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Assessment Of Spatio-Temporal Land Use/Cover Change And Its Effect On Land Surface Temperature In Bundi City, India

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Abstract
This study offers a reasonable investigation of the changes in land use and land cover (LULC) over the course of three decades (1991–2021) in Bundi city of Rajasthan. Remote sensing and GIS are the newest approaches for detecting changes in land use and land cover mapping. Data presentation, quality, and efficiency of the mapping are all enhanced by this technique. To study LULC variations in Bundi city, Landsat images (i.e., Landsat-5 and Landsat-8) obtained in the years 1991, 2001, 2011, and 2021 were used. For this study, a classification embraced of five classes—Crop Land, Barren & Shrubs Land, Vegetation, Water Bodies, and Built-Up Area—were considered. The interactive supervised classification technique was used to identify LULC. The findings of the study can help local governments impose urban planning laws, surge public awareness, and direct legislators in developing long-term sustainable planning and management methods. Land Use/Land Cover (LULC) changes have a large impact on Land Surface Temperature (LST). The LST is an indispensable indicator in environmental and climatological studies to understand the Earth's surface-atmosphere interactions.

Keywords: *Land use, satellite imagery, urbanization, Kappa coefficient, LST*

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I. Introduction

We are one of nature's most destructive forces, continuously modifying the environment to make it more conducive to our survival. The Earth's surface has changed dramatically throughout human history, with the construction of enormous walls, national border barriers, embankments, urban planning, industry, and agriculture. The conversion of natural vegetation to a human-induced landscape alteration typically leads in habitat fragmentation, degradation, and loss, which can have disastrous consequences for biodiversity (1). Changes in land use and cover are a significant component of global environmental change. Remote sensing data can be used to study changes in land use and cover, including changes in landscape structure, location, and quantity over time. Geospatial applications are the most effective way to assess land use and cover (2). Land use and management methods in India are fast changing as a result of the country's rapid population and economic growth, with substantial consequences for the urban environment (3). Urbanization has caused drastic changes in land cover (4). The term "land cover" refers to the natural layer that is present on the surface of the land, whereas the term "land use" relates to the activities that are carried out by humans on the land (5).

Many scholars around the world are keeping a watch on these transitions in land use, which are caused by the interaction of a society's physical demands, state, and cultural legacy with the land's intrinsic potential, in order to increase understanding of humans, the natural world, and natural resources (6). Natural resources are under immense pressure due to population increase, urbanization, climate change, economic growth, environmental degradation, and resource depletion (7). Rapid population growth has led to a shift from rural to urban areas due to factors such as employment, healthcare, and infrastructure. This has put additional stress on natural resources (8). Remote sensing and GIS are now cost-effective and time-saving for LULC changes at micro to macro scales, thanks to advancements in technology (9). Identifying temporal and spatial alterations in built-up area expansion and population growth is crucial for ensuring the city's sustainable future. Knowledge of historical, present, and future LULC changes allows for an accurate assessment of their socioeconomic and environmental impact. LULC change studies provide insights into rapidly changing areas, landcover types, transformations, land use rates, and factors of change (10).

Heatwaves and extreme summer temperatures are becoming more regular. They are predicted to become much more common in the northern hemisphere in the next decades, particularly in the Indian subcontinent, as rising temperatures arrive earlier and stay for longer periods (11). Furthermore, heatwaves are projected to increase in frequency, length, and intensity under climate change, according to various research (12). Various studies have been conducted on the relationships between LULC and Land surface temperature (LST) in India and across the globe. Researchers used geospatial technology to study the relationship between LULC and LST in various locations throughout the world. However, more research is needed to understand the impact of urban LULC on LST and urban heat islands, particularly in India. Land Surface Temperature (LST) refers to the earth's radiative skin temperature resulting from solar radiation (13). The amount of sunlight received by the earth's surface and the type of LULC affect this. This is a crucial indicator of the earth's energy balance and a fundamental metric for studying microclimates (14).

Several studies in India have examined disparities in LULC at both geographical and administrative levels. Haadiya et al 2024, analysed the land use of Jammu district of India using remote sensing (7), Prasad et al 2021 undertook spatio temporal analysis of land use and landcover in Delhi-NCR using satellite data (3), Pawar and Singh 2021 performed similar study for central Haryana using geospatial data (15), Kumar et al 2024 evaluated the dynamics of land use and land surface temperature of Hyderabad city (16), Ravi 2022 used remoted sensing for LULC detection of Jind district of Haryana (17). Yadav et al 2022 used satellite data to delineate Eru river watershed and Yadav et al 2023 used satellite data and GIS to identify the waste dumping site for Bundi city (18).

This study examines how Land Use/Land Cover Change (LULC) affects Land Surface Temperature (LST) in Bundi, Rajasthan. The study relies heavily on Landsat satellite data. Remote sensing data is commonly used to analyse environmental changes, including changes in land use, land cover, forest area, water bodies, and urbanization. To create strong and environmentally friendly urban areas that provide pleasant living conditions for their residents, actions must be taken to minimize LST effects while implementing measures to adapt.

II. Materials And Methods

Study Area

Bundi is located in southeast Rajasthan, a western state in India between latitudes $25^{0}23^{l}$N and $25^{0}29^{l}$N and longitudes $75^{0}35^{l}$E and $75^{0}40^{l}$E. It is located 210 kilometres southeast of Jaipur, the state capital. The city's population grew slowly, from 26478 in 1961 to 103286 in 2011. Summer temperatures in Bundi range from 42 to 48 degrees Celsius. The average rainfall during the monsoon season is between 650 and 750 mm. The temperature throughout the winter fluctuates from 3 to 8 degrees Celsius. This city is encircled by hills on three sides, creating a lovely setting. Its position, combined with its ancient architecture, make the city a significant element of the state's tourism map. The city has an area of 48.17 sq.kms divided into 60 wards.

Data base

Landsat imaging is the major data source for analysing changes in land use, land cover, and land surface temperature (LST). Pre-monsoon Landsat data is used to prevent cloud cover and improve analysis. Data for April was downloaded from NASA's Earth Explorer (USGS) data portal for identifying LULC and LST with 30 metre resolution. The present study is based on the thirty years data from 1991 to 2021. ArcGIS 10.8 software has been used to perform the study. Satellite pictures from 1991, 2001, 2011, and 2021 of the same months were used to minimize seasonal differences and improve classification accuracy. The study area's land use and cover were classified using optical bands, and land surface temperatures were generated using thermal infrared bands. The data was reprojected onto the 43N zone of the Universal Transverse Mercator (UTM) projection system.

Image Processing

This study uses the supervised maximum likelihood classification technique to analyse variations in LULC. It is an important technique for extracting numerical quantities from remote sensing satellite image data. In ArcGIS 10.8, supervised classification uses the False Colour Composite (FCC) to determine regions of interest for features including water bodies, vegetation, Barren & Shrubs land and built-up areas. Large number of pixels are taken from each category which forms the spectral signature. The spectral signature of each class is determined using reference data and pixel selection for each LULC type. Pixels define areas of a picture based on colour categories and spectral uniformity. To facilitate analysis and change detection, LULC types are classified into five categories. The satellite image resolution of 30 m makes it impossible to do more than five LULC classifications, hence this technique is utilized. LULC categories include water bodies, Barren & Shrubs land, vegetation, built up area and sparse vegetation or agriculture.

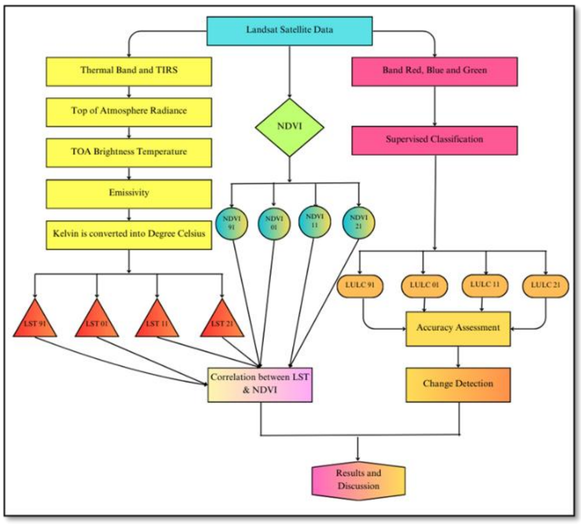

Figure 1: Flow chart of the Research Methodology

Accuracy assessment

The Kappa Coefficient, commonly known as Cohen's Kappa Score, is a statistic that assesses the agreement between predicted and actual values in a confusion matrix. It is a metric of classifier performance that is based on the traditional 2x2 confusion matrix. A kappa value of one indicates perfect agreement, whereas a value of zero indicates no agreement. There is no standard interpretation of the kappa statistic, however Landis and Koch regard 0-0.20 to be modest, 0.21-0.40 to be fair, 0.41-0.60 to be moderate, 0.61-0.80 to be significant, and 0.81-1 to be almost perfect. Fleiss rates kappas above 0.75 as outstanding, 0.40-0.75 as fair to good, and < 0.40 as poor. The kappa coefficient is computed as follows: $k = \frac{N\sum_{i=1}^{n} mi,i - \sum_{i=1}^{n}(GiCi)}{N^2 - \sum_{i=1}^{n}(GiCi)}$

Where:
- i is the class number
- N is the total number of classified values compared to truth values
- mi,i is the number of values belonging to the truth class i that have also been classified as class i (i.e., values found along the diagonal of the confusion matrix)
- Ci is the total number of predicted values belonging to class i
- Gi is the total number of truth values belonging to class i

Land cover change detection analysis

The land cover of 1991,2001,2011 and 2021were prepared by using the ArcGIS software while the change of LULC from 1991 to 2021 was done using the MOLUSCE tool of QGIS software.

Estimation of Land Surface Temperature (LST)

It is calculated using the methodology given below. This is for Landsat 8 imagery.

Top of Atmosphere (TOA) Radiance: the top of the atmosphere is the boundary where solar energy enters the planet while top of the atmosphere radiance is the electromagnetic radiation received from the sun or emitted by the earth's surface at the top of the atmosphere. Thermal infrared digital number is converted into spectral radiance.

$$L\lambda = ML \times QCaL + AL$$

Where, $L\lambda$ = TOA Spectral Radiance
ML = Radiance Multiplicative band
QCaL = Quantized and calibrated standard product pixel values (DN)
AL = Radiance Add band
For Landsat 5 and 7 imagery we use the following formula
$L\lambda = (\frac{L\,max\,\lambda - L\,min\,\lambda}{Qcalmax - Qcalmin}) \times (Qcal - Qcalmin) + Lmin\lambda$
Where, $L\lambda$ = TOA Spectral Radiance
Qcal = Quantized calibrated pixel value in DN
Lminλ = Radiance minimum of Band 6
Laxλ = Radiance maximum of Band 6

Qcalmax = Maximum quantized calibrated pixel value of Band 6
Qcalmin = Minimum quantized calibrated pixel value of Band 6

Top of Atmosphere Brightness Temperature: Spectral radiance data can be converted to the TOA brightness temperature using the thermal constant values in metadata file to degree Celsius. This is same for all Landsat images.

$$BT = k_2 \;/\; L_n(k_1 \;/\; L\lambda + 1) - 273 \cdot 15$$

Where, BT = Top of Atmosphere Brightness Temperature
K_2 = Calibration Constant 2
K_1 = Calibration Constant 1
Lλ = TOA Spectral Radiance

Table 1: Thermal Band Calibration Constants

Sensor	Constant K_1 (Watts/(m^2 * sr * μm))	Constant K2 Kelvin
Landsat 8 OLI	774.8853	1321.0789
Landsat 7 ETM	666.09	1282.71
Landsat 5 TM	607.76	1260.56

Calculation of Normalized Differential Vegetative Index (NDVI):

It quantifies vegetation by measuring the difference between near infrared and red light. It is calculated using near infrared (band 5) and red (band 4).

NDVI = (NIR – Red) / (NIR + Red)

Based on NDVI values proportion of vegetation (PV) is calculated.

$PV = [\ (NDVI – NDVImin) / (NDVI + NDVImax)]^{2}$

Land surface emissivity:

It is a geophysical parameter which determines the microwave radiative transfer over land and is calculated from NDVI values.

E = 0.004 x PV + 0.986

Where, E = Land surface emissivity
PV = Proportion of vegetation

Land Surface Temperature (LST):

It is the radiative temperature which is calculated using top of atmosphere brightness temperature, wavelength of emitted radiance and land surface emissivity.

$$LST = \frac{BT}{\left[1 + \left(\left(\frac{\lambda BT}{p}\right) ln\, E\right)\right]}$$

Where, LST = Land Surface Temperature
BT = Top of Atmosphere Brightness Temperature
λ = (≈11.5 μm) is the effective wavelength of emitted radiance,

E = Land surface emissivity and $p = h\left(\frac{c}{\sigma}\right)$ where, σ is the Boltzmann constant, h is Planck's constant and c is the velocity of light

The LST values were calculated using the 6th band of the Landsat 5 TM and Landsat 7 ETM the and the 10th band of the Landsat 8 OLI/TIRS imageries and emissivity data created from the NDVI.

III. Results And Discussion

LULC Classification and Change Detection

The estimates for the LULC classification were done for the years 1991,2001,2011 and 2021. The classified LULC maps of Bundi city are presented in Figure 2 and quantified in Table 2.

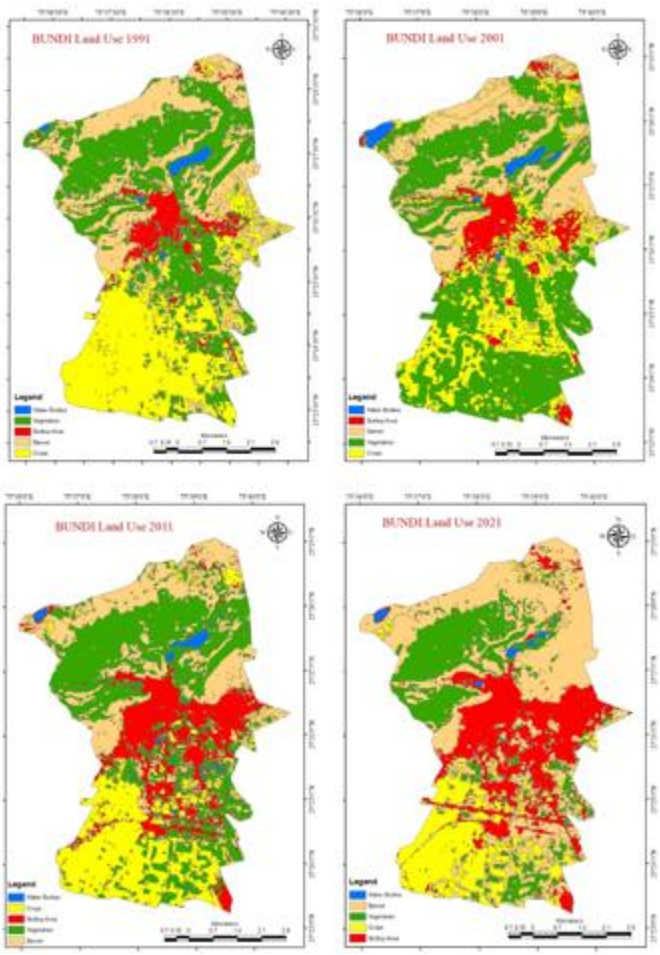

Figure 2 Classified LULC of Bundi city from 1991 to 2021

The classes used are water bodies, vegetation, Barren & Shrubs land, built up area and agricultural or cropland. In Bundi city, built-up land increased from 3.03km^2 (6.29%) in 1991 to 10.73km^2 (22.28%) in 2021, making it the most prevalent of the five LULC kinds.

Table 2: LULC distribution in 1991,2001,2011 and 2021

LULC Type	1991		2001		2011		2021	
	Area (in km^2)	Area in%	Area (in km^2)	Area in%	Area (in km^2)	Area in%	Area (in km^2)	Area in%
Water bodies	0.44	0.91	0.79	1.64	0.64	1.33	0.31	0.64
Vegetation	15.94	33.09	20.67	42.91	16.58	34.42	9.19	19.08
Built up area	3.03	6.29	3.88	8.05	8.38	17.40	10.73	22.28
Barren & Shrubs	13.45	27.92	11.17	23.19	11.91	24.72	19.94	41.40
Crops	15.31	31.78	11.66	24.21	10.66	22.13	8	16.61
Total	**48.17**	**100.00**	**48.17**	**100.00**	**48.17**	**100.00**	**48.17**	**100.00**

Agricultural and forest land declined from 15.31 km^2 (31.78%) and 15.94 km^2 (33.09%) in 1991 to 8 km^2 (16.61%) and 9.19 km^2 (19.08%) in 2021, respectively. Meanwhile, water bodies remained mostly untouched. Between 1991 and 2021, the proportion of Barren & Shrubs lands increased from 27.92% to 41.4%. Urbanization has led to a decline in agricultural land and an increase in built-up areas. The LULC classification and change detection suggest that Bundi city's urbanization plays a significant role in the shift from natural to built-up land.

Accuracy Assessment

Satellite image classification requires accuracy checks and assessments to ensure quality (19). The accuracy assessment is an important phase in the LULC classification process. Accuracy evaluation measures the quantitative accuracy with which pixels were assigned to land cover classes (20). The accuracy of the classification was performed with the help of a confusion matrix. The confusion matrix and accuracy of LULC classification in 1991, 2001, 2011 and 2021was done and the results were 0.839, 0.819, 0.874 and 0.855 respectively. Although the images were carefully identified, there was some discrepancy between built-up and open spaces due to similar reflectance values. Increasing the number of ground training locations did not improve classification accuracy. The result of overall accuracy is above 80%, which is strong agreement of land use and land cover classification studies.

Change Detection

Changes in LULC are measured as a percentage of total land area. Positive numbers imply enhanced classifications, whereas negative ones show decline. In 2021, the urban and built-up LULC class area has grown by 16%, while other LULC classes, such as shrubs and barren land, has risen by 13% (Table 3 and Figure 3). Table 3 indicate that there is slight decline in the area of water bodies, while there is a considerable decline in the area of vegetation and croplands. The agricultural area has gone for the urban expansion.

Table 3: LULC change analysis for the years 1991 and 2021

LULC Type	1991		2021		Change in %
	Area (in km^2)	Area in%	Area (in km^2)	Area in%	
Water bodies	0.44	0.91	0.31	0.64	-0.27
Vegetation	15.94	33.09	9.19	19.08	-14.013
Built up area	3.03	6.29	10.73	22.28	15.985
Barren & Shrubs	13.45	27.92	19.94	41.4	13.473
Crops	15.31	31.78	8	16.61	-15.175

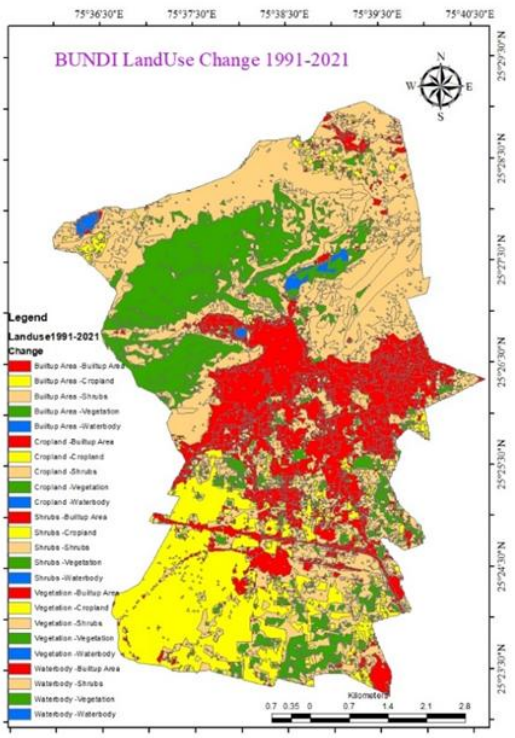

Figure 3 LULC changes from 1991 to 2021

Normalized Differential Vegetative Index (NDVI):

Vegetation cover is an important feature of the earth's surface. Its distribution, intensity, and consistency significantly impact land surface temperature in any area. Table 4 shows the vegetation covering in the research area using satellite images from 1991 to 2021, with ten-year intervals. NDVI values range from +1 to -1. Negative values indicate water bodies and lack of vegetative cover (21). On the other hand, positive values close to 1 indicate dense vegetative cover (22).

Table 4: Statistics of Normalized Differences Vegetation Index (NDVI)

	1991	2001	2011	2021
Minimum	-0.14286	-0.50413	-0.23913	-0.07096
Maximum	0.459119	0.556756	0.435028	0.528219
Mean	0.056214	0.066089	0.066116	0.195829
Standard Deviation	0.057883	0.602916	0.059969	0.072019

The trend in the mean NDVI value fluctuated, it increased from 1991 to 2021(Table 4). This indicates changes in the vegetative density.

Land Surface Temperature

Temperature data for the region was analysed from 1991 to 2021 in 10-year intervals. The maximum temperatures over the region had a slight variation as it lied between 43.98 degree Celsius to 48.12 degree Celsius. Meanwhile, the minimum temperatures varied from 0.89 degree Celsius to 7.37 degree Celsius.

Table 5: Statistics of Land Surface Temperature (LST)

	1991	2001	2011	2021
Minimum	27.52	26.67	27.52	29.74
Maximum	43.34	44.83	45.20	45.16
Mean	39.84	39.85	39.91	38.81
Standard Deviation	2.11	2.33	2.12	2.64

Table 5 shows the statistics of Land surface temperature for the time period 1991 to 2021. The mean temperatures remained around 40 degrees Celsius except in 2021 it was a bit lower as the minimum temperature this year had increased. LST maps are prepared (Figure 4) to depict the distribution of LST in the study area. The maximum LST was observed in 2021 as 45.2 degree Celsius and minimum LST was recorded in 1991 a 43.3 degree Celsius.

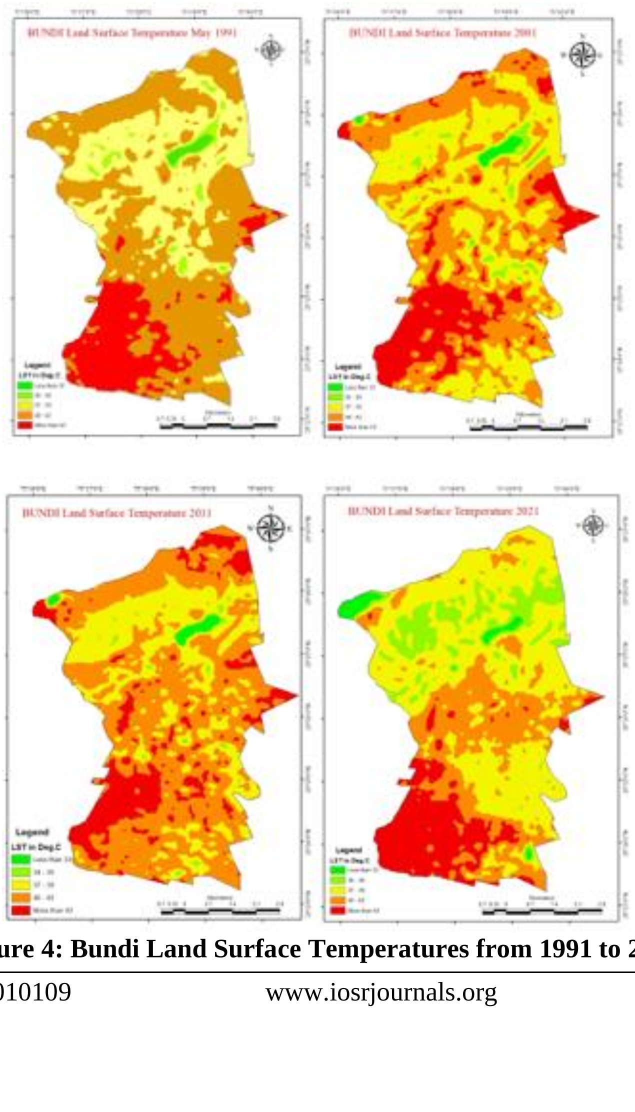

Figure 4: Bundi Land Surface Temperatures from 1991 to 2021

The results of Figure 4 show a common pattern that topography of the area has led to variations in LST. The lowest LST in all the years was recorded over the water bodies while the maximum LST was recorded in the south eastern parts of the study area which is close to the railway track and is open land used for crops. Vegetation plays a key role in moderating the temperatures and the figure 4 shows that as the vegetation declines in the area there is a gradual escalation in temperatures. The rise in temperatures can be linked to the increase in crop lands. During 2001, the green color of vegetation is because of orchards of guava which shrunk over the years because of urban expansion leading to new colonies and marriage gardens. To obtain correlation data, the "create fishnet" and "extract multi values to point" functions were used using ArcGIS. The data were then analyzed and shown using a scatter plot investigation tool in MS Excel. Using the ArcGIS software made it easier to examine the correlation and overall state of the study area. LST and NDVI for all four study years have negative correlation, with R square value of 0.1075, 0.4343, 0.2255 and 0.1575 respectively. The negative correlation means that the LST decreases as vegetation grows.

IV. Conclusions

The ecology, and long-term development of a region are all disturbed by LULC changes. Accurate and detailed information on LULC is essential for better long-term regional development at all levels. Ground truth verification increases the accuracy and dependability of geospatial technique-based results. Human activities are mostly responsible for the LULC transition in Bundi city. The built-up areas and barren lands have increased while the vegetation and crop land has reduced over the years. This is due to urbanisation which is worrisome.

The data also demonstrate that the area's LST varies due to terrain differences. The results show a strong negative relationship between LST and NDVI. To lower LST, farmers should focus on maintaining greenery. Urban green belts especially rooftop gardens can minimize the effect of LST on cities, creating a more environmentally friendly ecosystem. More research is required to fully appreciate the complex relationships between LULC change and LST, as well as establish effective land use management techniques that balance human demands with environmental equitability.

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References

[1] Taloor, A. K., Kumar, V., Singh, V. K., Singh, A. K., Kale, R. V., Sharma, R., Khajuria, V., Raina, G., Kouser, B., & Chowdhary, N. H. (2020). Land Use Land Cover Dynamics Using Remote Sensing And GIS Techniques In Western Doon Valley, Uttarakhand, India. In Advances In Geographical And Environmental Sciences (Pp. 37–51). Https://Doi.Org/10.1007/978-981-15-2097-6_4

[2] Ehlers M., Jadkowaski M.A., Howard R.R., Brostuen D.E. (1990) Application Of SPOT Data For Regional Growth Analysis And Local Planning. In Photogrammetric Engineering And Remote Sensing, Vol.58, Pp.175–180.

[3] Wilken, F., Wagner, P. D., Narasimhan, B., And Fiener, P. (2017). Spatio-Temporal Patterns Of Land Use And Cropping Frequency In A Tropical Catchment Of South India. In Applied Geography, 89, 124-132.

[4] Prasad, S., & Singh, R. B. (2018). Urbanization And Land Use/Land Cover Change In Varanasi City. In National Geographical Journal Of India, 64(1-2), 185-197.

[5] García-Á Lvarez, D.; Olmedo, M.T.C.; Mas, J.-F.; Paegelow, M. (2022) Land Use Cover Mapping, Modelling And Validation. A Background In Land Use Cover Datasets And Validation Tools; Springer International Publishing: Cham, Switzerland, Pp. 21–33. Https://Doi.Org/10.1007/978-3-030-90998-7_2.

[6] Taloor, A. K., Kumar, V., Singh, V. K., Singh, A. K., Kale, R. V., Sharma, R., Khajuria, V., Raina, G., Kouser, B., & Chowdhary, N. H. (2020). Land Use Land Cover Dynamics Using Remote Sensing And GIS Techniques In Western Doon Valley, Uttarakhand, India. In Advances In Geographical And Environmental Sciences (Pp. 37–51). Https://Doi.Org/10.1007/978-981-15-2097-6_4

[7] Saleem, Haadiya & Ahmed, Rayees & Mushtaq, Shaista & Saleem, Shahid & Rajesh, Mudigandla. (2024). Remote Sensing-Based Analysis Of Land Use, Land Cover, And Land Surface Temperature Changes In Jammu District, India. In International Journal Of River Basin Management. Pp.1-16. 10.1080/15715124.2024.2327493.

[8] Tacoli, C., Mcgranahan, G., And Satterthwaite, D. (2015). Urbanisation, Rural-Urban Migration And Urban Poverty. London: In Human Settlements Group, International Institute For Environment And Development.

[9] Giri, C., Pengra, B., Long, J., & Loveland, T. (2013). Next Generation Of Global Land Cover Characterization, Mapping, And Monitoring. International Journal Of Applied Earth Observation And Geoinformation, 25, 30–37. Https://Doi.Org/10.1016/J.Jag.2013.03.005

[10] Loveland, T. R., And Acevedo, W. (2006). Land Cover Change In The Eastern United States Status And Trends In Eastern United States Land Cover Pretty J, Noble AD, Bossio D, Dixon J, Hine RE, Penning De Vries FWT, And Morison JIL Resource-Conserving Agriculture Increases Yields In Developing Countries. In Environmental Science And Technology, 40 (4), 1114–1119

[11] Krishnan, R.; Sanjay, J.; Gnanaseelan, C.; Mujumdar, M.; Kulkarni, A.; Chakraborty, S. (2020) Assessment Of Climate Change Over The Indian Region. In A Report Of The Ministry Of Earth Sciences (Moes); Government Of India: New Delhi, India

[12] Perkins, S. E., Alexander, L. V., & Nairn, J. R. (2012). Increasing Frequency, Intensity And Duration Of Observed Global Heatwaves And Warm Spells. Geophysical Research Letters, 39(20). Https://Doi.Org/10.1029/2012gl053361

[13] John, J.; Bindu, G.; Srimuruganandam, B.; Wadhwa, A.; Rajan, P. (2020) Land Use/Land Cover And Land Surface Temperature Analysis In Wayanad District, India, Using Satellite Imagery. In Ann. GIS, 26, 343–360.

[14] Khandelwal, S.; Goyal, R.; Kaul, N.; Mathew, A. (2018) Assessment Of Land Surface Temperature Variation Due To Change In Elevation Of Area Surrounding Jaipur, India. In Egypt. J. Remote Sens. Space Sci. 21, 87–94.

[15] Pawar, S., & Singh, R. (2021). Geospatial Applications In Land Use/Land Cover Change Detection For Sustainable Regional Development: The Case Of Central Haryana, India. In Geomatics And Environmental Engineering, 15, 81–98.
[16] Pardeep Kumar, Pratyush Verma, Bhawna Yadav Et Al. (2024) Evaluating The Dynamics Of Land Use And Land Cover Changes In Relation To The Land Surface Temperature Of Hyderabad City, PREPRINT (Version 1) Available At Research Square [Https://Doi.Org/10.21203/Rs.3.Rs-3873203/V1]
[17] Kumar, Ravi. (2022). Remote Sensing And GIS-Based Land Use And Land Cover Change Detection Mapping Of Jind District, Haryana. 03. 869-874.
[18] Yadav, S., Khan, Z., & Sharma, D. K. (2022). Morphometric Analysis To Infer Hydrological Behaviour Of ERU Watershed, Western India. In IOSR Journal Of Humanities And Social Science, 27(3), 46–54. Https://Doi.Org/10.9790/0837-2703084654
[19] Lillesand, T.; Kiefer, R.W.; Chipman, J. (2000) Remote Sensing And Image Interpretation; John Wiley & Sons: New York, NY, USA, Volume 4, ISBN 978-1-118-34328-9.
[20] Rwanga, S. S., And Ndambuki, J. M. (2017). Accuracy Assessment Of Land Use/Land Cover Classification Using Remote Sensing And GIS. In International Journal Of Geosciences, 8 (04), 611–622.
[21] Singh, P., & Javeed, O. (2020). NDVI Based Assessment Of Land Cover Changes Using Remote Sensing And GIS (A Case Study Of Srinagar District, Kashmir). In Sustainability, Agri, Food And Environmental Research, 8 (X), Http://Dx.Doi.Org/107770/Safer-V0N0-Art2174
[22] Jothimani, M., & Gunalan, J. (2021) Study The Relationship Between LULC, LST, NDVI, NDWI And NDBI In Greater Arba Minch Area, Rift Valley, Ethiopia. In Proceedings Of The 3rd International Conference On Integrated Intelligent Computing Communication & Security, Atlantis Highlights In Computer Sciences, (4)