NDVI and Land Surface Temperature Analysis of Asheville, North Carolina

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Abstract

Recent shifts in global climate patterns have heightened the need for studies on urban heat dynamics. In response, remote sensing technology has increasingly been used to analyze temperature variations within urban environments. Modern remote sensing techniques, particularly the analysis of the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST), provide valuable insights into urban heat-related phenomena, such as the urban heat island (UHI) effect. Examining the relationship between vegetation density and LST can help identify strategies to mitigate rising surface temperatures, particularly in urban areas.

To explore this relationship, an NDVI and LST analysis was conducted for Asheville, North Carolina. Asheville presents a unique case study due to its combination of rapidly developing urban areas and dense vegetation in the surrounding mountainous regions. Using data from NASA's Landsat 5 and Landsat 8 satellites, the study calculated NDVI and LST values from satellite imagery to: (1) analyze seasonal variations within the same year, (2) compare NDVI and LST trends over a 25-year period, (3) examine correlations between vegetation cover and surface temperature, and (4) apply these findings to broader urban and environmental management strategies. The resulting maps provide a visual representation of the NDVI-LST relationship, offering insights into urban temperature regulation and potential mitigation approaches.

1. Introduction

With the rise in global temperatures throughout recent years, having an understanding of the potential relationship between urban heat and vegetation density has never been more important. The use of remote sensing technology has become increasingly important in finding solutions to these increasing temperatures as well as acting as an aid in finding meaningful connections between contributing factors. Remote sensing offers the unique ability to analyze and quantify relatively complex factors in a time efficient and accessible manner. Developed models and indices are used during remote sensing analysis to create meaningful results. The Normalized Difference Vegetation Index (NDVI) (Rouse et al, 1974; Kriegler et al, 1969; Blanton and Hossain, 2020) is one of the most widely recognized and utilized vegetation indices (Hossain and Easson, 2021; Ahmed et al, 2021). It serves as an indicator of relative biomass and greenness (Boone et al, 2000; Hassan and Rahman, 2013; Hassan and Bourque, 2010) by leveraging the distinct reflectance properties of vegetation in the near-infrared (NIR) and red (R) regions of the electromagnetic spectrum. NDVI is calculated as a ratio of NIR and R reflectance values, effectively minimizing discrepancies caused by sensor variations, image quality issues (e.g., brightness), and other potential interferences. This index can be computed for a wide range of remote sensing sensors (Jensen, 2004; Ahmed et al, 2019) using Equation (1).

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

Land surface temperature, often referred to as LST, is the measure of the temperature at Earth's surface. Measuring the LST through remote sensing consists of utilizing radiance values and a series of conversions to get the surface temperature. Utilizing remote sensing techniques such as those discussed above, can help accelerate many fields of study and can contribute to the betterment of our world. The analysis of NDVI and LST within urban areas can help researchers understand what is leading to problems such as urban heat islands (UHI). Researching the relationship between LST and NDVI can facilitate research towards long-term solutions in various disciplines and fields. NDVI and LST analysis can help illustrate the possible relationship between vegetation density and reduced ground temperature, offering insight into possibly preventable increases in overall ambient temperatures, especially in urban areas.

The goal of this study is to gain a further understanding of the relationship between NDVI and LST by utilizing Landsat 8 and Landsat 5 data for Asheville, North Carolina. The main objectives are to analyze same-year seasonal differences in NDVI and land surface temperature, compare yearly NDVI and LST data across a 25-year period, observe the connections between NDVI and LST, and apply the results to a larger solution. This study aims to draw inferences towards the contributing factors for the established relationship between NDVI and LST.

1.1 Literature Review

There has been substantial research done on the relationship between NDVI and LST. The relationship between these two factors has been represented in historical and modern-day publications. Review of these publications is vital to ensure that a strong foundation of the principles is gained. Conducting an abbreviated literature review can also provide insight into successful and meaningful methods. Past research has shown that the relationship between NDVI and LST has many different and unique applications. Research investigating the relationship

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between surface temperature and NDVI goes back beyond the 2000's. The research conducted by Nemani et al (1991) demonstrates an early relationship between the two. This research focused on combining spectral vegetation indices (NDVI) with thermal infrared observations to provide an efficient method of parameterizing surface processes at larger spatial scales. The research resulted in the observation of a strong negative relationship between NDVI and the surface temperature. This relationship was observed across many different types of biomes. The research concluded that the "fraction" of vegetation cover has a very strong influence on the spatial variability of surface temperature.

Yedla and Mareddy (2024) conducted a study where they utilized NDVI, NDWI, and Land Surface Temperature from Landsat 5 and Landsat 8 imagery in order to do a temporal analysis. They focused their study on Telangana, India and found that throughout history there was a negative correlation between NDVI and land surface temperature. As the city has grown from 2000 to 2020, there has been a decrease in NDVI and an overall increase in land surface temperature.

Another study conducted by Subhanil (2021) on the seasonal variability of NDVI and LST in Raipur City, India. In addition to examining the relationship between NDVI and LST, this study did an analysis on the ecological status of the city in order to aid in future logical planning. The study looked at seasonal changes from 1991-1992 to 2018-2019. It was seen that the mean land surface temperature had a notable increase throughout the years. Based on the results, the post-monsoon season produced the best correlation between NDVI and LST with the monsoon season following, then the pre-monsoon, and finally the winter season. They found that roughly an equal portion of the land was under the dedicated excellent and worst categories of ecological condition, which can help provide important information to planners and other conservationists.

Yue et al (2005) conducted an analysis between land surface temperature and NDVI in Shanghai, China using Landsat 7 data. The study revealed a relationship between LST and NDVI when associated with urban land-use types and patterns within Shanghai. The study resulted in visual interpretations as well as statistical results that supported their findings. In addition to the relationship between NDVI and LST, the researchers also found a positive correlation between the Shannon Diversity Index (SHDI) and a negative correlation between SHDI and NDVI. This study showed that these relationships can be used to study urban ecological environments at a low cost and help examine the impact of urban land-use on the environment in Shanghai.

The study done by Syawalina et al (2022) showed that the relationship between NDVI and LST can be applied to a large range of problems. This study examined the relationship between NDVI and LST on geothermal manifestations in Toro, Central Sulawesi using Landsat 8 data. The NDVI and LST data that was gathered was used to determine the distribution pattern of surface temperature and vegetation density within the study area to connect the two to a relationship between the hot springs present within Toro. The results showed that there was an average temperature of 23-25 ℃ at a hot spring point and high vegetation density areas had a value of 0.35-0.60. That research revealed that NDVI and LST's inverse relationship can affect the identification process of geothermal conditions, however, it can still help identify potential geothermal manifestations.

The study conducted by Sun and Kafatos (2007) utilized the relationship between NDVI and LST as a means of drought prediction. The researchers found that the negative correlation between the two in the warm seasons and a positive correlation in the winter can help predict temperature related droughts throughout North America. They highlighted that the negative correlations between NDVI and LST are stronger than the relationship between NDVI and brightness temperature when looking at drought monitoring. The study suggests that the analysis of LST and NDVI can be a meaningful and successful way of predicting and monitoring droughts at a low cost.

These various studies show that there is a well-established relationship between NDVI and land surface temperature. Studies that emphasize this relationship can be dated back to before the 2000's. These highlighted studies illustrate that remote sensing is an efficient, accessible, and accurate way to study the relationship between vegetation density and land surface temperature. To make meaningful connections, it is necessary to pick a study site, analyze the relationship throughout multiple seasons/years, compute all necessary equations, and ultimately discuss the meaning of the results and how they may apply to a larger goal. The observation of the relationship between NDVI and LST can be applied to larger issues such as Urban Heat Islands (UHI) which are proving to be detrimental to both the environment and society. When conducting research to provide insight and possible solutions, following the proper steps is vital to collecting interpretable results.

1.2 Study Site

The study site for this project, as seen in Figure 1, is a subset of the greater Asheville area. Asheville is a city in the state of North Carolina. The city has seen steady population growth over the course of the last few decades and is one of the largest cities in Western North Carolina. Industries such as tourism and manufacturing have become increasingly popular and have contributed greatly to the growth of the city. The selected study site is inclusive of the major urban center which includes large and heavily travelled highways as well as rapid developments. In addition to designated urban areas, the site is inclusive of areas that have high densities of natural vegetation and have low human activity outside of the city center. The unique nature of the study site of Asheville, North Carolina allows for the observation of growing relations between NDVI and LST. The recent development of the city has led to the decrease of vegetation with an increase of developments, however, increasing conservation efforts have ensured the establishment of areas of high vegetation density and low human disturbance.

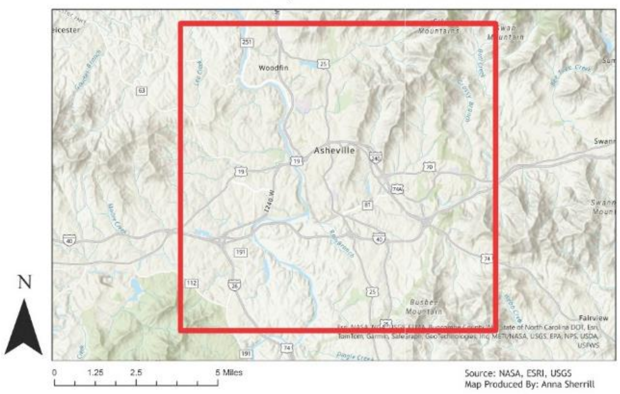

Figure 1: A map of the study site in Asheville, NC.

1.3 Data Used

There are many different types of satellite data that can be used when conducting an analysis of NDVI and LST. Different study sites consist of different requirements for data. Although one data source might work well for one data set, the same might not be said for another. This study focused on utilizing imagery from NASA's Landsat missions. The mission's spatial and temporal capabilities, as well as the accessibility of data, were best applicable to the selected study site of this research.

All the Landsat data that was used throughout the study was accessed online through the USGS Global Visualization Viewer (GloVis) (https://glovis.usgs.gov/)at free of cost. Landsat 5 data was used to acquire satellite imagery from the summer and winter seasons of Asheville, North Carolina in 1998. Landsat 5 is a satellite that was launched by NASA on March 1,1984. The satellite remained in commission for 28 years while transmitting over 2.5 million images. The satellite produced imagery with 30 m spectral resolution and 7 bands total (USGS). Two Landsat 5 images were analyzed, one image was acquired on January 11, 1998, and the other image was acquired on August 23, 1998. All data that was necessary for the LST calculation for Landsat 5 was found in the included text file from the level 2 package from GloVis. The imagery acquired from the Landsat 5 satellite offers important temporal analysis. This allows for current-day data from Landsat 8 to be compared to historical data. This helps create more meaningful connections.

Landsat 8 imagery was used to analyze data from the summer and winter seasons of 2023 for Asheville, North Carolina. Landsat 8 has operated since 2013 and produces imagery with 30 m spatial resolution. Landsat 8 also has 15 m resolution panchromatic image making up for a total of 9 OLI bands and 2 TIRS bands (USGS). Two Landsat 8 images were acquired. The winter season image was acquired on January 24, 2023, and the summer image was acquired on June 17, 2023. The level 2 Landsat 8 package from GloVis provided all needed values for the calculations of land surface temperature. This imagery contributes to the analysis of current-day imagery.

2. Methodology

The methodology of this study includes acquisition of Landsat satellite imagery for specific dates, carrying out various digital image processing techniques with the acquired Landsat imagery, calculating NDVI and land surface temperature (LST), creating meaningful maps, and analyzing the results to address the problems and solutions.

The processes that are involved in calculating NDVI and LST from satellite imagery have been reproduced many times. The general approach and strategy for the overall study was straightforward and can be summarized within the included flow chart (Figure 2). The first step in the process was accessing the data from GloVis. Once all the Landsat imagery, both for 2023 and 1998, was acquired it was then put into ERDAS Imagine for general image pre-processing. Pre-processing methods included stacking the necessary bands together as well as correcting any scanline errors through the provided toolbox in ERDAS Imagine. For the NDVI analysis of Landsat 5, Thematic Mapper bands 1-7 were used. These bands include the visible (Blue, Green, and Red) bands as well as the Near-Infra Red (NIR) and thermal bands. For the NDVI calculation for Landsat 8, the visible red band (band 4) and the near-infrared band (band 5) were stacked. For the calculations of the land surface temperature, the thermal infrared band (TIR), or band 10, was the only band needed for Landsat 8. For the calculation of LST for Landsat 5, the TIR band, or band 6 was used. After the proper bands were stacked, all the images were then subset to the same settings. Once the subset images were acquired the NDVI process was carried out. NDVI was calculated using Equations 2 and 3, which was derived from Equation 1 for Landsat 5 and Landsat 8 data.

$$NDVI\ (Landssat\ 5) = \frac{NIR\ (Band4) - Red(Band\ 3)}{NIR\ (Band4) + Red(Band\ 3)} \tag{2}$$

$$NDVI\ (Landssat\ 8) = \frac{NIR\ (Band5) - Red(Band\ 4)}{NIR\ (Band5) + Red(Band\ 4)} \tag{3}$$

The process of calculating NDVI was carried out through the unsupervised classification tool in ERDAS Imaging. This process for calculating the NDVI was repeated for all the 4 acquired Landsat images.

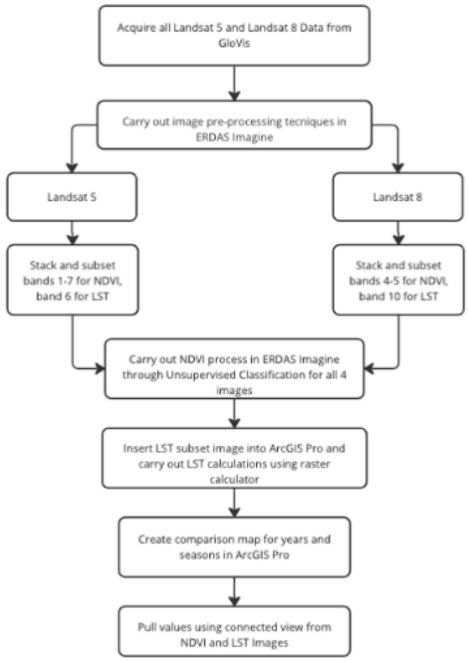

Figure 2: Flowchart demonstrating project workflow.

Once the calculations for NDVI were carried out for all the images, the calculations for the land surface temperature for each image were completed through the ArcGIS Pro raster calculator. The two different Landsat images had a similar process for calculating the land surface temperature, however there were some slight differences between the two. The process for calculating the LST using Landsat 5 uses Band 6 (Near-infrared). The Digital Number is converted to radiance through Equation 4. Following the solution to Equation 4, the radiance is then converted into LST (Kelvin) using Equation 5. The LST (in Kelvin) is then converted into Celsius using the standard conversion factor of –273.15. The conversion of the DN to the top of atmosphere radiance for Landsat 8 utilizes Equations 6 and 7. Following that conversion, the process for Landsat 8 was the same as described for Landsat 5. Table 1 shows the equation parameters used for the processes specific to each Landsat imagery. All the values were found in the respective text file from the image data.

$$L_\lambda = \left(\frac{LMAX_\lambda - LMIN_\lambda}{QCALMAX - QCALMIN}\right) - (QCAL - QCALMIN) + LMIN_\lambda \tag{4}$$

$$T = \frac{K2}{\ln\left(\frac{K1}{L_\lambda} + 1\right)} \tag{5}$$

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$$L_\lambda = ML \cdot Q_{cal} + AL - O_1 \quad (6)$$

$$L_\lambda = ML \cdot Band\ 10 + 0.10000 - 0.25 \quad (7)$$

L= TOA Spectral Radiance
ML = Radiance multiplicative Band
AL = Radiance Add Band
Qcal = Quantized and calibrated standard product pixel values
O_1= Correction value for band 10 (0.29)

After the completion of NDVI and LST calculation for all images, 5 values for NDVI and LST were gathered for each of the images across the different seasons and years. These five values act as additional data to support the relationship between NDVI and LST. After these values were collected, the images were imported into ArcGIS Pro to generate NDVI and LST maps for the study site. Each map contains a side-by-side comparison of the NDVI image and the LST image for the corresponding year. For example, one map contains the NDVI and LST imagery for 1998, another one for January 2023, etc. After the acquisition of necessary values from the imagery and generation of the maps (using comparable scales) the analysis of the results were initiated.

Sensor	Constant 1 - K1 (Watts/(m^2 * sr * μm))	Constant 2 – K2 Kelvin
Landsat 5 TM	607.76	1260.56
Landsat 8	774.8854	1321.0789

Table 1:Table showing constants used for Landsat 5 and 8 equations.

3. Results and Analysis

Landsat data were processed to quantify land surface temperature (LST) and the normalized difference vegetation index (NDVI), generating classified datasets. These datasets were then visualized through maps to illustrate the relationship between LST and NDVI. A universal color scale was applied: green represents high NDVI values, while red indicates low NDVI values. For LST figures, red corresponds to high land surface temperatures, whereas blue represents lower temperatures.

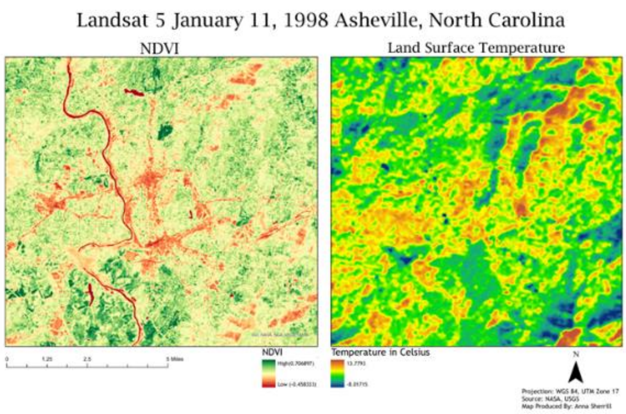

Figure 3: Same-year comparison of NDVI and LST of Landsat 5 Imagery from January 11, 1998.

Figure 3 presents the LST and NDVI visualization derived from Landsat 5 imagery captured on January 11, 1998, while Figure 4 depicts the corresponding visualization from Landsat 8 imagery acquired on January 24, 2023. Similarly, Figure 5 shows the processed results for Landsat 5 data from August 23, 1998, and Figure 6 illustrates the NDVI and LST values obtained from Landsat 8 imagery collected on June 17, 2023.

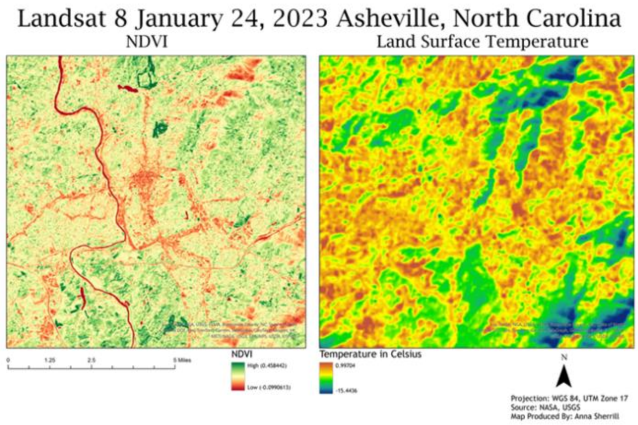

Figure 4: Same-year comparison of NDVI and LST of Landsat 8 Imagery from January 24, 2023.

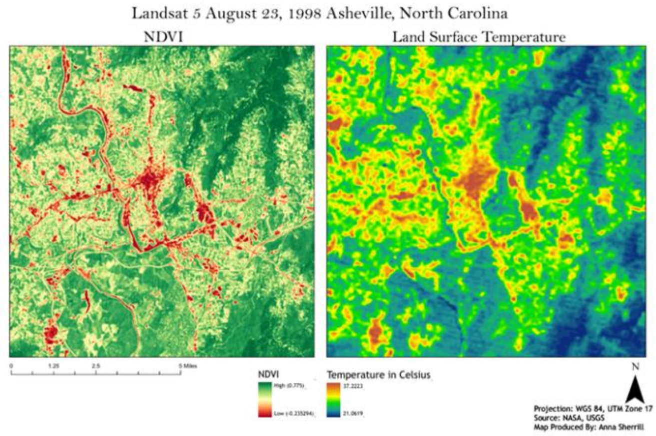

Figure 5: Same-year comparison of NDVI and LST of Landsat 5 Imagery from August 23, 1998.

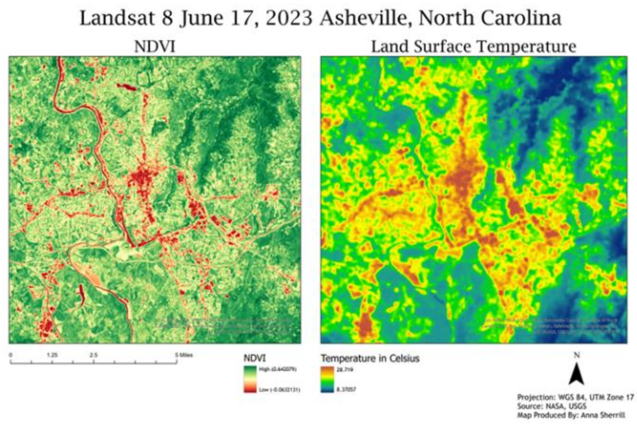

Figure 6: Same-year comparison of NDVI and LST of Landsat 8 Imagery from June 17, 2023.

To provide quantitative analysis, five designated points were selected from the acquired imagery for both winter and summer seasons across different years. The tables below facilitate direct

comparisons of NDVI and LST values, enabling same-year, seasonal, and cross-temporal analyses.
Table 2 presents the comparison of LST and NDVI values during the cold season for 1998 and 2023. Notably, Points 1 and 2 exhibit a decrease in NDVI values alongside an increase in land surface temperature between these years. However, Point 5 appears to be an outlier, warranting further investigation to determine the underlying factors influencing its values.

Point	NDVI 1998	Temperature in Celsius 1998	NDVI 2023	Temperature in Celsius 2023
Point 1	0.076923	3.966858	0.041276	5.019958
Point 2	0.042254	9.471832	0.178006	5.35887
Point 3	0.377778	2.934540	0.268619	3.645416
Point 4	0.105263	2.414490	0.306452	3.413147
Point 5	0.275362	6.504150	0.136187	8.038849

Table 2: NDVI and LST values taken from 5 points from imagery acquired during the cold season.

Table 3 compares LST and NDVI values for the warm season imagery from 1998 and 2023, based on the same five points. In this dataset, Points 1 and 4 demonstrate the expected trend of lower NDVI values corresponding to higher land surface temperatures.

Point	NDVI 1998	Temperature in Celsius 1998	NDVI 2023	Temperature in Celsius 2023
Point 1	0.016231	32.859772	0.524599	10.222260
Point 2	0.678571	21.941895	0.131341	23.466919
Point 3	0.631068	23.683380	0.487120	12.401794
Point 4	0.067961	33.262115	0.548225	10.031525
Point 5	0.716535	21.941895	0.108557	26.054810

Table 3: NDVI and LST values taken from 5 points from imagery acquired during the warm season.

4. Accuracy Assessment

An accuracy assessment evaluates the reliability of classified results, such as the developed maps in this study. Ideally, this assessment is conducted immediately after classification; however, due to time constraints, a full accuracy assessment could not be completed. Qualitative evaluation suggests that the results are accurate. However, limitations in resources and time prevented a quantitative accuracy assessment. Future applications of these methods should include an accuracy assessment to validate findings and enhance the robustness of the results.

5. Discussions and Conclusions

This research provides a visual representation of the relationship between land surface temperature (LST) and the normalized difference vegetation index (NDVI) across different years and seasons. In addition to visual maps, numerical representations were provided in tables to further illustrate this relationship. The maps demonstrate a clear inverse correlation between NDVI and LST, where areas with lower NDVI values correspond to higher LST values. The graduated color scale enhances this trend across different time periods and seasons. This relationship is most pronounced in imagery captured during the summer months (August and July), likely due to peak vegetation productivity and increased heat, making the correlation more distinct.

Beyond the visual representation in the maps, Tables 2 and 3 further reinforce this relationship. The figures generated throughout the study consistently show that a decrease in NDVI values corresponds with an increase in LST. This trend can be attributed to vegetation’s natural cooling effects. High NDVI values indicate dense, green vegetation, which cools the Earth's surface through processes such as transpiration and shading. As vegetation density increases, its cooling capacity strengthens, leading to lower surface temperatures. These trends are evident across different years, locations, and seasons, emphasizing the strong and widely applicable relationship between LST and NDVI. These findings can inform urban planning and development, highlighting areas in need of conservation and climate-sensitive interventions.

The insights gained from this research can serve as a foundation for further studies on the NDVI-LST relationship. Understanding these dynamics is crucial for addressing pressing environmental issues such as urban heat islands and rising global temperatures. Additionally, examining vegetation’s role in temperature regulation can guide research into plant species that either retain heat or enhance cooling efficiency. The implications of this research extend across multiple disciplines, including agriculture, urban development, environmental policy, conservation, and energy management. As global environmental challenges intensify, such studies become increasingly vital to sustaining planetary health.

Remote sensing has proven to be an effective and efficient tool for analyzing NDVI and LST, particularly in urban environments. It enables large-scale, accurate data collection, allowing for rapid yet precise analysis. The integration of remote sensing in research projects like this enhances our ability to monitor and address environmental changes, supporting data-driven decision-making in climate resilience and sustainable development.

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