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Time-Series Mapping of Land use and Land Cover (LULC) for Future LULC Forecasting using Geospatial Techniques: A Case Study of Chitwan District, Nepal

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Abstract:- This study employs a Cellular Automation-Artificial Neural Network (CA-ANN) model to predict Land Use and Land Cover (LULC) changes in Chitwan District, Nepal, using spatial variables. The model achieves high accuracy (Kappa value of 0.81), projecting LULC maps for 2020 and 2030. Results reveal notable changes. Agriculture shows a modest increase of 5.01% (2000-2010) but experiences successive declines of 4.55% (2010-2020) and 3.89% (2020-2030). Barren land undergoes a drastic reduction of -78.81% (2000-2010), followed by a slower decline of 39.00% (2010-2020) and a subsequent increase of 5.37% (2020-2030). Built-up areas consistently grow, with a significant rise of 41.02% (2000-2010), a remarkable surge of 209.09% (2010-2020), and a further increase of 38.45% (2020-2030). Forest cover sees a positive change of 6.99% (2000-2010), a reduction of 1.78% (2010-2020), and a subsequent positive change of 1.73% (2020-2030). Water bodies exhibit fluctuations, with a decrease of 4.42% (2000-2010), an increase of 37.73% (2010-2020), and a notable decrease of 24.35% (2020-2030). Land Surface Temperature (LST) trends indicate warming summers and cooling winters, aligning with global warming expectations. The study emphasizes the impact of urban development on rising temperatures and underscores the importance of vegetation in temperature regulation. Additionally, the increase in other wooded land from 2010 to 2020 is noted, followed by a decrease in 2030. Analysis of LST maps highlights higher temperatures in settlement areas, suggesting potential urban heat island effects. The study emphasizes the significance of considering LULC changes for effective environmental management in Chitwan District, Nepal.

Keywords:- *LULC Changes, CA-ANN Model, Land Surface Temperature (LST) Trends, Environmental Management.*

I. INTRODUCTION

Nowadays, over 50% of the worlds inhabitants reside in regions. It is expected that the urban population will continue to increase in the coming years(Li et al. 2019). Nepal, being a developing nation has a level of urbanization compared to other countries. However it stands out as one of the ten countries experiencing urbanization with an annual growth rate of 18.2%. Over the decades the country has observed an increase, in urban development that was not adequately planned(Raut, Chaudhary, and Thapa 2020). Urbanization is predominantly observed in a handful of cities well as numerous medium sized cities, in Nepal(Bakrania 2015). The mid-hills region of Nepal serves as a microcosm of these global and national challenges. Transitioning from a predominantly rural, agriculture-based lifestyle to a more urbanized and fragmented landscape, this region undergoes significant land-use changes. Historical agricultural expansion led to deforestation, contributing to a decline in forest cover. However, a recent shift has been observed, with a considerable portion of agricultural land now abandoned as urban migration gains momentum. Chitwan District, a focal point of economic activity and urbanization in Nepal, has experienced pronounced alterations in land use and land cover (LULC) in recent years. Population growth, urbanization, and industrialization have driven these changes, impacting surface temperatures and thermal regimes. Understanding the nuances of these transformations is critical for regional climate, hydrology, and biodiversity management. Therefore, this project aims to delve into the variations of LULC and their repercussions on land surface temperature (LST) in the Chitwan district, unraveling the driving mechanisms and proposing strategies for mitigation.

Urbanization, a central driver of change in Chitwan, manifests in the conversion of agricultural land to urban areas, deforestation, and infrastructure growth. In light of the growing importance of land resource monitoring and management, this study aims to forecast land use/cover for 2030 while examining land surface temperature trends from 2000 to 2020. Utilizing remote sensing data and geospatial techniques, the study aspires to develop a comprehensive model that not only predicts changes in land use/cover but also unravels the corresponding variations in land surface temperature at a regional level.

II. DATASETS AND METHODOLOGY

➢ *Datasets*

This study utilizes the following datasets in the table below. (Table 1).

Table 1 Datasets Used in This Study

Sr .No	Data	year	Details	Data Type	Source
1	Boundary		Administrative Boundary	Vector	Survey departmentof Nepal
2	DEM		Elevation &Slope maps	Raster(30m)	USGS
3	Rivers & Stream		Distance from Rivers maps	Vector	OSM
4	Roads		Distance from roads map	Vector	OSM
5	Landsat7-ETM	2000,2010	LULC & LST maps	Raster(30m)	USGS
6	Landsat-8 OLI &TIRS	2020	LULC & LST maps	Raster(30m)	USGS

➢ *Methodology*

For the stated objective, Chitwan District, Nepal, was chosen for LULC mapping, change analysis, and temporal LST analysis. Methodology steps are depicted in Figure 1

➢ *Lulc Classification*

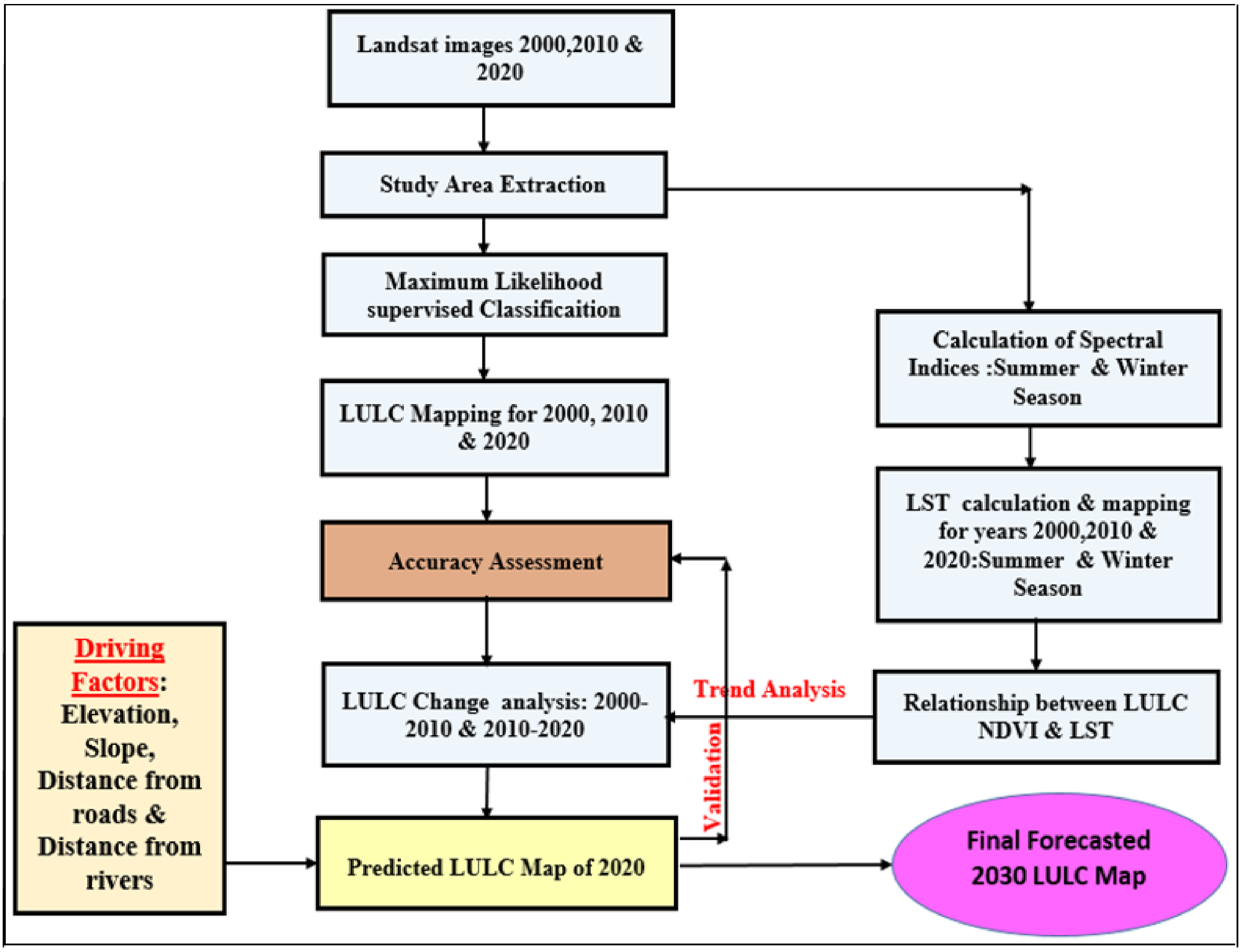

Fig 1 Flow Chart of the Work

➢ *Lulc Classification*

LULC maps were generated using ArcGIS 10.5 with supervised classification (maximum likelihood) from Landsat-7 and Landsat-8 imagery. Bands were stacked, pixel signatures identified via training samples, and accuracy assessed with a confusion matrix. Five LULC classes were defined (see Table 2).

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Table 2 Five Classes of LULC

Sr. No	Classification	Description
1	Water Bodies	Surface water, whether impounded in ponds, lakes, orreservoirs, orflowing as streams, rivers, wetlands and other bodies of water. Water bodies may be either fresh or salty
2	Forest	Deciduous forest, Evergreen forest, Scrubs forest,shrubland.
3	Built-up	Buildings and other artificial structures occupy theland.
4	Agriculture	A brief farmed area is followed by harvest and a cycle of bare soil.All arable land thatis either part of a crop rotation system or is keptin good agricultural and environmentalcondition.
5	Barren	Land that is sparsely vegetated shows signs of erosionand land deformation due to lack of adequate water, soil management and natural causes.

➢ *Estimation of LST*

In This study employed Google Earth Engine (GEE) to compute summer (June 1 to August 31) and winter (December 1 to February 28) Land Surface Temperature (LST) maps for 2000, 2010, and 2020. Landsat-7 and Landsat-8 images with less than 15% cloud cover were utilized. The thermal band was extracted, and mean values for each pixel were calculated to represent temperature patterns during the specified seasons across the years. Extraction methods of LST from the thermal band are as following steps:

- Step-1: Conversion of digital numbers to radiance/conversion to top of atmospheric (TOA) radiance.

For Landsat-7 TM imagery band 6 has been used as a thermal band and the following equation has been used to calculate spectral radiance (L_λ).

$$L_\lambda = LMIN_\lambda + \left[\frac{(LMAX_\lambda - LMIN_\lambda)}{(QCALMAX - QCALMIN) * QCAL}\right] \quad (1)$$

Where QCALMIN = 1, QCALMAX = 255, QCAL = Digital Number of each pixel $LMAX\lambda$ & $LMIN\lambda$ & amp; are the spectral radiances for the band6 at digital number. The value of $LMAX\lambda$ = 15.303 and $LMIN\lambda$ =1.238.

For Landsat-8 OLI imagery band 10 is the thermal band and to extract spectral radiance ($L\lambda$), the following equation has been implied.

$$L_\lambda = M_L * QCAL + AL \quad (2)$$

$L\lambda$ = Spectral Radiance of top of the atmosphere.

ML = the band- specific multiplicative rescaling factor (0.0003342)

AL = the band-specific additive rescaling factor (0.1)

QCAL = Quantized and Calibrated Standard Product Pixel value (band 10 image)

- Step-2: Transformation of spectral radiance to At-satellite brightness temperature (BT)

$$BT = \left(\frac{K2}{\ln\left[\left(\frac{K1}{L_\lambda}\right)+1\right]}\right) - 273.15 \quad (3)$$

Where.

BT = At-satellite brightness temperature

$L\lambda$ = TOA spectral radiance

K1 = Band constant

K2 = Band constant

273.15 helps to convert the temperature from Kelvin to Celsius

- Step-3: Proportion of vegetation (PV): Normalized Difference Vegetation Index (NDVI) is the main parameter to calculate the proportion of vegetation. It has been calculated as following

$$P_V = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}\right)^2 \quad (4)$$

- Step-4: Emissivity correction (ε): Land surface emissivity can be calculated using following equation

Land surface emissivity (ε) = 0.004*PV + 0.986 (5)

- Step-5: Calculation of land surface temperature:

$$LST = \left(\frac{BT}{\left[1+\left\{\left(\lambda * \frac{BT}{\rho}\right) * ln\varepsilon\right\}\right.}\right) \quad (6)$$

Where,

LST = Land Surface Temperature

λ = wave length of emitted radiance in meters (Markham and Barker, 1985)

$\rho = h * c/\sigma$ (1.438*10-2 m K),

σ = Boltzmann constant (1.38*10-23 J/K),

h = Planck's constant (6.626*10-34 J s),

c = velocity of light (2.998 * 108 m/s) and

ε = emissivity (ranges between 0.97 and 0.99)(Das et al. 2021b)

- *Prediction of the LULC Changes*

In this study, the forecasting of Land Use and Land Cover (LULC) changes is conducted using the Artificial Neural Network (ANN) through the MOLUSCE plugin in Quantum GIS version 2.18.24 software, with a specific focus on predicting the LULC maps for 2020 and 2030. The process involves integrating LULC maps from the years 2000 and 2010, coupled with crucial spatial variables such as elevation, slope, distance from roads, and distance from rivers. These variables, uniformly extracted in raster format, share consistent geospatial coordinates and a pixel size of 30 meters. The MOLUSCE plugin plays a pivotal role in computing area changes, producing a transition matrix, and creating an area change map, vividly illustrating shifts in water bodies, forests, built-up areas, agriculture, and barren land between 2000 and 2010.

To anticipate future changes in LULC, the ANN plugin, particularly the Multi-layer Perception model, leverages classified raster images of 2000 and 2010. It predicts LULC transitions for the upcoming years, assuming the continuity of existing patterns. The evaluation criteria encompass Pearson's correlation,Crammer's coefficient, and Joint information uncertainty for spatial variable correlation assessment. Additionally, the transition matrix and LULC changes between 2000 and 2010 are calculated, with the Kappa coefficient serving as a validation metric.

Quantifying alterations in land use/cover area between 2000 and 2010 provides insights into changes represented in square kilometers. For LULC forecasting, the ANN technique is employed, and the Kappa coefficient is measured for the validation of both real and predicted LULC maps. Incorporating Computational Intelligence, especially Artificial Neural Networks (ANN), for transitional potential mapping, the study utilizes LULC data as input for calibrating and modeling LULC changes. Parameters for predicting the LULC map for 2020 include a neighborhood of 1, iterations totaling 1000, a hidden layer consisting of 10 nodes, and a learning rate of 0.001.

- *Validation of Model*

The LULC assessment extensively employed the Kappa coefficient for validation, comparing the predictedand actual LULC maps of 2020. The overall kappa value was calculated using a defined expression(Kamaraj and Rangarajan 2022).

$$kappa = (po - pe)/ (1 - pe) \qquad (7)$$

Where p_o denotes the proportion of actual agreements and p_e denotes the proportion of expected agreements.

$$po = \sum_{i=1}^{c} p_{ij} \qquad (8)$$

$$p_e = \sum_{i=1}^{c} p_{iT} p_{Tj} \qquad (9)$$

Where pij denotes the i-th and j-th cells in the contingency table, piT denotes the sum of all cells in the i-th row, pTj denotes the sum of all cells in the j-th column, and c denotes the raster category count.The analysis identified Elevation, Slope, distance from roads, and distance from rivers as key variables, achieving a high Kappa value of 0.81 and 86.34% correctness. Projecting LULC for 2020 using 2000 and 2010 data yielded a satisfactory Kappa value of 0.63, confirming the significant influence of these variables on the predicted LULC map in Chitwan district. Predictions extended to 2020 and 2030, validated through the Kappa coefficient, as summarized in Table 3.Table 3 Combinations of Spatial variables and Kappa coefficient.

Table 3 Kappa Coefficient of Spatial Variables Combinations

Sr. No	**Spatial variable combinations**	**Percentage of kappa correctness**	**Kappa Coefficients**
1	Elevation, Slope, Distance from rivers,Distance from roads	86.34%	0.81

- *Correlation Between LST and NDVI*

Correlation coefficients are vital in environmental studies, indicating the strength and direction of relationships between variables. Pearson's correlation, employed in our research, measures the connection between NDVI and Land Surface Temperature (LST). The formula used for calculation is shown in equation (5).(Das et al. 2021b).

$$\boldsymbol{r} = (\boldsymbol{\Sigma xy}) - (\boldsymbol{\Sigma x})(\boldsymbol{\Sigma y}) / \sqrt{[\boldsymbol{\Sigma x^2} - (\boldsymbol{\Sigma x})^2][\boldsymbol{n\Sigma y^2} - (\boldsymbol{\Sigma y})^2]} \qquad (10)$$

Where,

r: This represents the correlation coefficient, a measure of the strength and direction of the linear relationship between two variables.
x: This refers to the first variable in dataset.

y: This refers to the second variable in dataset.

Σxy: This term denotes the sum of the product of corresponding values of x and y in dataset. Σx: This is the sum of all values of x in dataset.

Σy: This is the sum of all values of y in dataset.

n: This represents the number of data points in dataset.

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III. RESULT AND DISCUSSION

➢ *Land Use Land Cover Change Analysis*

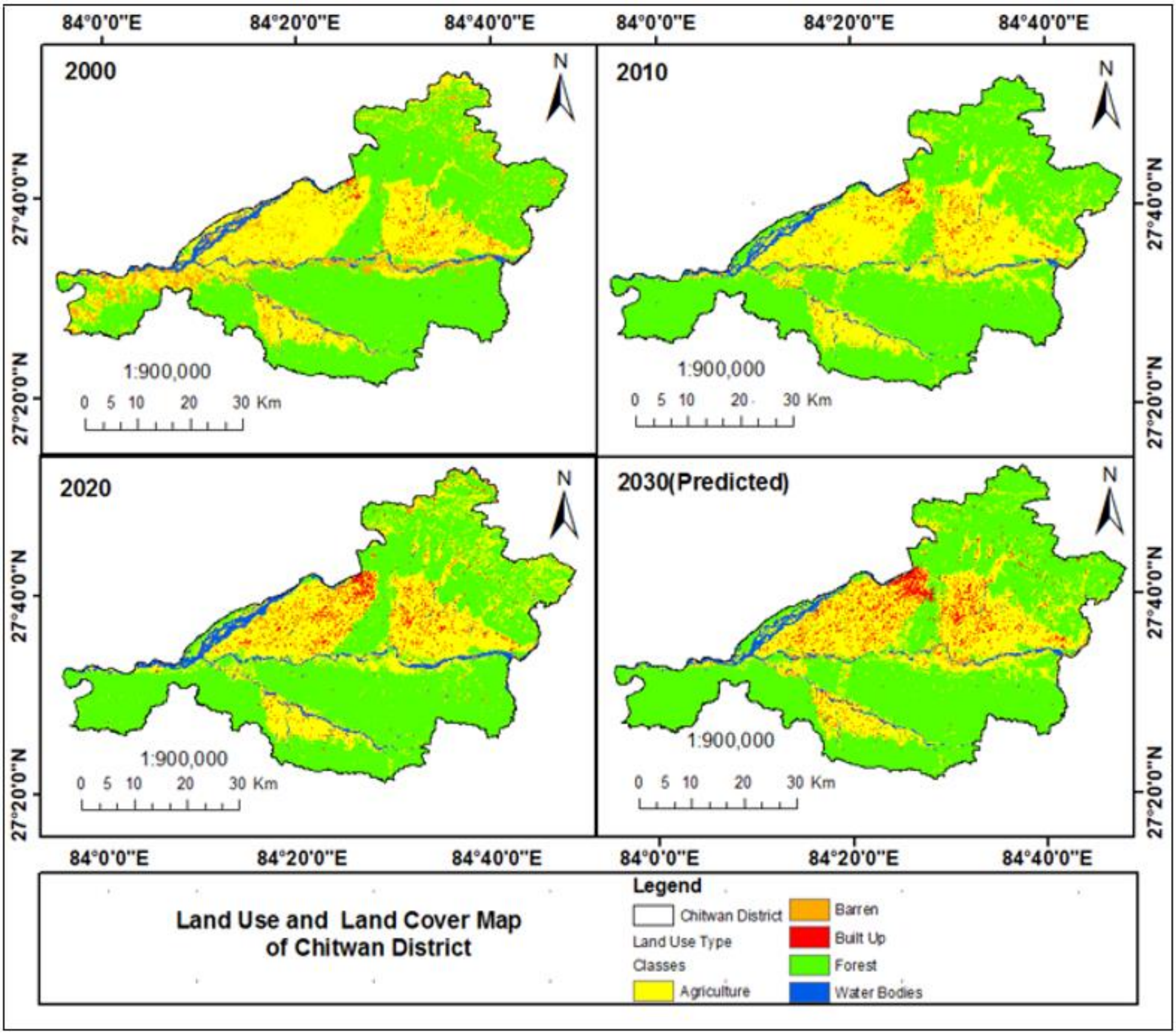

Fig 2 Land Use and Land Cover Changes of Chitwan District from 2000 to2030

Table 4 LULC Area of Year 2000, 2010, 2020 and 2030.

	2000		2010		2020		2030	
LULC	**Area in Km^2**	**% ofarea covered**	**Area in Km^2**	**% of area covered**	**Area in Km^2**	**%of area covered**	**Year2030**	**% of area covered**
Agriculture	692.73	30.85	727.42	32.40	694.32	30.93	667.34	29.72
Barren	163.21	7.27	34.59	1.54	21.10	0.94	22.23	0.99
Built Up	15.28	0.68	21.54	0.96	66.59	2.97	92.19	4.11
Forest	1300.84	57.94	1391.73	61.99	1366.93	60.88	1390.60	61.94
WaterBodies	73.07	3.25	69.85	3.11	96.20	4.28	72.77	3.24

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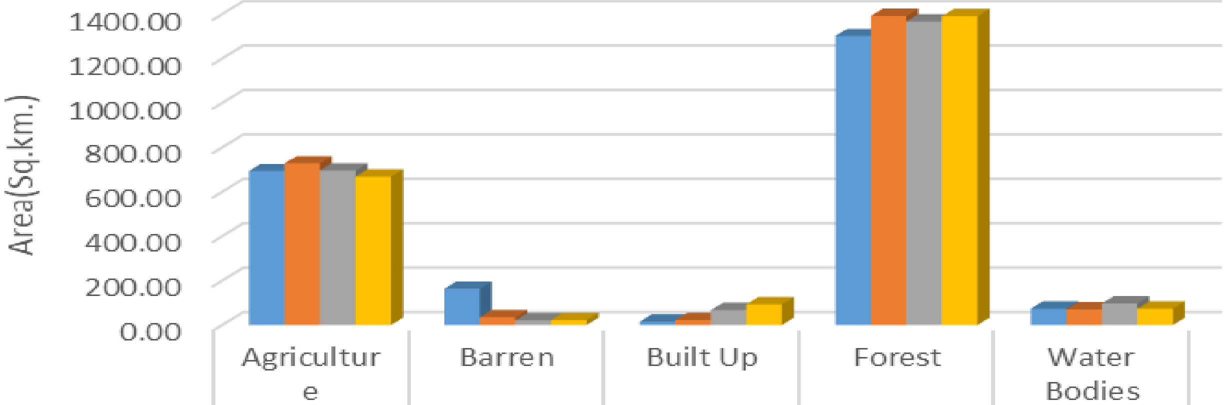
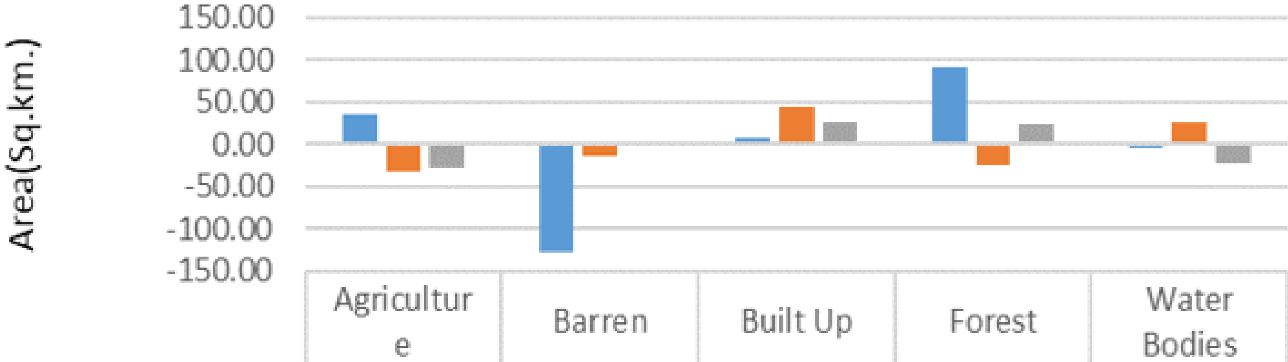


	Agriculture	Barren	Built Up	Forest	Water Bodies
Year 2000	692.73	163.21	15.28	1300.84	73.07
Year 2010	727.42	34.59	21.54	1391.73	69.85
Year 2020	694.32	21.10	66.59	1366.93	96.20
Year 2030	667.34	22.23	92.19	1390.60	72.77

Fig 3 Land Use and Land Cover Change (2000 to 2030)



	Agriculture	Barren	Built Up	Forest	Water Bodies
Year(2000-2010)	34.69	-128.62	6.27	90.89	-3.23
Year(2010-2020)	-33.10	-13.49	45.04	-24.80	26.35
Year(2020-2030)	-26.98	1.13	25.61	23.67	-23.42

Fig 4 Gain and Loss of LULC (2000 to 2030)

During the classification overall accuracy 90.05%, 91.71%, 90.12% and kappa coefficient 0.88,0.90,0.88 was obtained for the LULC 2000,2010 and 2020 respectively.The analysis of land use and land cover (LULC) dynamics across the observed years reveals intriguing patterns in the transformation of the study area. By examining the variations in different LULC categories, we gain valuable insights into the changing landscape and its potential implications. The following overview highlights the key trends in LULC distribution from 2000 to the projected year 2030.Figure 4.10.InChitwan district, the land cover dynamicsover the specified time intervals reveal significant changes across various classes. Agriculture exhibited expansion from 2000 to 2010, with a positive change of 34.69 square kilometers, but then experienced successive contractions of -33.10 and -26.98 square kilometers from 2010 to 2020 and 2020 to the projected year 2030, respectively. Barren land, marked by a drastic negative change of -128.62 square kilometers from 2000 to 2010, showed a slower decline (-13.49 square kilometers) in the subsequent decade and a slight increase (1.13 square kilometers) from 2020 to 2030. Built-up areas witnessed consistent growth, with positive changes of 6.27, 45.04, and 25.61 square kilometers in the respective intervals. Forest cover exhibited a positive change of 90.89 square kilometers from 2000 to 2010, followed by a reduction of –24.80 square kilometers from 2010 to 2020. However, from 2020 to 2030, there was a positive change of 23.67 square kilometers, indicating a potential reversal or conservation effort. Water bodies experienced fluctuations, with a slight decrease (-3.23 square kilometers) from 2000 to 2010, followed by positive changes of 26.35 and a subsequent notable decrease of -23.42 square kilometers in the next two intervals as shown in Figure 3.2 and Figure 3.3.These dynamic changes underscore the complex interplay of agricultural practices, urbanization, conservation efforts, and natural processes in shaping the land cover of Chitwan over time.

- *Temporal Analysis of LST*

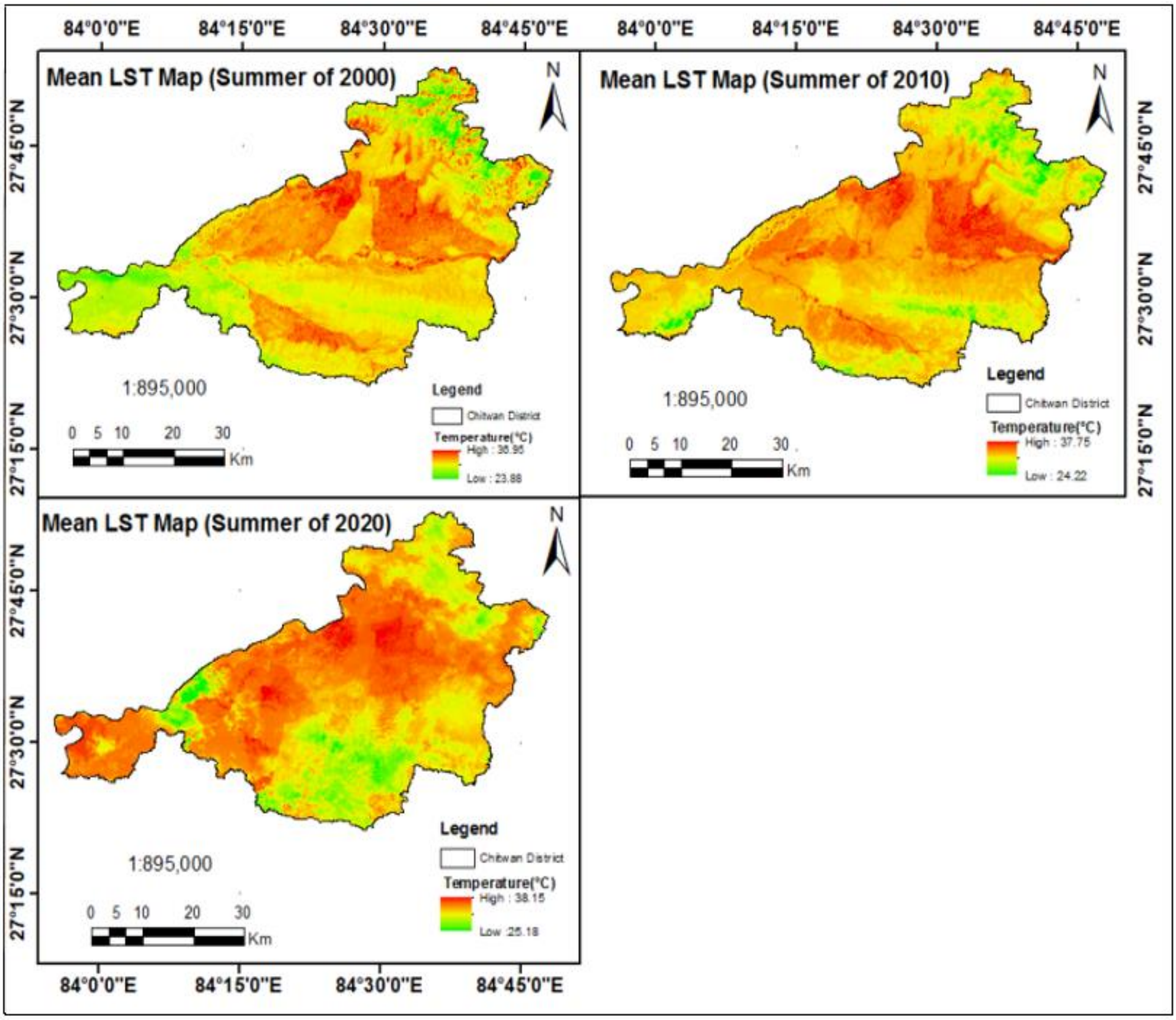


Fig 5 Mean LST Maps Summer (2000 To 2030)

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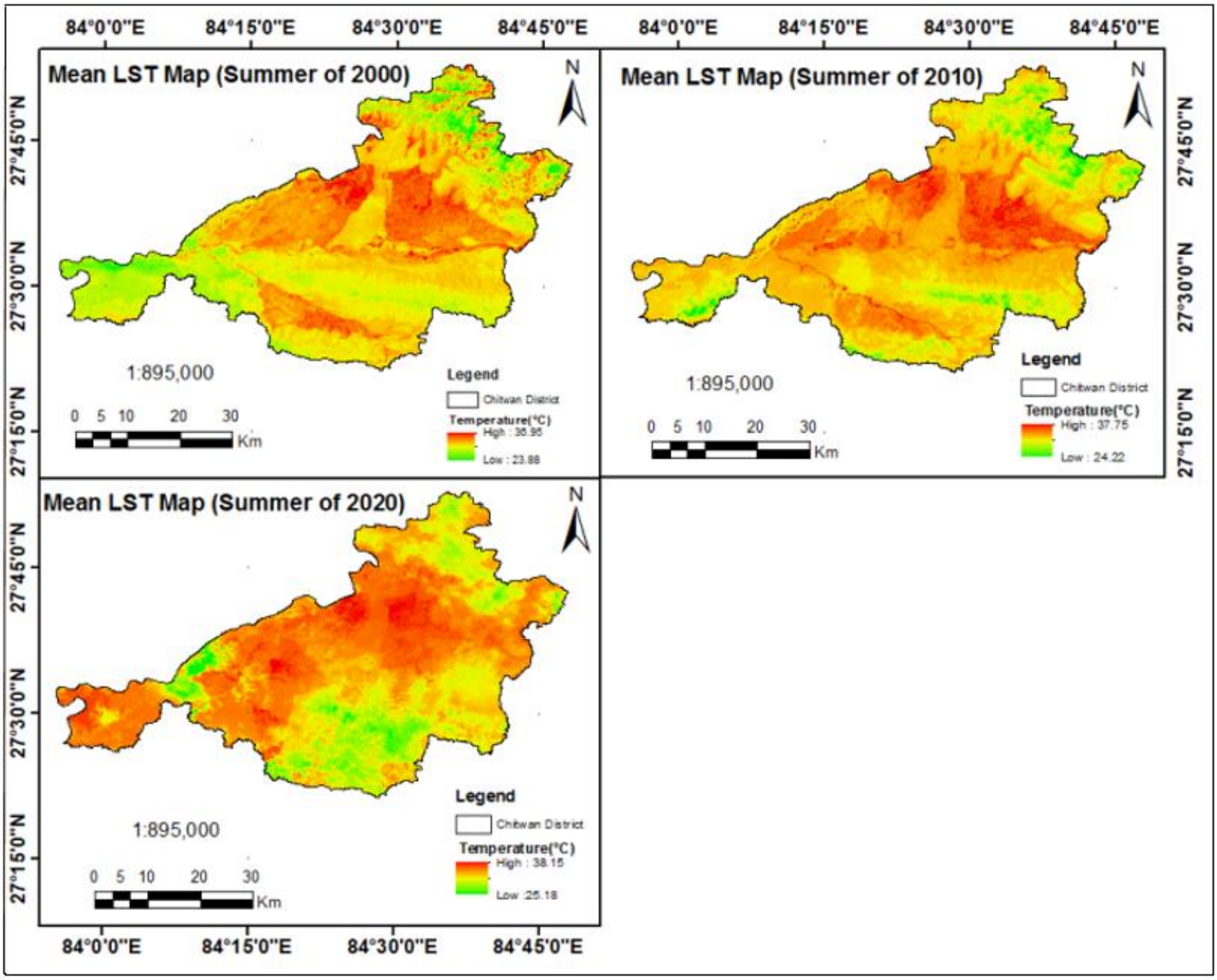

Fig 6 Mean LST Maps Winter (2000 To 2030)

Table 5 LST in Summer Season

Summer Temperature (°C)				
Years	Min	Max	Mean	Changes (Mean temp)
2000	23.88	36.95	30.41	-
2010	24.22	37.75	30.98	0.57
2020	25.18	38.15	31.66	0.68

Table 6 LST in Summer Season

Winter Temperature (°C)				
Years	Min	Max	Mean	Changes (Mean temp)
2000	14.72	25.85	20.28	-
2010	14.05	24.81	19.43	-0.85
2020	12.93	22.97	17.95	-1.48

In Chitwan District, the Summer Season Land Surface Temperature (LST) exhibited a gradual warming trend from 2000 to 2020.(figure3.4). The mean summer temperature increased from 30.41°C in 2000 to 31.66°C in 2020, indicating a rise of 1.25°C over two decades. The decadal heating trends during summer were 0.57°C and 0.68° in the 2000 to 2010 and 2010 to 2020 respectively.(table5).

Conversely, the WinterSeason LST in Chitwan District showcased a cooling trend over the same period.(figure3.5). The mean winter temperature decreased from 20.28°C in 2000 to 17.95°C in 2020, reflecting a notable cooling of 2.33°C over the two-decade span. The most substantial cooling occurred between 2010 and 2020, with a decrease of 1.48°C.(table 5).

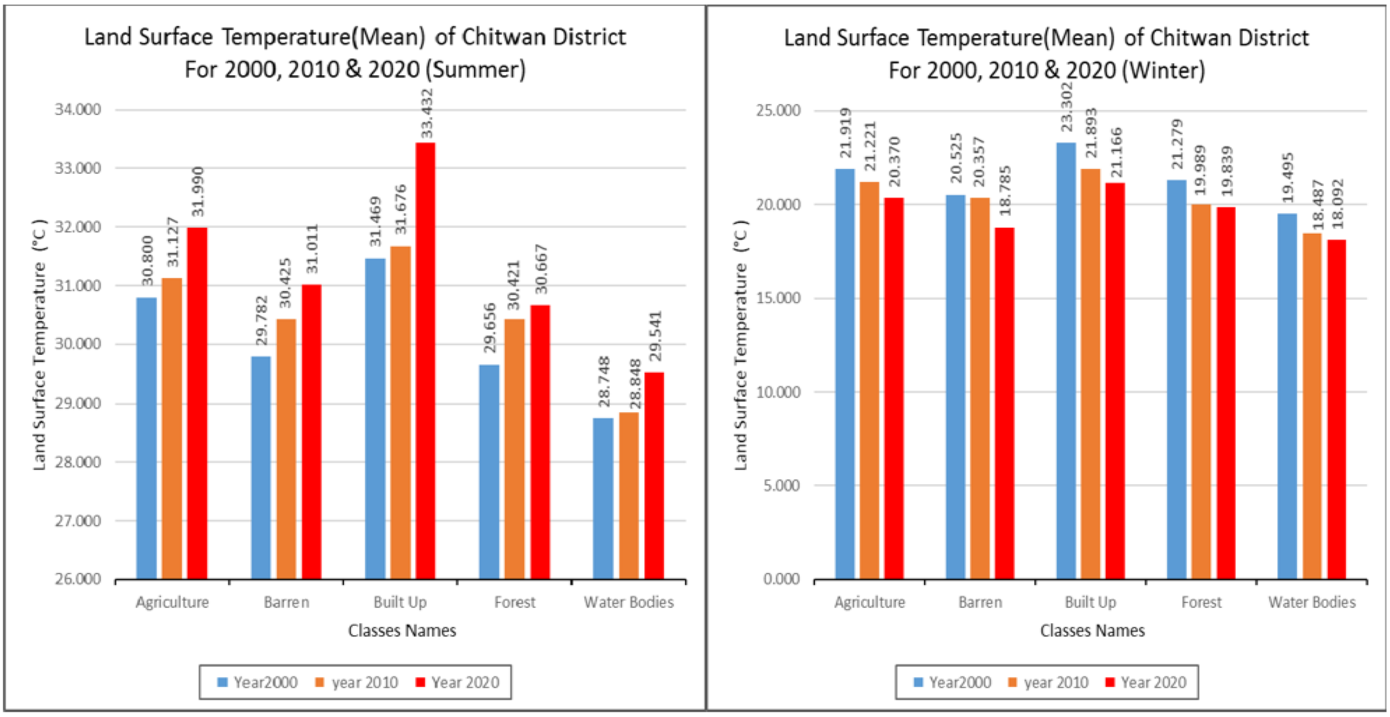

Fig 7 Relationship between LULC and LST (2000 to 2020)

In Chitwan District's summer season, Land Surface Temperature (LST) analysis across different Land Use and Land Cover (LULC) classes for 2000, 2010, and 2020 reveals warming trends. Agriculture and barren land consistently heat up, with LST values increasing. Built-up areas, indicating the urban heat island effect, show a notable temperature rise. Forested areas exhibit a slight warming, and water bodies also experience increased temperatures. Built-up areas consistently display the highest temperatures, underscoring their significant role in overall warming trends across LULC classes (see Figure7).

In Chitwan District's winter season, examining Land Use and Land Cover (LULC) classes and Land Surface Temperature (LST) for 2000, 2010, and 2020 reveals distinct patterns. Agricultural and barren land show consistent cooling, with LST decreasing. Built-up areas exhibit a cooling trend over the two decades, despite consistently displaying the highest winter temperatures. Forested areas and water bodies also indicate cooling. Overall, a cooling trend is observed in the winter season from 2000 to 2020 (see Figure 7).

➢ *Relationship Between LST and NDVI*

In In this study, Pearson correlation coefficients between Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI) were computed for 2000, 2010, and 2020 summer seasons in Chitwan District. The obtained coefficients of -0.60, -0.57, and -0.54 (see Figure 3.6-3.7-3.8) reveal a consistent negative correlation, indicating an inverse relationship between rising LST and decreasing NDVI. This suggests that higher temperatures correspond to lower vegetation density during the summer in Chitwan District, providing valuable insights into the impact of temperature variations on vegetation cover.

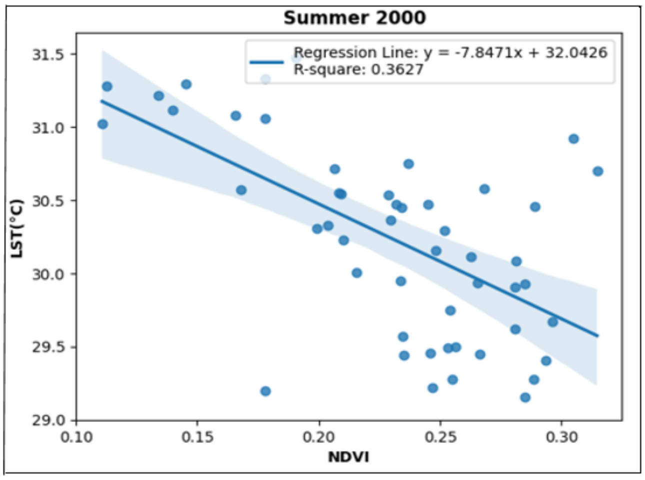

Fig 8 Relationship between LST and NDVI in 2000 (Summer Season)

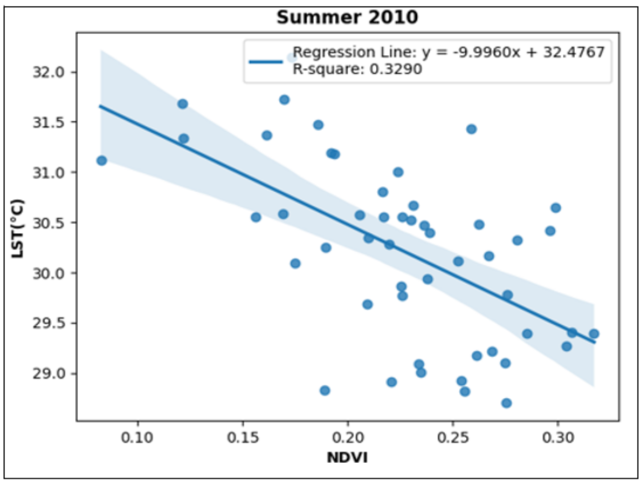

Fig 9 Relationship between LST and NDVI in 2010 (Summer Season)

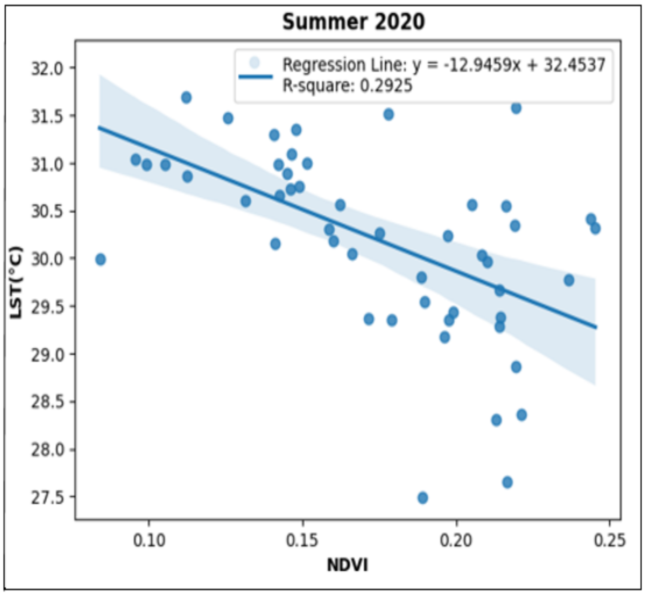

Fig 10 Relationship between LST and NDVI in 2020 (Summer Season)

IV. CONCLUSION

The In summary, this study highlights the significance of forecasting Land Use and Land Cover (LULC) changes in Chitwan District, employing the ANN Cellular Automation model. The model's high accuracy in predicting 2020 LULC maps and subsequent projections for 2030 underscore its efficacy in understanding landscape dynamics. Forecasts for 2030 indicate decreasing agricultural and water areas, a slight increase in barren land, and substantial growth in built-up areas. Stability in forested areas suggests ongoing conservation efforts, while seasonal Land Surface Temperature (LST) trends align with global expectations, emphasizing the impact of urbanization on local temperatures. The negative correlation between LST and normalized difference vegetation index (NDVI) underscores the role of vegetation in temperature regulation. Forested area decline contributes to the warming trend, emphasizing the need for proactive measures in sustainable urban planning and vegetation conservation.In conclusion, integrating these insights into land management strategies is crucial for Chitwan District's sustainable development and resilience to changing environmental conditions.

RECOMMENDATION

Conducting region-specific Land Use and Land Cover (LULC) studies is vital for customizing development plans in Nepal's diverse geography, especially in Chitwan District. Promoting collaborative planning among federal, provincial, and local bodies is essential for a unified approach to urbanization strategies in the district. Prioritizing green infrastructure in metropolitan areas, including Chitwan, will contribute to enhancing ecological balance and fostering sustainable practices. It's crucial to implement climate-resilient water management, invest in resilient infrastructure, and encourage eco-friendly transportation options in Chitwan District for a comprehensive and environmentally conscious approach todevelopment.

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➢ *Conflict of Interest*

The authors declare that they have no known competing financial interests or personal relationships that could appeared to influence the work reported in this paper.

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