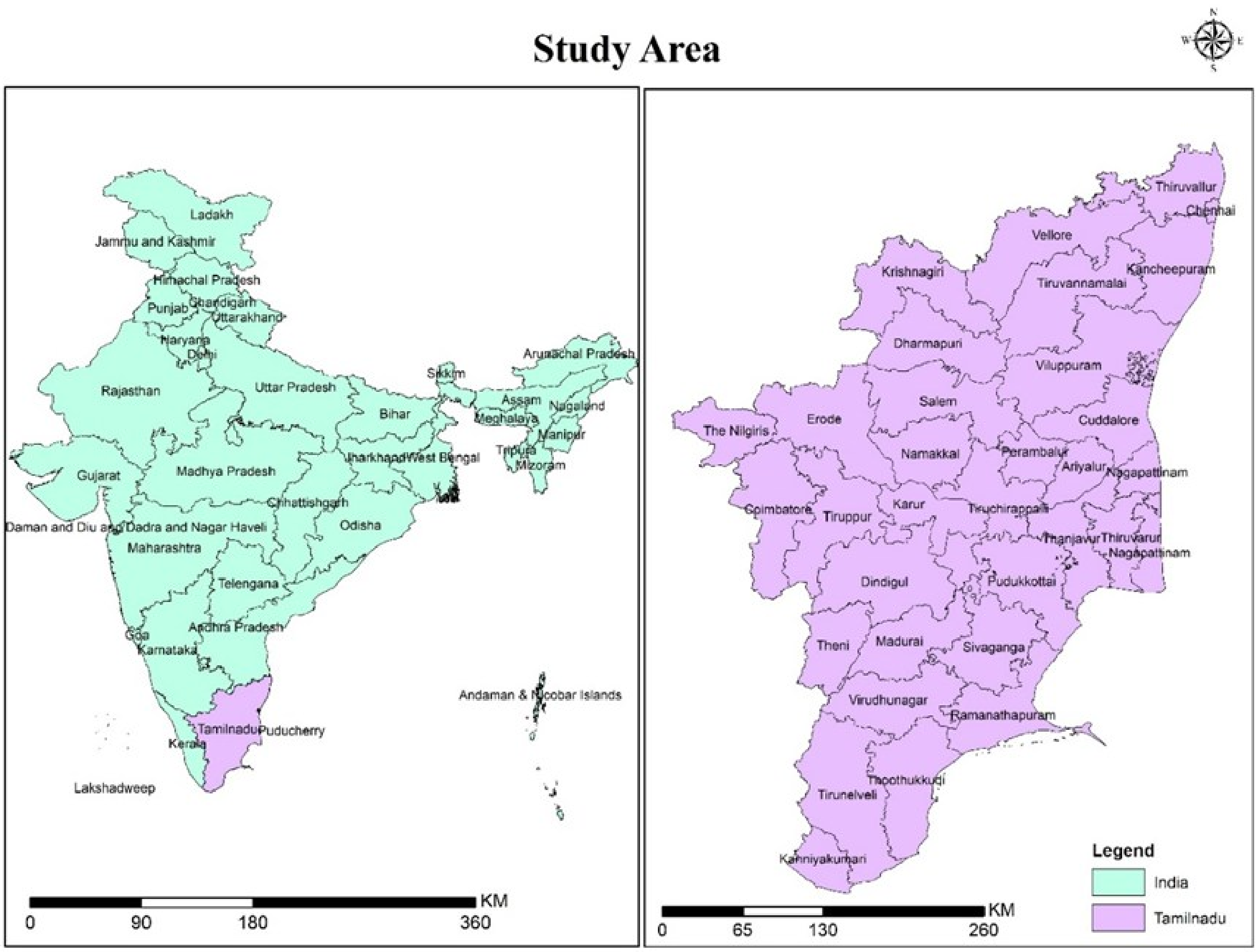

Fig. 1. Study area Map.

Nadu from 2014 to 2023, providing a comprehensive dataset for analysis.

Correlation analysis

A Pearson correlation study was performed to examine the link between NDWI and LST throughout Tamil Nadu. This statistical technique helps quantify the strength and direction of the relationship between NDWI (as a proxy for vegetation moisture) and LST (representing surface temperature). The Pearson correlation coefficient (r) was calculated for each district, providing insight into how changes in surface temperature affect vegetation water content. A negative correlation would suggest that higher temperatures reduce moisture, which could indicate drought conditions. In contrast, a positive correlation would indicate a simultaneous increase in both variables.

The Pearson correlation coefficient was computed using the following formula (4):

$$\frac{\sum(Xi - \tilde{x})(Yi - \tilde{Y})}{\sqrt{\sum(Xi - \check{X}) \wedge 2 \ \sum(Yi - \tilde{y}) \wedge 2}} \qquad \text{(Eqn.2)}$$

where Xi and Yi represent the NDWI and LST values for each district, and $\tilde{X}$ and $\tilde{Y}$ are their respective means.

Regression analysis

Linear and polynomial regression models were employed to further investigate the relationship between NDWI and LST. Regression analysis allowed the study to quantify the extent to which LST could predict NDWI values, offering a potential framework for drought prediction based on temperature data.

Linear regression: A linear regression model was used to explore the direct relationship between NDWI and LST. The model is expressed by the following equation (5):

$$NDWI = \beta_0 + \beta_1 * LST \qquad \text{(Eqn.3)}$$

where β_0 is the intercept and β_1 represents the slope of the line, indicating the impact of LST on NDWI.

Polynomial regression: Polynomial regression models of degree 2 (quadratic) and degree 3 (cubic) were applied to capture potential non-linear relationships between NDWI and LST. These models allow for a more nuanced understanding of how temperature affects vegetation moisture (5):

Quadratic model:

$$NDWI = \beta_0 + \beta_1 * LST + \beta_2 * LST^2 \qquad \text{(Eqn.4)}$$

Cubic Model:

$$NDWI = \beta_0 + \beta_1 * LST + \beta_2 * LST^2 + \beta_3 . LST^3 \qquad \text{(Eqn.5)}$$

These models were designed to capture more complex relationships that may not be well-represented by a simple linear model.

Model evaluation and cross-validation: To ensure the robustness of the regression models, 5-fold cross-validation was performed. This technique divides the dataset into five subsets, training the model on four subsets and testing it on the remaining one, iterating through all possible combinations. The performance of each model was evaluated using the following metrics:

Mean squared error (MSE): Measures the average of the squared differences between the observed and predicted NDWI values.

R-squared (R^2): Indicates the proportion of variance in NDWI that can be explained by LST, reflecting the model's goodness of fit.

The comparison of MSE and R-squared values across the linear and polynomial models helped identify the most suitable model for predicting NDWI based on LST.

Software and tools used

MODIS datasets were downloaded from USGS Earth Explorer and Google earth engine prompts**.** Data analysis was conducted using Python, utilizing libraries such as Pandas for data manipulation, Scikit-learn for regression modeling and cross-validation, and Matplotlib for visualization. This ensured a consistent and reproducible workflow, enabling accurate statistical analysis and model validation.This methodological framework provided a comprehensive analysis of the relationship between LST and NDWI across Tamil Nadu, offering insights into the spatial and temporal variability of drought conditions in the state.

Results and Discussion

The correlation analysis between NDWI and LST across the districts of Tamil Nadu showed varying degrees of association, with Pearson correlation coefficients ranging from 0.17 to 0.91. Districts such as Perambalur (0.91), Namakkal (0.89), and Dindigul (0.88) demonstrated strong positive correlations, indicating a robust relationship between temperature and vegetation moisture content (Table 1 & Fig. 2). In these regions, increases in LST were associated with decreases in NDWI, implying that higher temperatures contribute to reduced vegetation water content, potentially leading to drought conditions (6). Consequently, these districts are more susceptible to drought, with LST as a reliable indicator of moisture stress.

On the other hand, districts such as the Nilgiris (0.17) and Tirunelveli (0.44) exhibited weaker correlations between NDWI and LST, suggesting that in these areas, surface temperature is not the primary driver of vegetation moisture variations (7). This may be attributed to localized climatic conditions and dense forest cover, which can buffer the effects of temperature changes on vegetation. For example, The Nilgiris is characterized by cooler temperatures and high-altitude forests, which maintain stable moisture levels due to frequent cloud cover and lower temperatures. Similarly, Tirunelveli has regions with well-irrigated agricultural areas where vegetation moisture may not respond as directly to surface temperature fluctuations due to regulated water supply.

In contrast, districts with higher correlations, such as Perambalur and Namakkal, often experience dry or semi-arid conditions where surface temperature has a more direct influence on vegetation moisture. In these areas, agricultural practices play a significant role; reliance on rainfed agriculture makes crops particularly vulnerable to temperature-induced moisture stress. Additionally, soils with lower water retention capacity, such as sandy or loamy soils, exacerbate moisture loss under high temperatures. Cultivating temperature-sensitive crops, like pulses and certain grains, also contributes to stronger correlations between LST and NDWI, as these crops are more susceptible to drought under increasing temperatures.

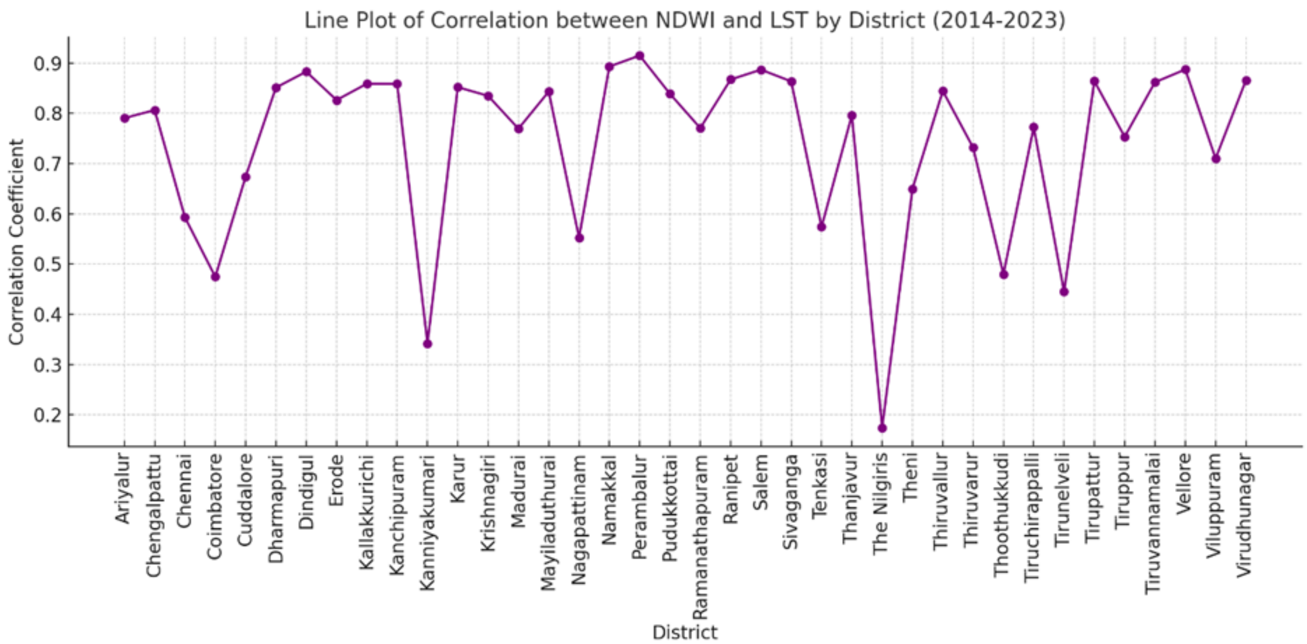

Fig. 2. Correlation between NDWI and LST

Table 1. Correlation value of the Districts in Tamil Nadu

S. No	District	Correlation (NDWI vs LST)
1	Ariyalur	0.79
2	Chengalpattu	0.81
3	Chennai	0.59
4	Coimbatore	0.47
5	Cuddalore	0.67
6	Dharmapuri	0.85
7	Dindigul	0.88
8	Erode	0.83
9	Kallakkurichi	0.86
10	Kanchipuram	0.86
11	Kanniyakumari	0.34
12	Karur	0.85
13	Krishnagiri	0.83
14	Madurai	0.77
15	Mayiladuthurai	0.84
16	Nagapattinam	0.55
17	Namakkal	0.89
18	Perambalur	0.91
19	Pudukkottai	0.84
20	Ramanathapuram	0.77
21	Ranipet	0.87
22	Salem	0.89
23	Sivaganga	0.86
24	Tenkasi	0.57
25	Thanjavur	0.8
26	The Nilgiris	0.17
27	Theni	0.65
28	Thiruvallur	0.84
29	Thiruvarur	0.73
30	Thoothukkudi	0.48
31	Tiruchirappalli	0.77
32	Tirunelveli	0.44
33	Tirupattur	0.86
34	Tiruppur	0.75
35	Tiruvannamalai	0.86
36	Vellore	0.89
37	Viluppuram	0.71
38	Virudhunagar	0.87

The correlation results indicate that while NDWI and LST are valuable indicators in regions where temperature strongly influences vegetation moisture, they may not fully capture drought conditions in districts like The Nilgiris and Tirunelveli. This highlights the need for incorporating complementary variables, such as soil moisture or precipitation data, to achieve a more comprehensive drought assessment in areas with weaker correlations. Including these additional factors can provide a more accurate understanding of drought dynamics in these districts, as they account for environmental conditions that are less influenced by temperature alone.

Building on the correlation analysis, we applied regression models to explore the relationship between NDWI and LST further. Three regression models—linear, quadratic (degree 2), and cubic (degree 3)—were chosen to assess how well LST could predict NDWI values (Table 2). The selection of these models allowed us to explore simple and more complex relationships between LST and NDWI. The linear model was used as a baseline to determine if a straightforward, proportional relationship exists where

Table 2. Table showing regression

S.No	Model	R-squared	Mean Squared Error
1	Linear Regression	0.446113764	0.001643524
2	Polynomial Regression (Degree 2)	0.363515163	0.002022574
3	Polynomial Regression (Degree 3)	-0.047706258	0.00388974

temperature changes consistently affect vegetation moisture. The quadratic model was included to capture potential non-linear dynamics, particularly in cases where the impact of temperature on moisture intensifies at certain thresholds. Lastly, the cubic model accounted for even more complex interactions that might include multiple inflection points, reflecting nuanced vegetation responses to varying temperature ranges. The linear regression model yielded an R-squared value of 0.527, indicating that about 52.7% of the variation in NDWI could be explained by LST (Fig. 3). The positive regression coefficient (0.0166) suggested that, in general, higher LST values correspond to higher NDWI values. However, the spread in the data points indicates that other environmental factors might also influence NDWI (7, 8).

The quadratic regression model (R-squared = 0.528) offered a slightly better fit than the linear model. It effectively captured minor non-linearities in the NDWI-LST relationship (Fig. 4). However, the improvement was marginal, indicating that a linear trend could still explain most of the NDWI-LST relationship (9). The cubic regression model (R-squared = 0.534) performed similarly to the quadratic model, with minimal improvement in the R-squared value (Fig. 5). Although the cubic model captured more complex behavior at the extremes of LST, its higher mean squared error (MSE) indicated that it might overfit the data, making it less generalizable.

To evaluate the robustness of the regression models, we employed 5-fold cross-validation (Fig. 6). The linear regression model performed best overall, with an average MSE of 0.00164 and an R-squared value of 0.446, demonstrating its relative strength in predicting NDWI based on LST across different districts. Although the polynomial models captured additional complexity, they did not significantly improve predictive accuracy and exhibited higher MSE values during cross-validation (3). This suggests that although non-linear relationships exist between NDWI and LST, the linear model provides a more reliable and interpretable fit, especially for general use in drought monitoring.

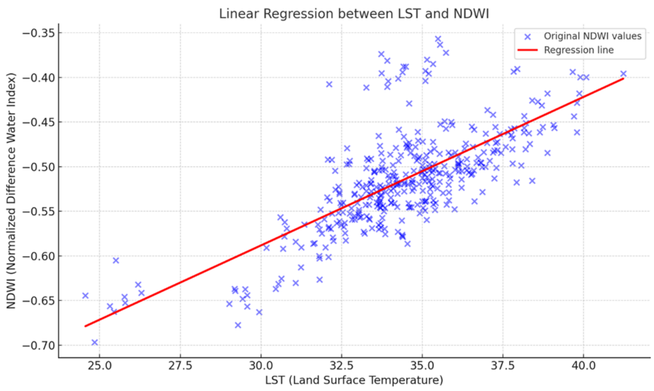

Fig. 3. Linear Regression between LST and NDWI

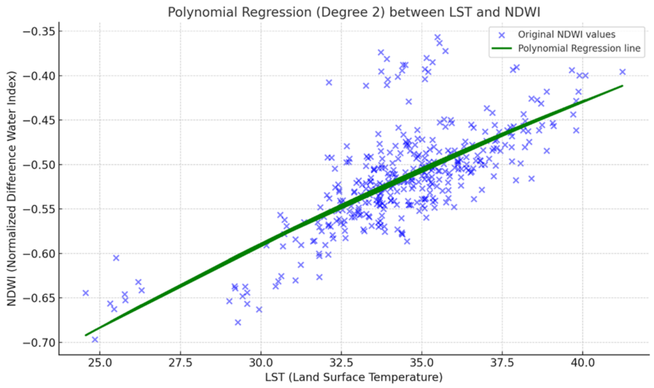

Fig. 4. Polynomial Regression between LST and NDWI

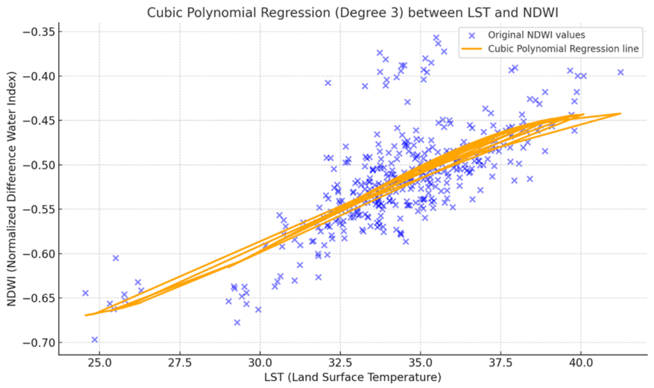

Fig. 5. Cubic Polynomial Regression between LST and NDWI

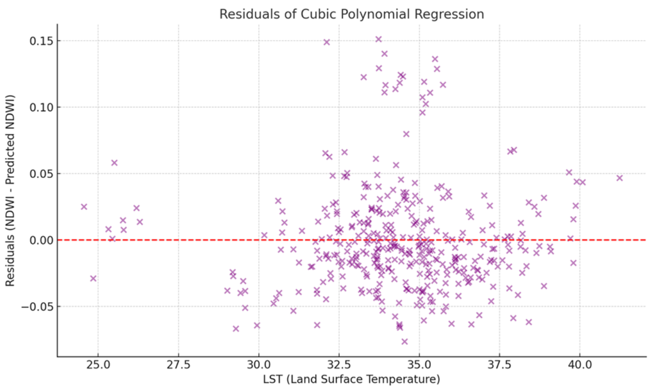

Fig. 6. Residuals of Cubic Polynomial Regression

The findings from correlation and regression analyses indicate that in districts with strong correlations (e.g., Perambalur, Namakkal), LST can be a useful predictor of vegetation moisture content and drought conditions. However, the relatively moderate R-squared values and the performance of the polynomial models suggest that LST alone is insufficient to fully explain NDWI variations, especially in districts with weaker correlations (10). This underscores the need for integrating other environmental variables—such as rainfall, soil moisture, and land cover—into predictive models to improve drought detection accuracy (11).

In districts like The Nilgiris, where the correlation between NDWI and LST is weak, relying on LST for drought monitoring may not be appropriate. Instead, alternative indicators that better capture the specific environmental dynamics of these regions should be explored. Conversely, districts with stronger NDWI-LST correlations can benefit from a simpler linear model for drought prediction, using LST as a reliable proxy for vegetation moisture.

In summary, the study highlights the spatial variability of the NDWI-LST relationship across Tamil Nadu. While LST is a valuable indicator for drought monitoring in some regions, it may need to be supplemented with additional variables in areas where temperature is not the primary factor driving vegetation water content. The results of this analysis provide a foundation for more accurate drought detection frameworks, which can inform decision-making and resource allocation in drought-prone regions of Tamil Nadu. The findings can directly support drought policy by enabling more targeted interventions, such as prioritizing water resources and irrigation support in districts with high LST-NDWI correlations. Furthermore, farmers and policymakers can use these insights in agricultural practices to implement adaptive strategies, like altering crop choices or irrigation schedules based on temperature trends. Future studies should consider integrating other remote sensing indices and machine learning approaches to develop more robust and comprehensive drought prediction models, further enhancing these applications for better drought preparedness and resilience in Tamil Nadu (12, 13).

Conclusion

This study examined the relationship between LST and NDWI across districts in Tamil Nadu to assess their utility for drought monitoring from 2014 to 2023. The results revealed a strong correlation between LST and NDWI in several districts, such as Perambalur and Namakkal, indicating that higher temperatures are associated with lower vegetation moisture content, making LST a reliable indicator for drought in these regions. However, weaker correlations suggest that other environmental factors influence vegetation moisture in districts like the Nilgiris, highlighting the need for additional drought indicators. Regression analysis confirmed that a linear model reasonably balances simplicity and predictive accuracy for most regions, though polynomial models did not significantly improve performance.

Overall, this study demonstrates that while LST is a useful proxy for vegetation moisture in many parts of Tamil Nadu, integrating other environmental variables will improve drought prediction and monitoring, especially in regions with weak LST-NDWI relationships. Future research could explore the potential for combining remote sensing data with ground-based observations, such as soil moisture and precipitation data, to provide a more comprehensive picture of drought conditions. Additionally, examining new indices such as the Vegetation Health Index (VHI) or the Soil Moisture Index (SMI) could enhance the accuracy of drought monitoring. Further studies might also investigate the role of specific crop types and land cover variations, as these factors could influence the effectiveness of LST and NDWI for drought assessment in different regions.

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Authors' Contributions

SJ carried out the experiment observation and drafted the manuscript. RJ guided the research by formulating the concept and approved the final manuscript. SP guided the research by formulating the research concept. BK and DP participated in the data analysis and performed the statistical analysis. RK conceived of the study and participated in its design and coordination. NKS and BS participated in the data analysis and revised manuscript. All authors reviewed the results and approved the final version of the manuscript.

Compliance with Ethical Standards

Conflict of interest: Authors do not have any conflict of interests to declare.

Ethical issues: None

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT by OpenAI for data analysis and visualisation. After using this tool/service, the authors reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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