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Spatio-Temporal Analysis of Land Use Changes and their Impact on Temperature and Vegetation in Dimapur District

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Abstract

Anthropogenic changes in land use and cover (LULC) have a substantial impact on ecosystems worldwide. Deforestation and urbanization contribute to rising Land Surface Temperature (LST). This study investigates the interrelationship of LULC, Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), and LST in Dimapur District over 1991, 2001, 2011, and 2021. Landsat-5 TM, Landsat-7 ETM+, Landsat-8 OLI/TIRS data were utilized for analysis. Using the maximum likelihood technique from the supervised classification method, LULC changes were assessed. Findings reveal a 20.07 % forest reduction and an 135.32 % built-up increase from 1991 to 2021. Mean LST surged from 17.24°C (1991) to 26.98°C (2021). There is a positive association between LST and NDBI (0.43 to 0.71) and a negative correlation between LST and NDVI (0.14 to 0.45) according to the correlation analysis. To delve further into the relationship between NDVI, NDBI, and LST, Geographically Weighted Regression (GWR) was designated. While the R2 adjusted values for NDBI and LST ranged from 0.82 to 0.99 during the years, the R2 adjusted values for NDVI and LST stayed constant at 0.99. Land management and development must be prioritized, and government officials and legislators must diligently monitor changes in LULC, LST, NDVI, and NDBI.

Key words: LULC, LST, NDVI, NDBI

Introduction

The term "land use land cover" (LULC) refers to the approach to surface mapping that takes into account various land use activities and the corresponding land cover features. It involves studying the land's natural and anthropogenic elements, including things like grasslands, wetlands, and water bodies, as well as things like urban development, farming, forestry, and mining. (Hussain et al., 2022 and Jalayer et al., 2022). Many fields depend on LULC mapping and monitoring, including biodiversity protection, urban planning, environmental management, natural resource evaluation, studies of climate change. Insights like this aid policymakers in pinpointing problem regions, establishing conservation priorities, and planning long-term strategies for land use (Abijith and Saravanan, 2022). It is becoming more important to identify changes in LULC as a result of rising urbanization and the demand for basic human necessities. Longitudinal studies of land alteration patterns and the causes contributing them are urgently needed due to the ever-increasing agricultural expansion and infrastructure development (Ritse et al., 2020).

Among the many immediate and distant effects of urban expansion is a rise in land surface temperature (LST). (Keerthi and Chundeli, 2023).

The need of evaluating agricultural land, crop production regions, and wooded areas for future planning is growing as urban growth and environmental fluctuation persist. In this way, we can be sure that the requirements of our expanding population will be adequately met in the future (Shah et al., 2022). Two primary indices for vegetation and built-up estimation are the Normal Difference Vegetation Index (NDVI) and the Normal Difference Built Index (NDBI). One spatial biophysical metric that can be used to analyze the effect of LULC changes on regional temperatures is the normalized difference vegetation index (NDVI), which distinguishes between vegetated and non-vegetated areas. (Singh et al., 2024).

Over the recent years, the NDVI, NDBI and LST has commonly been employed to characterize the spatiotemporal characteristics of LULC.

The Dimapur District in Nagaland is now experiencing a significant increase in urbanization. The district has experienced urban expansion due to the combination of a growing population, increased economic activities, and infrastructure development. This process entails various issues pertaining to land use planning, housing, transportation, and environmental conservation. The conversion of agricultural and forested lands, as well as the restoration of wetlands for urban and infrastructure development, leads to the extensive removal of vegetation. This puts significant pressure on urban ecosystems and adds strain to nearby ecologically sensitive areas. This phenomenon is particularly noticeable in major urban centers in Nagaland, such as Dimapur and Kohima (Yadav and Shinde, 2015).

Few studies have been conducted to examine the LULC variations in Nagaland. Ritse et al., (2020) discovered that there was a loss in agricultural land in both the Dimapur and Kohima districts between 1998 and 2018, when four major LULC classes were identified. Hiese et al., (2020) examined the land use changes that have occurred in Nagaland during the past ten years, both spatially and temporally (2005-2016). It has been noted that the practice of jhum cultivation has had a major role in the dynamic shift in land cover and use. Neog (2022) examined the changes in land cover and use in Dimapur City, their pattern, and their effect on land surface temperature (LST). The impact of population-induced land use and land cover change on LST development in the Dimapur urban region is supported by the bigger positive connection between population and built-up areas and LST and the stronger negative association between vegetation and population and LST.

Kikon et al., (2022) used the Mono-window technique to obtain the land surface temperature (LST) spatial distribution for Kohima Sadar for the years 2009, 2015, and 2020.

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The findings suggested that there was a positive association between LST and BUI and a negative correlation between LST and NDVI. Kikon et al., (2023) analysed land surface temperature (LST), land use land cover (LULC), normalized difference vegetation index (NDVI), normalized difference built-up index (NDBI), and urban thermal field variance index (UTFVI) over Kohima Sadar on a kilometre scale.

Based on the comprehensive review of existing literature, it is evident that previous studies have primarily focused LULC and LST analysis in Dimapur district. However, there is a notable gap in the literature regarding the integration of NDVI, NDBI indices and LST with LULC analysis. In light of this, our study aims to bridge this gap by investigating the spatiotemporal dynamics of LULC in Dimapur for the years 1991, 2001, 2011, and 2021, while also incorporating the inter relationship of NDVI and NDBI with LST to comprehensively assess the temporal and spatial characteristics of the generated LULC data.

Materials and Method

Study Area

One of the "Seven Sisters" of the North East Region, Nagaland is the sixteenth state in India. The state's borders are as follows: South of the state is Manipur, north is Arunachal Pradesh and part of Assam, west is Assam, and east is Myanmar. Its total size is 16,579 square kilometres. The yearly rainfall spans around 7 months, from April to October, and ranges from 1500 to 2500 mm. There is a temperature range of 4°C to 35°C.

The location of Dimapur is southwest of Nagaland. Dimapur, the eighth district of Nagaland, was founded in December 1997 and is located between latitudes 25°48′ and 26°00′ North and longitudes 93°30′ and 93°54′ East. Assam borders the district on the north and west, Kohima borders it on the east, and Peren District borders it on the south. The average temperature is 24.0°C, and there is 1560 mm of rainfall annually. The centre of commerce for Nagaland is Dimapur. There have been noteworthy changes in the weather patterns over the years in Dimapur District of Nagaland. Modifications in temperature, precipitation, and monsoon patterns are among these changes. Seasonal weather patterns in Dimapur have changed, resulting in more unpredictable rainfall, modified monsoon start and withdrawal dates, and sporadic extreme weather occurrences like intense rainstorms or droughts.

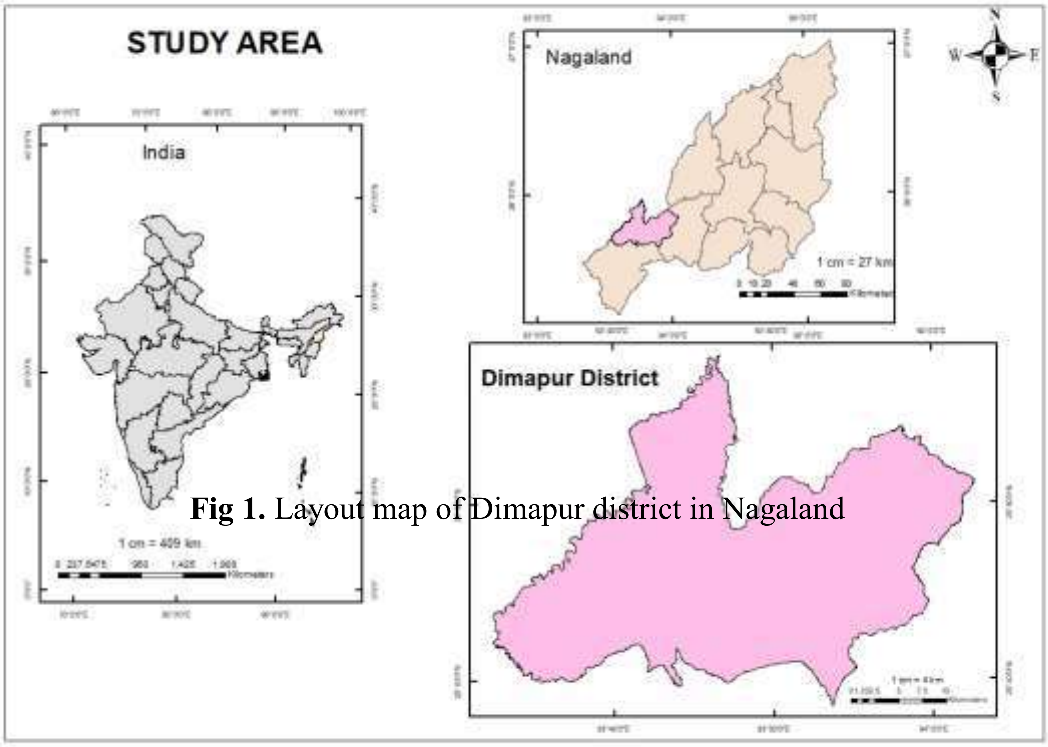

Fig 1. Layout map of Dimapur district in Nagaland

Data Collection and Data Pre-Processing

Landsat images were downloaded from the United States Geological Survey (USGS) website (https://earthexplorer.usgs.gov). The landsat images were downloaded for the years 1991 (Landsat 5 Thematic Mapper (TM)), 2001 (Landsat 7 Enhanced Thematic Mapper Plus (ETM+)), 2011 (Landsat 5 TM) and 2021 (Landsat 8 Operational Land Imager (OLI) and the Thermal InfraRed Sensor (TIRS)). The Landsat images selected were accurate, clear, precise and most importantly cloud cover free. Free cloud cover ensures accurate processing of images.

To enhance the overall quality of the satellite photos, both geometric and radiometric modifications were applied. The black border with no data values of the raster image was eliminated using the copy raster.

Land use land cover

Based on the existing land use distribution of study area, the study area is categorized into six broad LULC classes namely as forest land (dense/open forests, tall grass, scrub lands etc.), water body (rivers, lakes, ponds and reservoirs), built up (rural and urban built up, commercial, industrial, transportation), agricultural land (crop fields and farm lands), wasteland (land areas of exposed soil and barren area due to anthropogenic influence), shifting cultivation. The maximum likelihood technique from supervised classification method was chosen to perform image classification in Arc GIS 10.5. This method has three stages as training, class allocation and testing (Mathur and Foody, 2008).

Accuracy Assessment

To perform the accuracy assessment of LULC in Arc GIS, 273 random points were generated using the "Create Random Points" tool. The land class values at these points were extracted from the LULC maps with the "Extract Values to Points" tool. These points were then verified using Google Earth Pro to ensure accurate land class representation. The classification accuracy of satellite images can be assessed by calculating overall accuracy and Kappa Coefficient (K). The overall accuracy can be estimated by determining user and producer accuracy (Hussain et al., 2022; Hu et al., 2023 and Naeem et al., 2022)

Estimation of NDVI

NDVI was calculated for the monitoring of vegetation area. The NDVI values were estimated as follows (Wang et al., 2003):

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

Where, NIR is near-infrared band (TM and ETM band 4, OLI band 5)

R is the red band (TM and ETM band 3, OLI band 4).

Plants' leaves reflect near-infrared radiation (NIR), whereas chlorophyll absorbs it. An elevated NDVI suggests a high concentration of vegetation. On the other hand, there is little to no vegetation potential if the NDVI is low. Regions with exposed rock, sand, or snow are correlated with extremely low NDVI values (below 0.1).

High values (0.2 to 0.3) indicate tropical and temperate rainforests, whereas moderate values (0.6 to 0.8) represent grasslands and shrublands (Hu et al., 2023).

Estimation of NDBI

The NDBI was used to calculate built-up lands (Pal and Ziaul, 2017)

$$NDBI = \frac{MIR-NIR}{MIR+NIR} \quad (2)$$

Where,

MIR is the band 5 (Landsat TM and ETM+) or band 6 (Landsat OLI) and

NIR is the band 4 (Landsat TM and ETM+) or band 5 (Landsat OLI).

Estimation of Land Surface Temperature (LST)

The joint temperature of all entire things that exist on Earth is referred to as the LST (Hussain and Karuppannan, 2021). Multispectral Landsat photos from satellite observatories will be utilized to analyze the Land Surface Temperature. The steps for calculation of LST are given (NASA 2000):

1) Lλ values were estimated to spectral radiance for LANDSAT 5 TM and LANDSAT 7 ETM by Equation (3 and 4).

$$L_\lambda = \left(\frac{LMAX_\lambda - LMIN_\lambda}{QCALMAX - QCALMIN}\right).(QCAL - QCALMIN) + LMIN_\lambda \quad (3)$$

In the case of LANDSAT 8,

$$L\lambda = M_L \times QCAL + \Delta_L \quad (4)$$

Where, Lλ is the spectral radiance, QCAL is the quantized calibrated pixel value in DN, $LMAX_\lambda$ is the Spectral radiance scaled to QCALMAX in (Watts/ (m^2 * sr * μm), $LMIN_\lambda$ is the Spectral radiance scaled to QCALMIN in (Watts/ (m^2 * sr * μm), QCALMIN is the Minimum quantized calibrated pixel value (corresponding to LMINλ) in DN, QCALMAX is the Maximum quantized calibrated pixel value (corresponding to LMAXλ) in DN, ML is the band-specific multiplicative rescaling factor from the metadata, Δ_L is the band-specific additive rescaling factor from the metadata.

2) The spectral radiance value was changed to temperature (Orimoloye *et al.*, 2018).

$$T = \frac{K_2}{ln\left(\frac{K_1}{L\lambda}+1\right)} \quad (5)$$

Where,

T is the effective satellite temperature in Kelvin, K1= Calibration constant 1(watts/meter squared*ster*μm), K2 = Calibration constant 2(watts/meter squared*ster*μm), Lλ = Spectral radiance.

3) Temperature which was in Kelvin was converted to Celsius (C°)

$$T\,(C°) = T(K) - 273.15 \quad (6)$$

Inter relationship of NDVI, NDBI and LST

The correlation between NDVI, NDBI and LST were analysed by using correlation and regression analysis and geographical weighted regression (GWR). Firstly, the "Create Fishnet" tool in data management tool was used with 50 rows and 50 columns. NDVI, NDBI and LST values were added using the "Extract Multi Values to Points" in spatial analyst tool. More than 1000 sample points were collected uniformly throughout the study area. In addition to simple regression, Geographically Weighted Regression (GWR) is employed to explore the influence of spatial characteristics. GWR calculates regression coefficients that vary spatially, taking into account a diverse set of observations from the data attributes. The scatterplots generated from the data are employed to obtain GWR coefficients, where LST serves as the dependent variable and NDVI and NDBI act as explanatory variables. Notably, GWR coefficients demonstrate a higher degree of robustness compared to those derived from simple regression analysis. (Keerthi and Chundeli, 2023).

Results and Discussion

Land use Land cover

The supervised classification was used to create the LULC maps for the year 1991, 2001, 2011 and 2021 with 10 years interval. Table 1 and Figure 2 depicts the LULC analysis of all the four different years. The major land use in Dimapur district is forest land covering 75.24% of the area in 1991. However, in 2021 there is about 20.07% decrease in forest land with a total of 524 km^2. One of the major reasons of the decreasing trend is due to the conversion of agricultural and forest land for urban uses and infrastructure in major urban centres like Dimapur (Yadav and Shinde, 2015). The built-up land has shown 135.32% increase in a span of thirty years followed by agriculture with a 39.95% increasing trend. There was a decrease in agriculture from 181.98 km^2 to 171.39 km^2 in between 2001to 2011 which later increased to 193.38 km^2 in the year 2021. Water body has reduced from 3.13 km^2 in 1991 to 2.41 km^2 and shifting cultivation from 16.96 km^2 to 11.16 km^2.

Table 1: LULC area changes from 1991 to 2021

	1991		2001		2011		2021			
	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Change (km^2)	Change (%)
Forest Land	655.98	75.24	607.53	69.68	562.02	64.42	524.33	60.16	-131.6	-20.07
Water Body	3.13	0.36	3.69	0.42	4.23	0.48	2.41	0.27	-0.72	-23
Urban body	57.41	6.58	64.67	7.42	112.39	12.93	135.10	15.49	77.69	135.32
Agriculture	136.17	15.61	181.98	20.87	171.39	19.66	193.38	22.18	55.21	39.95
Barren Land	2.17	0.24	2.57	0.29	4.35	0.50	5.44	0.62	3.27	150.69
Shifting Cultivation	16.96	1.94	11.39	1.31	17.43	2.00	11.16	1.28	5.8	-34.20
Total	871.82	100.00	871.82	100.00	871.82	100.00	871.82	100.00		

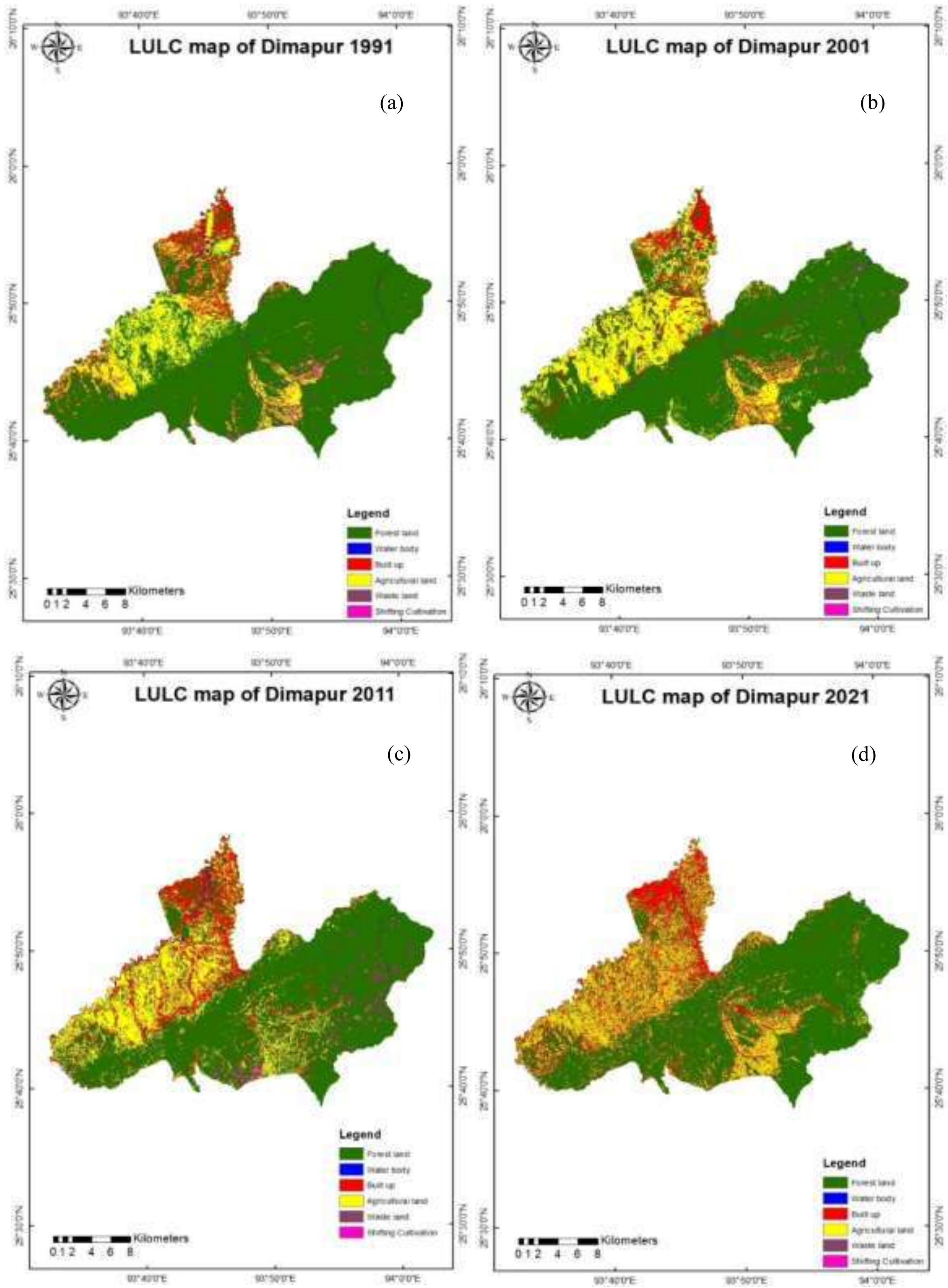

Fig 2. LULC maps of Dimapur for the year 1991(a), 2001(b), 2011(c) and 2021(d)

Accuracy Assessment

The user accuracy, producer accuracy, overall accuracy and Kappa coefficient were determined. The error matrix for the assessment for different LULC classes for four years is represented in Table 2 and Table 3.

Table 2: Values of User Accuracy and Producer Accuracy

	User Accuracy				**Producer Accuracy**			
	1991	**2001**	**2011**	**2021**	**1991**	**2001**	**2011**	**2021**
Forest body	94	92.1	89.6	90.6	90.3	90.3	89.6	90.6
Water body	86.6	86.2	87	86.9	89.6	96.1	96.4	90.9
Built Up	86.7	90.1	90.7	89.2	93.8	97.8	94.2	92.5
Agricultural land	90.1	90.9	91.8	88.4	85.1	86.2	90.3	88.4
Wasteland	82.7	81.4	84.8	85.1	85.7	88	84.8	76.6
Shifting cultivation	85.7	90.3	88.8	85.7	83.3	77.7	80	85.7
Average	87.64	88.5	88.7	87.65	87.9	89.35	89.21	87.45

Table 3: Values of Overall Accuracy and Kappa Coefficient

Year	**Overall Accuracy**	**Kappa Coefficient**
1991	88.3	85.7
2001	86.9	89.3
2011	89.3	97.9
2021	88.4	85.5

NDVI, NDBI and LST

The NDVI maps were generated for the year 1991, 2001, 2011 and 2021 and represented in fig 3. NDVI values were observed to be the highest in the year 1991 which varied between 0.73 to - 0.31. In 2001, 2011 and 2021 the values ranged between 0.59 to – 0.26, 0.58 to - 0.25 and 0.58 to – 0.19 respectively. Regions with the highest NDVI values, like forests and vege

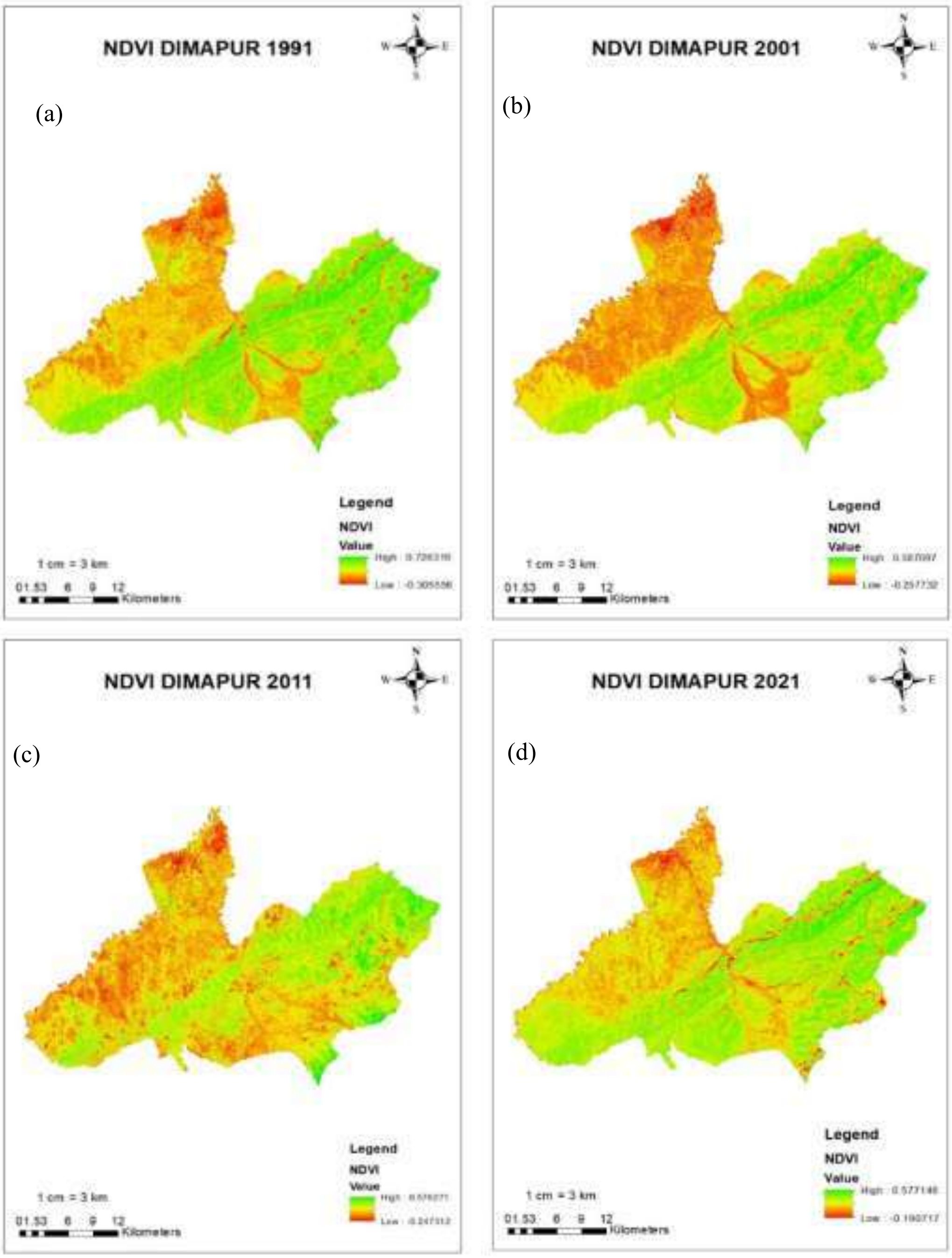

Fig 3. NDVI maps of Dimapur for the year 1991(a), 2001(b), 2011(c) and 2021(d).

tenc , such as barren land water bodies, and urban areas, typically indicate lower productivity. The NDVI value is greater in forested regions compared to barren land, and this difference can significantly impact the observed greenness of vegetation across the entire study area as seen by satellites (Hu et al. 2023). The average NDVI values for the year 1991, 2001, 2011 and 2021 are 0.22, 0.16, 0.17 and 0.2 respectively. In figure, higher NDVI values are represented in green colour and lower values are represented in red colour.

The NDBI maps of Dimapur district for four different years was generated and represented in fig 4. NDBI values were highest in the year 2011 ranging from 0.66 to –0.22. Furthermore, in 1991, 2001 and 2021 the values ranged from 0.47 to – 0.53, 0.45 to –0.55 and 0.40 to – 0.43. Higher NDBI values were concentrated in the Northern part which is the major urban hub of the district. Slightly high values were also noticed in the Southern part of the district. NDBI is a valuable indicator for assessing the extent of urban development. It helps to identify areas with increased impervious surface.

The LST maps is generated for the year 1991, 2001, 2011 and 2021 and represented in fig 5. In the year 1991 the region experienced moderate LST ranging from 9.95 to 24.54˚C. In the year 2001 lowest, minimum temperature was observed with 5.8˚ C. The highest maximum temperature was observed in the year 2021 with 36.04˚C and highest minimum temperature of 17.93˚C. In comparison with the LULC map the built-up area recorded higher temperature ranging from 18.36 to 24.54˚C in 1991 and 26.87 to 36.04˚C in 2021. A straight line has been generated on the LST maps with 5 sample points. Point a and c which are within the built-up areas showed higher LST values ranging between 17 to 24.5˚C, 16 to 24.8˚C, 18 to

25˚C and 24 to 36˚C in the year 1991, 2001, 2011 and 2021 respectively. Point b, situated in close proximity with water body registered LST < 20˚C for all the years.

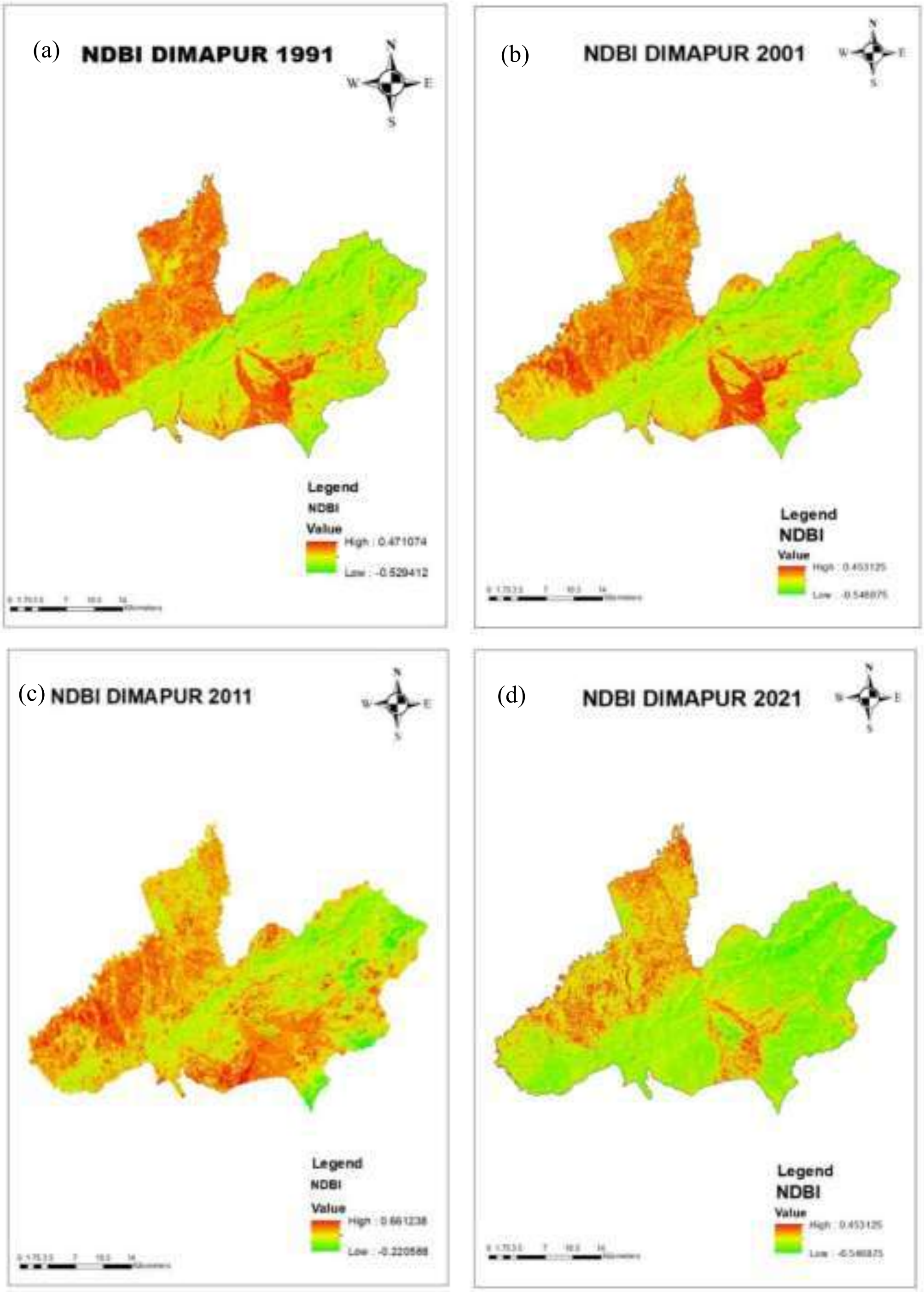

Fig 4. NDBI maps of Dimapur for the year 1991(a), 2001(b), 2011(c) and 2021(d)

Since Dimapur is characterized by small sized water bodies, their influence on LST of the surrounding area is shown to be less pronounced. Point d, e and f which are located within the forest land exhibited lower LST values (< 15˚C).

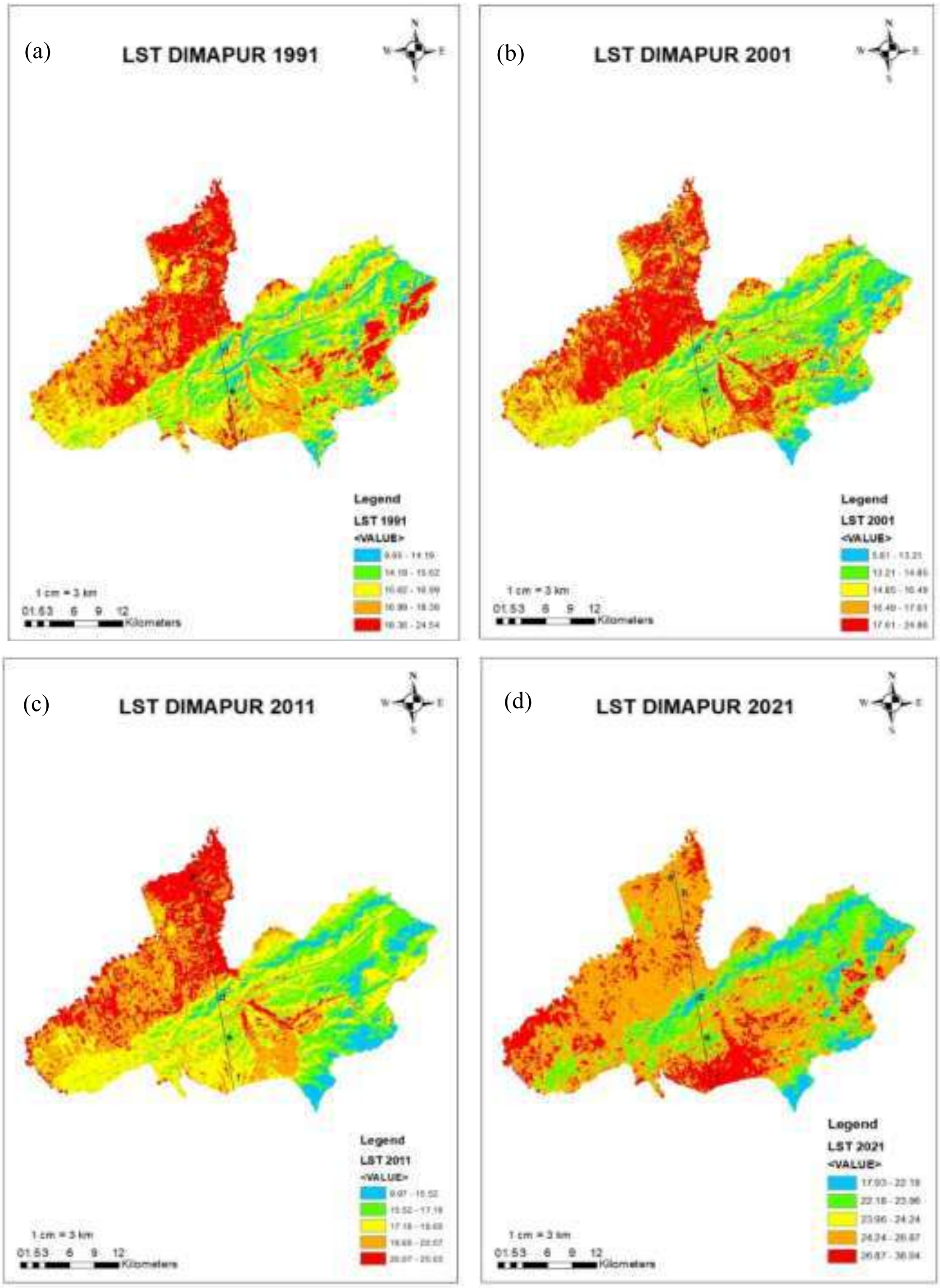

Fig 5. LST maps of Dimapur for the year 1991(a), 2001(b), 2011(c) and 2021(d).

Inter relationship of NDVI, NDBI and LST

The scatterplots depicting the relationship between NDVI and LST for the years 1991, 2001, 2011 and 2021 reveal a negative correlation. This implies that as NDVI values decrease, there is an associated increase in temperatures, suggesting a correlation between declining vegetation health (NDVI) and rising LST over the specified years. An adjusted R^2 value for LST vs NDVI for the years 1991, 2001, 2011 and 2021 were 0.14, 0.22, 0.12, 0.46 respectively (Fig 6).

In Fig 7, the correlation coefficient between NDVI and LST is illustrated for the years 1991 ($R^2 \sim 0.55$), 2001 ($R^2 \sim 0.71$), 2011 ($R^2 \sim 0.43$) and 2021 ($R^2 \sim 0.62$). The findings lead to the conclusion that there is a positive correlation between LST and NDBI. Several studies have also identified a similar consistent pattern between NDVI, NDBI and LST (Alademomi et al. 2022, Ghouri et al. 2022, Keerthi and Chundeli 2023, Singh et al. 2023).

Furthermore, Geographically Weighted Regression (GWR) was employed to further investigate the relationship between NDVI, NDBI and LST (Table 4). The R^2 adjusted value between NDBI and LST ranged from 0.82 to 0.99. The R^2 adjusted value between NDVI and LST were 0.99 for all the years. Compared to the correlation and regression analysis, which ignores the regionally weighted characteristics of the data set, GWR coefficients showed a greater correlation between the indices and the LST.

The research suggests that urbanization, as indicated by the substantial positive correlation between LST and NDBI has a direct impact on the increasing LST. Additionally, the negative correlation between LST and NDVI implies a decrease in vegetative health as LST rises. Analysis of LST maps reveals an upward trend in minimum, maximum, and average temperatures spanning from 1991 to 2021 (Fig 5). The findings imply that alterations in

LULC have a notable influence on both the level and trend of LST. The trend of declining vegetation and escalating built-up areas over the years contributes to the increasing levels of LST, highlighting the need for intervention and strategic planning to mitigate the effects of urbanization on local temperature and vegetative health. This research provides valuable insights that can guide interventions aimed at balancing urban development with environmental conservation to address the escalating temperature and declining vegetative health in Dimapur district.

Table 4: Geographically Weighted Regression (GWR) values for the year 1991, 2001, 2011 and 2021.

Indices	**Year**	**Bandwidth**	**Effective number**	**Sigma**	**AICc**	**R2**	**R2 Adjusted**
NDBI	1991	1776.73	193.86	0.96	15926.14	0.82	0.79
	2001	1776.73	211.96	1.23	14195.34	0.96	0.95
	2011	1776.73	235.43	1.31	8214.03	0.99	0.99
	2021	1776.73	248.19	0.83	3066.97	0.99	0.99
NDVI	1991	1776.73	247.06	1.03	3589.41	0.99	0.99
	2001	1776.73	225.22	1.21	3934.72	0.99	0.99
	2011	1776.73	251.06	1.01	3532.45	0.99	0.99
	2021	1776.73	251.68	0.85	3112.03	0.99	0.99

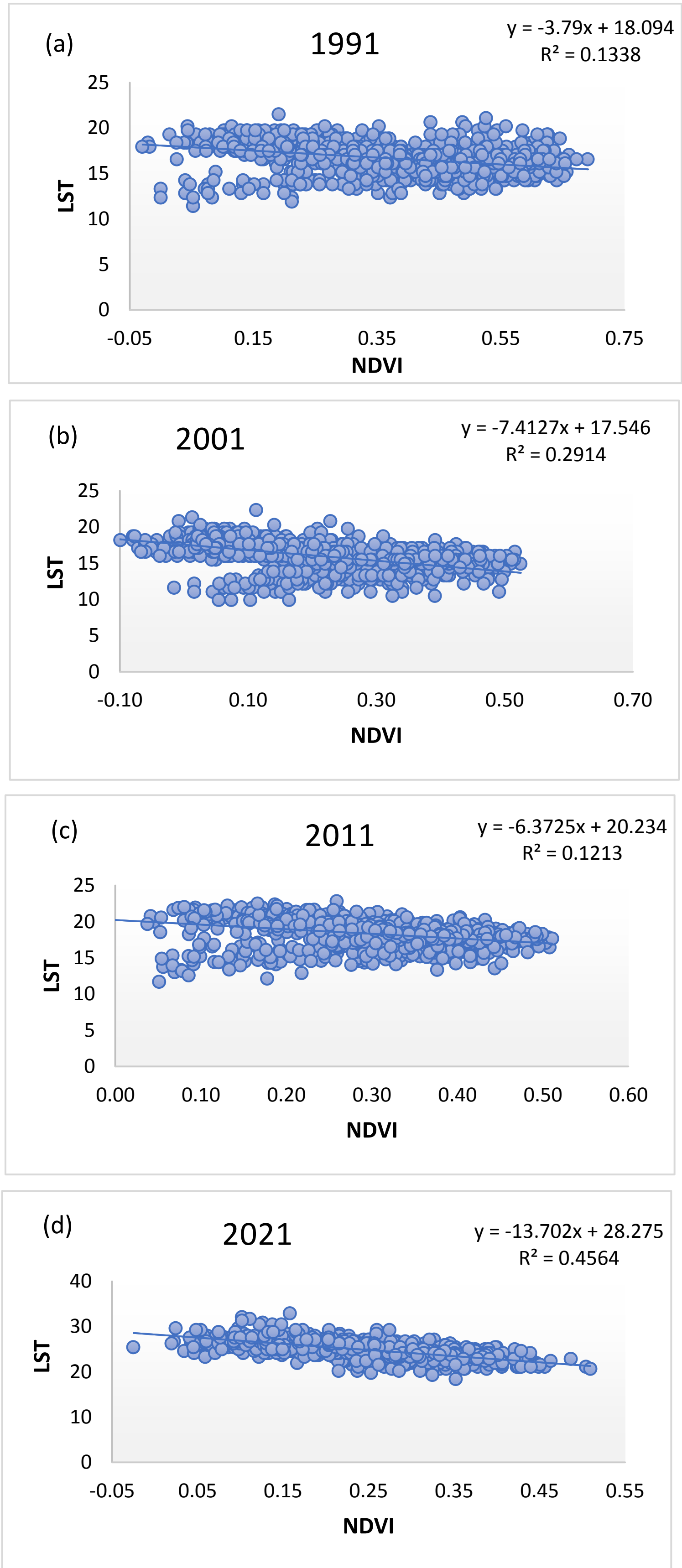

Fig 6. Correlation coefficient LST and NDVI for the year 1991(a), 2001(b), 2011(c) and 2021(d)

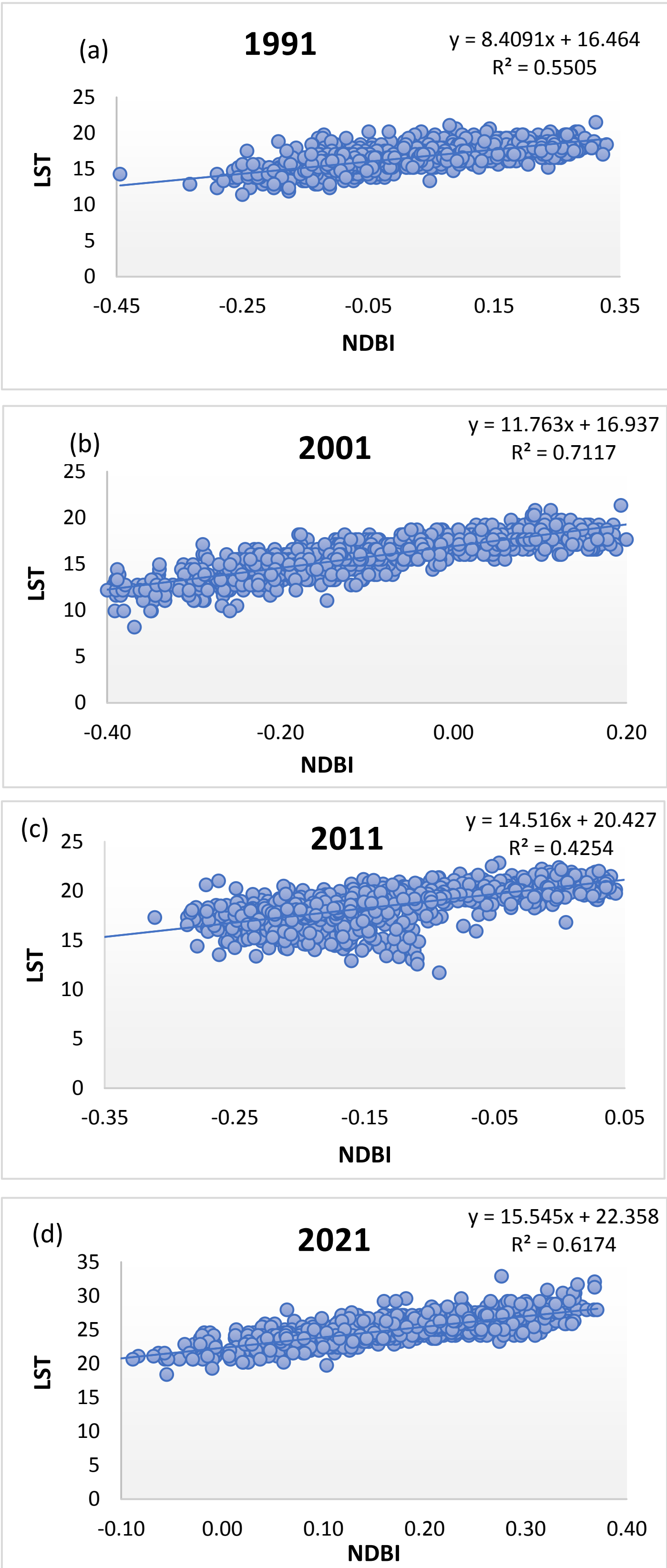

Fig 7. Correlation coefficient LST and NDBI for the year 1991(a), 2001(b), 2011(c) and 2021

Conclusion

In this study, the interrelationship and spatial temporal changes of LULC, NDVI, NDBI and LST for Dimapur district is studied for four different years with a 10 years interval from 1991 to 2021. The forest area in Dimapur is decreasing primarily due to deforestation for purposes like agriculture, urban expansion, and infrastructure development, along with factors such as illegal logging and forest fires. Built-up areas consistently exhibit significantly higher LST, while forest land displays lower LST values (fig 5). The most significant change in the district occurred in the built-up area, which experienced nearly a three-fold increase, expanding from 57.41 km² in 1991 to 135.10 km² in 2021 (Table 1). The most significant reduction in area was observed in the Shifting Cultivation class, which decreased by approximately 34.20%. The Forest class also showed a notable reduction of 20.07%, decreasing from 655.98 km² in 1991 to 524.33 km². Simultaneously, the mean LST has also risen, climbing from 17.24°C in 1991 to 26.98°C in 2021.

The association between NDVI, NDBI, and LST is examined through correlation coefficients and Geographically Weighted Regression (GWR). The correlation coefficient between NDVI and LST was negative, indicating an inverse relationship, while the correlation coefficient between NDBI and LST was positive, suggesting a direct relationship. GWR yielded coefficients with a minimum value of 0.79 and a maximum value of 0.99. The study's findings for Dimapur District, indicating a decline in forested areas, an expansion of built-up regions, and an associated rise in Land Surface Temperature, offer policymakers valuable insights for informed urban planning, environmental conservation, and climate change adaptation strategies tailored to the specific needs of the region. This information can guide resource allocation and community engagement efforts to promote sustainable development and enhance resilience to environmental changes.

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Disclosure of interest

The authors report no conflict of interest.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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