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Utilizing remote sensing data and ArcGIS for advanced computational analysis in land surface temperature modeling and land use property characterization

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Abstract

This paper provides a summary of the remote sensing analysis conducted, which utilized satellite images to model changes in land cover and their influence on Land Surface Temperature (LST). The primary determinant of surface overheating is identified as vegetation, with water bodies playing a significant role in LST regulation. Conversely, areas with bare soil and built-up infrastructure contribute to elevated LST levels. Therefore, it emphasizes the importance of implementing measures like urban forestry, creating water bodies, preserving existing ponds, and minimizing construction activities to prevent further increases in LST and mitigate ecological damage. Even in cases where tree planting isn't feasible, introducing shrub-type vegetation in barren urban areas is recommended as an effective means to resist soil heat buildup. Consequently, increasing vegetation cover is highlighted as a crucial factor in controlling LST within both urban and non-urban environments.

Keywords: LST; Band; Thematic Mapper.

1. Introduction

The composition of land surfaces and the presence of water bodies have a significant impact on the local environment. Land Surface Temperature (LST) is important in hydrology, meteorology, and climatology because it plays a critical role in the physical processes of the local terrain. It is a key parameter in understanding the Earth's surface energy balance. LST is especially important in calculating the net radiation budget at the soil surface and in monitoring crop growth and vegetation dynamics. It also serves as an important indicator of interactions between local climate and ground conditions, such as the nursery effect. Variations in land surface characteristics, which include factors such as vegetation cover, land-use patterns, and surface impermeability, have a noticeable impact on LST (Uddin & Swapnil, 2021). The ongoing urbanization process has resulted in the expansion of urban areas, causing significant changes in land surface properties. In the context of global warming, LST emerges as a relevant indicator, with a strong relationship to factors such as vegetation, water bodies, and, most notably, urban development (Uddin & Mondal, 2020). LST is a valuable source of information about surface attributes and climate dynamics, making it useful in a variety of environmental scenarios (Weng & Yang, 2004). Ullah et.at (2023) and Shakil et al. (2013) find the best scenario of a job shop production which will be helpful for reducing step for the remote sensing work at the experiment. Hossain et al. (2023) also shows how electricity generation is done from moving vehicles which is very useful for this work as there are several works in remote sensing for land work.

Land Surface Temperature (LST) assumes a pivotal role within the intricate energy dynamics and processes of evapotranspiration, encompassing dynamic energy interactions between the Earth's surface and the atmosphere (Alsultan et al., 2005). LST, distinct from Land Surface Air Temperature (LSAT), encompasses the complete spectrum of heating and cooling occurring at the Earth's surface and exhibits more rapid fluctuations compared to air surface

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temperature. LSAT, conversely, represents the air temperature in immediate proximity to the Earth's surface, as recorded by meteorological stations, while LST characterizes the actual surface temperature of the land itself. Consequently, the phenomenon of land surface heating is intricate and regulated by a multitude of variables, including surface emissions, soil moisture content, surface material composition, and incident solar radiation (Liew & Cust, 2021; Rinner & Hussain, 2011).

Nazma et. al (2014) and Rahman (2015) interpret how supplier selection may affect the Electronics sectors for an industry that plays significant role for Land surface remote sensing work. Rahman et. al (2023) considers the cryptocurrency system which is the most important factor for any sector for choosing mapping and materials for smooth operation running for remote sensing. Rahman et. al (2023) uses the machine learning algorithm which is very useful for this study specifically for the performance prediction of the surface image accuracy which will be generated from satellite when there will be big data. Sifat et al (2023) implements big data tool in his three different papers that we have included in this paper for MapReduce and Apace spark which is the future work for large volume of data sorting work for land surface image collection. Specifically, when the data size is more this research is very important. They use Multimode clusters with data compression methods and try to compare them which is significant for the expansion of our research when we select huge data. Syed at el. (2023) describes gently how Brain tumor classification with transfer learning across the multiple classes for healthcare purposes image processing which can be great source of our research specifically to sort out image from satellite image analysis using deep learning. Fayshal et al. (2024), Khalekuzzzaman et al (2023), Hasan et al (2023), and Adnan et al. (2023) describes gently how the effects of LST affect the world land surface in different manners.

LST has a negative impact on both ecosystems and the atmosphere, influencing factors like increased terrestrial radiation and changes in heat flux exchanges within the atmosphere (Alsultan et al., 2005). LST is a valuable resource for understanding diverse land surface dynamics, making it important in a variety of fields such as climate studies, ecology, hydrology, vegetation monitoring, soil moisture estimation, and geology (Tang et al., 2008; Wan & Dozier, 1996). Hence, LST stands as a pivotal factor in the evaluation of exchanges of energy at both the Earth's surface and within the atmosphere, facilitating the examination of environmental alterations spanning local, regional, and global scales (Lo & Quattrochi, 2003; Wan & Dozier, 1996). The realm of satellite-based remote sensing is increasingly recognized as an indispensable instrument, providing data across various spatial and temporal resolutions, which proves indispensable for research endeavors in fields such as climatology, geography, ecology, and hydrology. In this context, Thermal Infrared Remote Sensing (TIR) emerges as a robust and potent technique, enabling the acquisition of data pertaining to the physical attributes of the Earth's surface through the assessment of energy reflection, radiation, and emission levels (Dousset & Gourmelon, 2003; Kiage et al., 2007). Consequently, remote sensing has garnered widespread acceptance and has evolved into a valuable monitoring tool across various scientific applications, including meteorological studies and beyond.

Land Surface Temperature (LST), which is typically measured in Kelvin or Celsius (Rajeshwari & Mani, 2014), is facing heightened challenges as greenhouse gas levels in the atmosphere rise. This rise in LST has dreadful consequences, contributing to the thawing of glaciers and ice masses in Arctic regions, and triggering events such as floods, sea level rise, and other natural disasters. Furthermore, LST surges disrupt tropical climatic equilibrium, resulting in irregular precipitation patterns (Rahman & Dedieu, 1994; Ullah et al., 2019). This rising LST has a significant impact on the Earth's vegetation cover, with a strong reliance on factors such as vegetation health, land use characteristics (including urbanization or barren areas), and the presence of water bodies. Estimating LST across large areas was historically difficult before the advent of Earth Observation Satellites (EOS) (Khandelwal et al., 2018). LST was typically calculated at specific sample points and then interpolated to generate isotherms for converting point-based data into larger spatial datasets (Mallick et al., 2008). Most isothermic LST maps were created using spatial interpolation techniques and data collected at specific observation sites. Satellite imagery is an important tool for obtaining detailed information about land cover types and patterns, including vegetation, water bodies, and bare soil. Furthermore, satellite data helps to improve understanding of how topography influences surface conditions (Zhao et al., 2019). Kamal et. al (2019) gives empirical evidence by using RFID technology for warehouse management by android application which has great impact on land surface sensing as we can apply this technology for detection purpose. Parvez et. al (2022) gives a Great discussion on ergonomics factor in his two different research paper of students from which we consider the human working posture for the efficiency measurement of worker in the land surface because ergonomics factors are one of the most crucial matters for their camera and sensing purpose based on which data can be changed greatly. Ullah et al. (2023) describes very gently in his three different papers regarding manufacturing excellence, scheduling operation and equipment efficiency from which we can consider the Equipment and component selection for the Land surface remote sensing during measurement as everywhere there is efficiency of human and machines. Shakil et. al (2013) interprets the process flow chart for a jute mill which is very informative for our research though this field is different, but we have analyzed that process flow is very helpful for any types of measurement and analysis work. Ullah et.at (2023) finds the best scenario of a job shop production which will be helpful for land surface image processing.

Satellite technology advancements and the deployment of high-resolution sensors have transformed the spatial monitoring of Land Surface Temperature (LST). With the use of thermal ultraviolet bands from satellites such as Landsat, it is now possible to estimate LST across large areas in a single operation. Numerous researchers have relied on Landsat imagery to create land use and land cover images. Nonetheless, due to the vast diversity of land surfaces and the complexities associated with eliminating atmospheric interferences, remotely sensing land surface temperatures remains a difficult task. LST has been widely used in a variety of scientific studies (Crago et al., 1995; Diak & Whipple, 1995). It is essential for calculating surface urban heat, forecasting building energy consumption, and assessing heat-related risks (Deng & Wu, 2013; Hu & Brunsell, 2012; Mathew et al., 2016). In the current context of rapid global industrialization and urbanization, LST has received considerable attention as the world grapples with the consequences of global warming. LST data is an important indicator of how the Earth's surface temperatures have changed over time. As a result, it provides a valuable tool for estimating the extent of climate change and assessing global greenhouse gas emissions in this critical context.

2. History of LST

Over the years, a multitude of research initiatives have been launched to enhance our comprehension of how alterations in land surface characteristics influence Land Surface Temperature (LST). Beginning as early as the 1960s, scientists have harnessed the potential of remotely sensed data to derive and simulate various vegetation-related biophysical factors, with the Normalized Difference Vegetation Index (NDVI) standing out as a prominent and widely employed parameter in this endeavor. An intriguing revelation stemming from these investigations is the inverse correlation discerned between LST and NDVI, signifying that the presence of vegetation exerts a cooling influence on surface temperatures (Weng, 2001). Recent advancements in remote sensing technology, coupled with strides in computational techniques, have catapulted the study of LST dynamics to new heights. These progressions have been further buoyed by the escalating availability of data from a diverse array of sensors. Remarkably, researchers have been able to establish a robust and consistent linear relationship spanning various seasons, linking LST to the percentage of impervious surface area (%ISA) (Yuan & Bauer, 2007). This discovery augments our understanding of how urbanization and changes in land surface properties can significantly impact LST across different climatic conditions and temporal contexts.

In an investigative foray across diverse vegetation types in the region of Gujarat, India, an interesting pattern emerged: desert-based agriculture exhibited the highest surface temperatures, followed by rain-fed agriculture, irrigated agriculture, and forests. This intriguing discovery implies that fluctuations in vegetation cover play a more significant role in determining surface temperatures than the rapid shifts induced by climatic factors (J. Sobrino & Caselles, 1990). This insight underscores the notion that when examining Land Surface Temperature (LST), which exhibits both temporal variability and spatial heterogeneity, it is imperative to consider its interaction with stable environmental features such as terrain characteristics and land cover (Fan et al., 2014). This interplay between vegetation, land cover, and LST adds a layer of complexity to our understanding of the Earth's surface temperature dynamics, particularly in regions with diverse land use and vegetation patterns. LST, along with near-surface air temperature, is a key variable in studies ranging from hydrology to biodiversity to energy balance to climate change (J. A. Sobrino et al., 1996). Vegetation, soil moisture, elevation, solar zenith angle, and topographic effects all have a significant impact on their interrelationship (Lai et al., 2013).

Thermal remote sensing data has proven to be a valuable tool in scrutinizing the response of topsoil characteristics to changes in Land Surface Temperature (LST) over time, particularly in arid environments. One intriguing observation that has surfaced is that specific land surface features exhibit consistent LST patterns during one time period but undergo significant variations in another, contingent upon the dynamics of the seasons (Ali & Shalaby, 2012). This insight highlights the intricate interplay between LST and the temporal variability in topsoil attributes, shedding light on how these environmental factors influence each other in arid regions. Furthermore, it's widely acknowledged that within the troposphere, for a stationary atmosphere, air temperature exhibits a decline with increasing altitude. This fundamental meteorological principle is referred to as the environmental lapse rate (J. A. Sobrino & Raissouni, 2000). The environmental lapse rate signifies the rate of temperature decrease per unit increase in height within a vertical column of air above the Earth's surface. Notably, the exact magnitude of this rate, ranging from 50 to 100 degrees Celsius per 1000 meters, is contingent upon prevailing moisture conditions. This understanding of the environmental lapse rate is pivotal in comprehending how temperature gradients change with altitude in the atmosphere and is a crucial factor for various scientific studies, particularly those focusing on atmospheric and environmental dynamics.

Many LST studies cover large areas ranging from a few square kilometers to several thousand square kilometers, with significant elevation variations across such vast areas (Zhang, 2009). The impact of settlements on the surrounding meteorological components, regardless of size, has long been a source of concern, particularly in urban climates (Oke, 1982). In recent years, remote sensing research into the Urban Heat Island (UHI) phenomenon has accelerated, owing to significant advances in image precision and cost-effectiveness (Jin et al., 2005b).

2.1. Impacts OF LST on climate change

Extreme temperatures and heatwaves are inherent natural events that can yield severe repercussions for both human societies and the natural environment. Large urban areas, owing to their high population densities and concentration of valuable assets, stand particularly exposed to the perils associated with elevated temperatures. A glaring illustration of this vulnerability is the European heatwave experienced in August 2003, which exacted a devastating toll with an estimated 35,000 to 50,000 casualties within the cities of the continent, as reported by the United Nations Human Settlements Program in 2007. In a global context, the European heatwave of July, during the same year, held the dubious distinction of ranking fifth among the top ten natural disasters of 2007, causing the loss of 567 lives across southern Europe and the Balkans. Over the course of recent decades, extensive research endeavors have been dedicated to delving into various facets of the Urban Heat Island (UHI) phenomenon, which characterizes localized urban areas experiencing elevated temperatures compared to their surrounding regions. Notably, contemporary technologies such as Geographic Information Systems (GIS) and remote sensing have played pivotal roles in unraveling the intricacies of urban climates (Fayshal et al., 2023). These advancements have facilitated significant progress in the field, as exemplified by the capacity to monitor and study heatwave events within urban settings (Jin et al., 2005a).

Land Surface Temperature (LST), a significant parameter within the Earth's surface energy equilibrium, holds extensive utility across the domains of hydrology, meteorology, and climatology (Khalekuzzaman et al., 2024). LST plays a pivotal role in the determination of the net radiation budget at the Earth's surface, the surveillance of crop and vegetation conditions, and serves as a vital gauge for comprehending the greenhouse effect and the reciprocal exchange of energy between the Earth's surface and the atmosphere. The assessment of Land Surface Temperature represents a potent approach for forging connections between seasonal variations and shifting weather patterns. This temperature data yields indispensable insights into the physical attributes and climatic attributes of the Earth's surface, both of which are pivotal factors in a multitude of environmental processes (Dousset & Gourmelon, 2003; Lu & Weng, 2007).

2.2. Role of remote sensing in land surface temperature retrieval and application

Remote sensing is the practice of acquiring information about an object or a phenomenon without direct physical contact, a concept that aligns with the definition by (Kiefer et al., 2004), who describe remote sensing as the art of collecting data about an object or event from a distance. In essence, remote sensing involves the retrieval of data concerning a target object or phenomenon from a significant distance, a process highly esteemed by geographers (Rahman et al., 2023). Consequently, remote sensing stands as a pivotal technology, especially in environmental monitoring endeavors, offering a wealth of environmental information. In contemporary GIS analysis, remote sensing has proven to be an indispensable tool (Mizan et al., 2023). In terms of efficacy, research trends and findings consistently demonstrate that remote sensing surpasses traditional methods like field-based surveys. It's noteworthy, however, that some studies have brought attention to the limitations of remote sensing. For instance, in the realm of GIS analysis, (Carver et al., 1995) have advocated for field-based surveys as an alternative to remote sensing, particularly in environmental classification, modeling, and evaluation support. Concerns have also arisen regarding the high costs associated with acquiring remotely sensed data, a point raised by Osborne et al., (2001) and Raup et al., (2007). Bastiaanssen et al., (2000) have also emphasized the scarcity of experts as a hindrance to the widespread adoption of remote sensing technology.

Nonetheless, remote sensing outperforms field surveys consistently. (Foody and Curran & Blackburn, 1994) cited a variety of applications, including environmental classification, terrestrial global environment research, monitoring changes in land cover, assessing regenerative states in tropical forests, monitoring snow cover, assessing urban land use, and a variety of other uses. (Clevers, 1997) emphasized its advantages in fields such as agriculture, where the timely and quantitative presentation of information was widely accepted. Furthermore, the cost of accessing satellite data has steadily declined in recent years. Indeed, organizations such as the USGS have made Landsat ETM+, TM, and MSS data freely available (NASA 2013), lowering the cost of research. Governments worldwide are heavily investing in satellite services to acquire remotely sensed data for national development purposes. Major investors include India (Indian Space Research Organization 2008), the United States, China, and Russia, all contributing to a projected surge in the number of remote sensing professionals to meet the growing demand

2.2.1. ARCGIS

ESRI's ArcGIS software system is a comprehensive GIS software system. This integrated platform is intended for the development of operational GIS solutions and includes a number of components. It contains a geographic information model for simulating real-world phenomena as well as tools for storing and managing geographic data in files and databases. ArcGIS includes a collection of pre-built applications for data creation, editing, manipulation, mapping, analysis, and dissemination. It also provides web services, which deliver content and functionality to networked software clients. ArcGIS can run on a variety of platforms, including mobile devices, laptops, desktop computers, and servers. This versatile software simplifies a wide range of geographic tasks, from data production and editing to integration, management, modification, analysis, mapping, and reporting, making it user-friendly. Furthermore, ArcGIS Online extends its capabilities with web services that are accessible via web-enabled devices, browsers, and applications (Maguire, 2008).

2.2.2. Landsat mission

The Landsat program, originating from the launch of the Earth Resources Technology Satellite on July 23, 1972, stands as the world's most enduring initiative for acquiring satellite images. This program underwent changes and advancements, culminating in the latest addition, Landsat 8, launched on February 11, 2013. Throughout the years, Landsat satellites have amassed a vast collection of images, stored both in the United States and at various Landsat receiving stations globally. These images serve a multitude of purposes, encompassing applications in global change research, agriculture, cartography, geology, forestry, regional planning, surveillance, and education. Landsat 7 data comprises eight spectral bands and is conveniently accessible through the USGS's 'Earth Explorer' website, offering spatial resolutions spanning from 15 to 60 meters and a temporal resolution of 16 days. To facilitate retrieval, Landsat images are commonly grouped into scenes, each spanning approximately 115 miles in length and width (or 100 nautical miles, or 185 kilometers). Various sensors have been deployed as part of the Landsat program, including the Multispectral Scanner (MSS) on Landsat I through 5, the Thematic Mapper (TM) on Landsat 4 and 5, and the Enhanced Thematic Mapper Plus (ETM+) on Landsat 7. The Operational Land Imager (OLI) for optical bands and the Thermal Infrared Sensor (TIRS) for thermal bands are used by Landsat 8. The band designations, band passes, and pixel sizes for the Landsat instruments are-

Table 1 Landsat 1-5 Multispectral Scanner (MSS)

Landsat 1-5 MSS	**Landsat 4-5**	**Wavelength**	**Resolution**
	MSS	(micro-meters)	(meters)
Band 4 - Green	Band I - Green	0.5 - 0 6	60
Band 5 - Red	Band 2 - Red	0.6 - 0 7	60
Band 6 - Near Infrared NIR	Band 3 - NIR	0.7 - 0 8	60
Band 7 - NIR	Band 4 - NIR	0.8 - 1 1	60

Table 2 Landsat 4-5 Thematic Mapper (TM)

Bands	**Wavelength (micro-meters)**	**Resolution (meters)**
Band 1 - Blue	0.45 -0 52	30
Band 2 - Green	0.52 -0 60	30
Band 3 - Red	0.63 - 0 69	30
Band 4 - NIR	0.77 -0 90	30
Band 5 - SWIR 1	1.55 - 1 75	30
Band 6 - Thermal	10.40 - 12.50	60*(30)
Band 7 - SWIR 2	2.09-2 35	30
Band 8 - Panchromatic	0.52 - 0 90	15

Table 3 Landsat 7 Enhanced Thematic Mapper Plus (ETM+)

Bands	Wavelength (micro-meters)	Resolution(meters)
Band I - Blue	0.45-0.52	30
Band 2 - Green	0.52-0.60	30
Band 3 - Red	0.63-0.69	30
Band 4 - NIR	0.76-0.90	30
Band 5 - Shortwave Infrared (SWIR) 1	1.55-1.75	30
Band 6 - Thermal	10.40-12.50	120*(30)
Band 7 - SWIR 2	2.08-2.35	30

* TM Band 6 was acquired at 120-meter resolution, but products are resampled to 30meter pixels.

Table 4 Landsat-8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)

Bands	Wavelength (micro-meters)	Resolution (meters)
Band I - Ultra Blue (coastal/aerosol)	0.435 - 0.451	30
Band 2 - Blue	0.452 - 0.512	30
Band 3 - Green	0.533 - 0.590	30
Band 4 - Red	0.636 - 0.673	30
Band 5 - NIR	0.851 -0.879	30
Band 6 - SWIR 1	1.566 - 1.651	30
Band 7 - SWIR2	2.107 - 2.294	30
Band 8 - Panchromatic	0.503 - 0.676	15
Band 9 - Cirrus	1.363 - 1.384	30
Band 10 - Thermal I	10.600 - 11.190	100* (30)
Band 11 - Thermal 2	11.500 - 12.510	100* (30)

* ETM+ Band 6 is acquired at 60-meter resolution, but products are resampled to 30-meter pixels.

A fused silica minor epoxy, approximately the size of a dinner plate at 230 mm (9 inches), was affixed to three invar tangent bars connected to a base made of Ni/Au brazed Invar. This assembly was part of a Serrurier truss configuration featuring four "Hobbs Links," a concept developed by Dr. Gregg Hobbs. The ingenious design ensured that the secondary mirror could only oscillate along the primary optic axis, maintaining focus even when the 360 mm (14 inches) beryllium scan mirror vibrated (Dhara et al., 2023). This engineering innovation allowed the United States to develop LANDSAT several years ahead of the French SPOT satellite, which was the first to use CCD arrays for direct imaging without a scanner. However, by 1984, LANDSAT data costs had surged due to the commercialization efforts initiated under the Carter administration, later realized under the Reagan administration. Consequently, SPOT data became a more cost-effective choice for satellite imaging. The Multispectral Scanner's Focal Plane Array (FPA) was a 4x6 array consisting of 24 square optical fibers, each extruded to an incredibly small 0.005 mm (0.0002 inches) square fiber tip. While orbiting in a 1.5-hour polar path, these fibers underwent a sweeping scan spanning degrees, requiring a launch from Vandenberg Air Force Base. The fiber optic bundle was embedded within a fiber optic plate, connected to a relay optic device, and then routed to six photodiodes and 18 photomultiplier tubes arranged on a 7.6 mm (0.30 inches) thick aluminum tool plate. This entire apparatus was counterbalanced against the 230 mm telescope on the opposite side and incorporated into a frame, which was then securely fastened to the silver-loaded magnesium housing

The scan monitor, strategically positioned beneath the magnesium housing, was critical to the multispectral scanner's effectiveness. This component was made up of a diode-based light source and a sensor that was strategically placed at the ends of four flat mirrors. These mirrors were set at angles that required the light beam to reflect 14 times as it passed through the three mirrors. During its journey, the beam collided with the beryllium scan mirror eight times and bounced off the flat mirrors eight times. The sensor only collected data from three locations: the scan ends and the midpoint. Remarkably, these minimal data points sufficed to determine the multispectral scanner's precise direction by interpolation between them. The information gathered by the scan monitor was instrumental in calibrating the scanning data for accurate mapping display.

Landsat-7 ETM+ images began to show Scan Line Corrector (SLC) failures after May 31, 2003. The SLC, which consisted of two small mirrors synchronized with the movement of the main ETM+ scan mirror, was designed to compensate for the spacecraft's forward motion, ensuring that scans ran in parallel. Without the SLC, imaging would take place in a zig-zag pattern, with some regions duplicated while others remained unimaged. Approximately 22% of the data in scenes captured without a functional SLC was missing. The USGS, NASA, and Hughes Santa Barbara Remote Sensing formed an Anomaly Response Team (ART) to investigate potential causes, the majority of which pointed to a mechanical SLC issue. Given the lack of a backup SLC, this implied that the situation was likely permanent (Uddin et al., 2023). Although an electrical failure was deemed unlikely, on September 3, 2003, the USGS approved a conversion to the spacecraft's redundant electrical harness. However, this did not solve the SLC issue, necessitating a return to the primary electrical harness. The ART ultimately determined the SLC issue to be mechanical and permanent (Fayshal et al., 2023). Landsat 7 continued collecting data, with missing data in the products being supplemented using additional Landsat 7 data selected by users. Landsat 8 joined the mission in 2013.

2.3. Important indices

Here is the definition of some important indices that are used in this study

2.3.1. NORMALIZED Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is a widely used tool for assessing vegetation, particularly due to its simplicity in handling complex multispectral imagery. NDVI's popularity is attributed to its compatibility with most multispectral sensors equipped with visible and near-infrared ranges. These sensors can be mounted on various platforms, including satellites, aircraft, and unmanned aerial vehicles (UAVs).

NDVI calculates vegetation levels by comparing near-infrared light (highly reflected by vegetation) to red light (absorbed by vegetation). NDVI values always range from -1 to +1. While specific thresholds for different land covers don't exist, negative values typically indicate water, values near +1 indicate lush greenery, values near zero signify urban areas devoid of green vegetation, values between 0.2 and 0.4 often represent shrubs and grasslands, and values between 0.6 and 0.9 correspond to dense vegetation like temperate and tropical forests or robust crop growth. However, despite its utility, NDVI's widespread use, especially in UAV applications, raises concerns of potential misapplication by users without remote sensing expertise.

2.3.2. NORMALIZED Difference Water Index (NDWI)

The Normalised Difference Water Index (NDWI) is a tool for detecting and tracking changes in the content of surface water. It highlights water features by utilizing reflected near-infrared radiation and visible green light while minimizing the influence of soil and terrestrial vegetation. NDWI can also provide estimates of water turbidity based on remotely captured digital data. NDWI enhances the visibility of water-related characteristics while simultaneously reducing the prominence of vegetation and soil through zero or negative values by leveraging green band wavelengths to maximize water reflection and absorbing near-infrared wavelengths to minimize reflectivity. NDWI values, like NDVI, range from 1 to -1, with readings above 0.5 indicating the presence of a water body (Uddin et al., 2022).

2.3.3. LAND Surface Emissivity (LSE)

Land surface emissivity (LSE) is a fundamental property of natural materials that is frequently used to determine material composition, particularly for silicate minerals, even though its value varies depending on viewing angle and surface roughness. As a result, LSE is critical in a wide range of applications, including soil formation research, erosion assessment, estimation of sparse vegetative cover, monitoring changes in such cover, bedrock mapping, resource exploration, and precise estimation of surface energy budgets (Fayshal et al., 23).

2.3.4. Normalized Difference Built-up Index (NDBI)

Remote sensing images are valuable for monitoring urban land cover changes due to their ability to offer comprehensive and up-to-date insights. The Normalized Difference Built-up Index (NDBI) is a commonly used method for automating the mapping of built-up areas. It effectively identifies these areas by applying mathematical operations to recalibrated Normalized Difference Vegetation Index (NDVI) and Normalized Difference Vegetation Index (NDBI) images derived from Thematic Mapper (TM) data, producing NDBI values that range from -1 to 1. However, despite its usefulness in mapping urban built-up regions, the NDBI has certain limitations.

3. Conclusion

The paper focuses on analyzing the spatial distribution of Land Surface Temperature (LST) with a specific emphasis on its relevance in urban heat island research, climate change investigations, and evapotranspiration studies. It underscores the importance of considering elevation changes and establishing LST-elevation relationships across various seasons in a particular region. The study area's semi-arid climate is highlighted, making it clear that the findings might not be directly transferable to other climatic conditions. The challenges posed by cloud cover in satellite imagery during the monsoon season are addressed, stressing the need for selecting cloud-free images for accurate LST measurements. While recognizing the value of statistical data in enhancing the reliability of LST measurements, the study highlights the extensive efforts undertaken to achieve precision in the results. Moreover, it anticipates that this research will serve as a valuable guideline for future studies aiming to attain pinpoint accuracy in LST measurement and analysis.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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