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Factors Influencing the Spatial Distribution of Land Surface Temperature Dynamics in Birendranagar Municipality of Nepal

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Abstract Nepal is urbanizing rapidly despite its status as one of the world's least urbanized countries. Here, urbanization is marked by unplanned growth, weak policies, inadequate law enforcement, and political interference, contributing to increased land surface temperatures (LST) in municipal and metropolitan areas. Primary data for the study is derived from satellite imagery provided by the USGS, while secondary land use data is sourced from Nepalese government records and updated through fieldwork. The minimum observed LST is 19°C, and the maximum is 37°C, calculated using brightness temperature values and appropriate conversion equations or models. This study examines LST distribution across different land uses (cropland, forest, and built-up areas) within municipalities, noting that urban areas generally exhibit higher LST values compared to rural areas. Factors such as proximity to water bodies, vegetation index (NDVI), and elevation are analyzed. The study area of Birendranagar Municipality covers two sample areas: one encompassing entire municipalities and another focused on the riverside buffer zone. Key findings reveal a positive correlation between LST and distance to water bodies in large samples and a negative correlation in smaller samples. LST is notably higher in built-up areas than in agricultural and forested areas. LST is inversely proportional to altitude and NDVI. The study recommends that future urban planning carefully consider LST dynamics and their relationship with water bodies to mitigate temperature rise challenges.

Keywords: *Land surface temperature, Water sources, Land use, Spatial Distribution*

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1. Introduction

Nepal has experienced rapid urbanization since 1970 [1,2], with an annual increase of 3.0% and predicted to continue until 2050 [3]. Urbanization primarily developed along East-West postal highways and mid-hill districts [4]. Most civilizations originated near water, and land surface changes alter climate, ecology, and land cover, promoting heat storage and trapping. This leads to urban heat islands, causing temperature differences between urban and rural areas, affecting human health, energy consumption, and air quality.

Land surface temperature (LST) is a crucial factor in urban heat islands, influencing heat fluxes, energy exchanges, regional climates, and surface energy balance [5]. It impacts surface heat islands, urban climate, evapotranspiration, forest fire monitoring, geological investigations, and crop productivity. Remotely sensed thermal infrared data can be used for large-scale analysis [6] and is influenced by atmospheric influence and surface parameters [7]. Water bodies, such as rivers, streams, and lakes, have been found to have a cooling effect on surrounding temperatures. As distance from water bodies increases, surface impact diminishes, leading to a 0.78°C temperature increase [8]. This study uses Landsat 9 Operational Land Imager and Thermal Infrared Sensor satellite data from 2022 of Birendranagar Municipality (Figure 1) to investigate the cooling impacts of water bodies on LST in medium-sized cities. Birendranagar has a total area of 24453.06 hectares of land and a total population was 1,53,863 from Census data 2021, with a population density of 629 (population per square kilometre). The research aims to understand the interaction between distance to water bodies and surface temperature, the distribution of agriculture and forest land, and the relationship between LST with Normalized Difference Vegetation Index (NDVI) and elevation. Preprocessing steps are included to ensure data consistency and accuracy. Satellite-based LST measurements can be influenced by urban canopy layers, including buildings and vegetation, and can be affected by shadows, surface emissivity, and thermal admittance.

Factors like population density, built-up density, building heights, and humidity are not considered. This research aims to improve understanding of land surface temperature (LST) in cities, identifying areas prone to heat stress, assessing urban heat mitigation strategies, and enhancing climate resilience and public health for sustainable urban development.

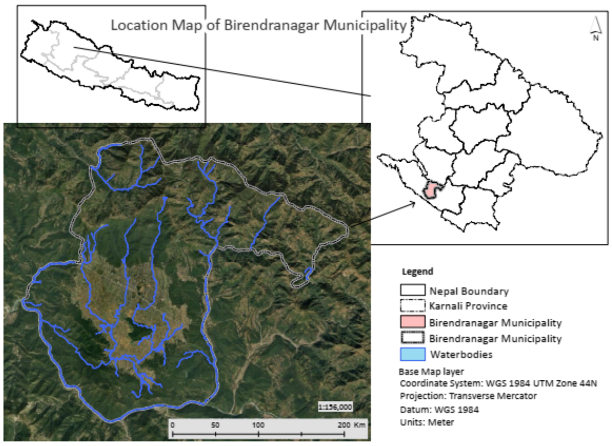

Figure 1. Study area map

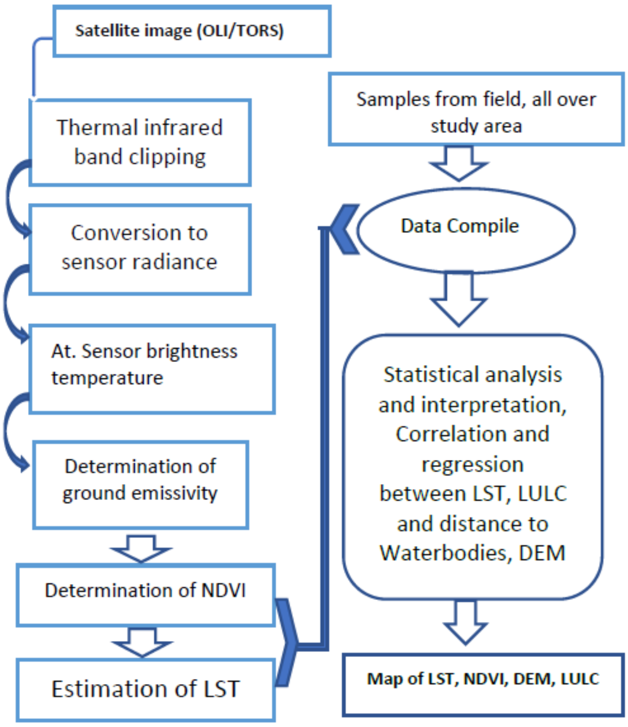

Figure 2. Conceptual framework

2. Materials & Methods

As shown in the conceptual framework (Figure 2), the Landsat-9 OLI (Operational Land Imagery) L1TP sensor satellite image of 2022 was downloaded from the United States Geological Survey [9]. The month of March has been chosen in accordance with local weather conditions and the best available cloud-free satellite imagery, which is 7.17% and band resolution 30 m for spectral index analysis and thermal LST estimate. NASA processed these data to generate radiometric and atmospheric correction algorithms for the Level 1 products [10]. The collected Landsat 8-9 (OLI/TIRS) data is available on the USGS website in geometrically corrected form, and therefore, no geometric correction was applied [11]. The land surface temperature and normalized difference vegetation index are scientifically calculated. Land use data is secondary data derived from Nepalese government agencies, Department of Survey, 2020, and is updated in 2022. Land use classifications such as other, industrial area, public services, cultural locations, and commercial area are merged and referred to as built-up areas. As a result, there are four major land surfaces: agricultural land, forests, water bodies, and built-up areas.

2.1. Preprocessing

Landsat 9 Level-1 data products, provided by the United States Geological Survey (USGS), undergo basic preprocessing steps, such as radiometric and geometric corrections to ensure data consistency and accuracy. These corrections adjust for factors such as sensor calibration, geometric distortions, and Earth's curvature [12,13,14]. Direct processing of radiance images from Landsat 9 Level-1 data may be appropriate in certain situations, like low-atmospherically sensitive applications where atmospheric effects have a lower impact on the thermal measurements.

Step 1: Radiance Image Calculation: The radiance image is calculated to get spectral radiance. These coefficients convert the raw DN values to radiance units [13,15].

$L\lambda = ML * Qcal + AL$ (1)

Step 2: Radiance Temperature Calculation: The top of the brightness temperature, an estimate of the emitting surface's temperature, is obtained by converting the spectral radiance data using the thermal constant values of the metadata file [16].

$BT = K2 / In (k1 / L\lambda + 1) - 273.15$ (2)

2.2. Processing

Step 3: The Normalized Difference Vegetation Index (NDVI) [17]:

$NDVI = (NIR – RED) / (NIR + RED)$ (3)

Step 4: Proportion of vegetation (Pv) [18]:

$PV = ((NDVI – NDVI\ min) / (NDVI\ max – NDVI\ min))^2$ (4)

Step 5: LSE (Land Surface Emissivity) [19]:

$E = 0.004 * PV + 0.986$ (5)

0.986 corresponds to a correction value of the equation.

Step 6: LST (Land Surface Temperature) [20]:

$LST = BT/(1 + (\lambda * BT/p) * ln(E))$ (6)

Where,

BT = top of atmosphere brightness temperature (°C)

H = planck's constant = 6.626*10ʌ-34 J S

E = land surface emissivity

C = velocity of light = 2.998*10ʌ8 m/s

p = h*c/s=1.4388*10ʌ-2mK = 14388 μmK

λ = wavelength of emitted radiance (11.5 μm)

s = boltzmann constant = 1.38*10ʌ-23 JK

2.3. Data Integration

The sample points are retrieved from ArcMap by locating the centre point of a 250x250 meter grid. There are two areas of interest: the first one is the Birendranagar municipality boundary that covers a 24453.06-hectare area with 3832 sample points (Figure 3), and the second is the chosen region with a 1000 m buffer of the Jhupra River with 228 points (Figure 4). The nearest distance between 228 sample locations and water bodies (proximity to water/PW) is measured. The Jhupra River covers 25.71 ha, which is 5.7% of the total 446.78 ha waterbodies, and was chosen above other rivers because it runs through three types of land cover: forest, agricultural land, and built-up extents. The other major rivers connected to agriculture and forest areas are relatively uninhabited. The NDVI (Figure 5), LST (Figure 6 and Figure 7), LULC (Figure 8), DEM (Figure 9), and distance to water data are converted into point data. All of these data were combined with field sample data, which were utilized as input variables in the correlation and regression model using Excel and the Statistical Package for the Social Sciences (SPSS).

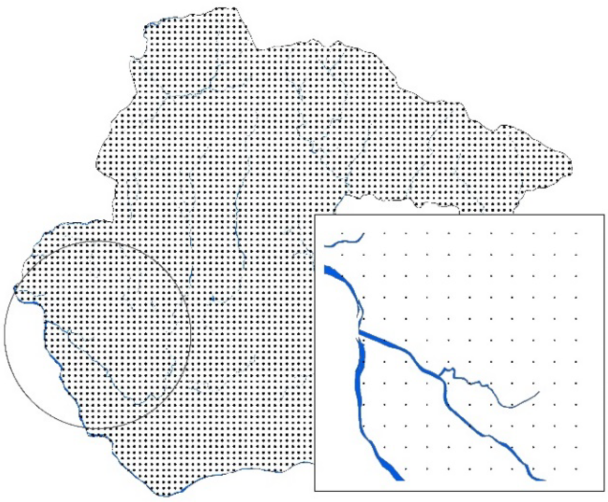

Figure 3. Large sample plot of 250x250 meter grid and waterbodies

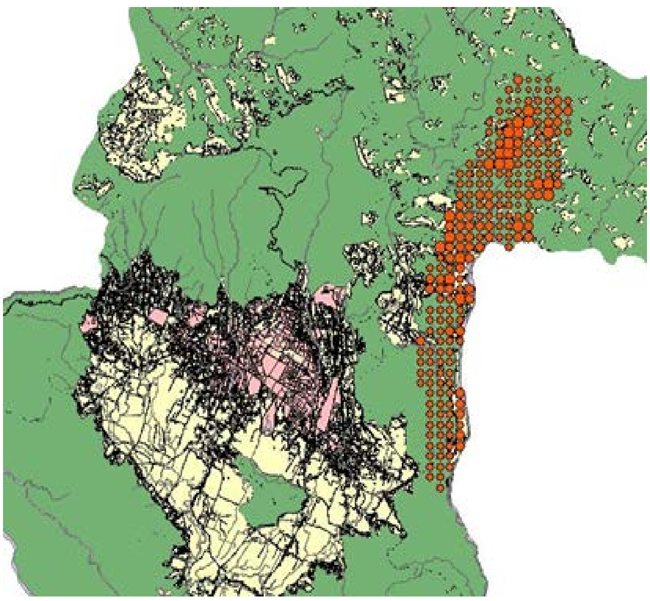

Figure 4. Small sample plot 1000meter buffer along Jhupra Khola

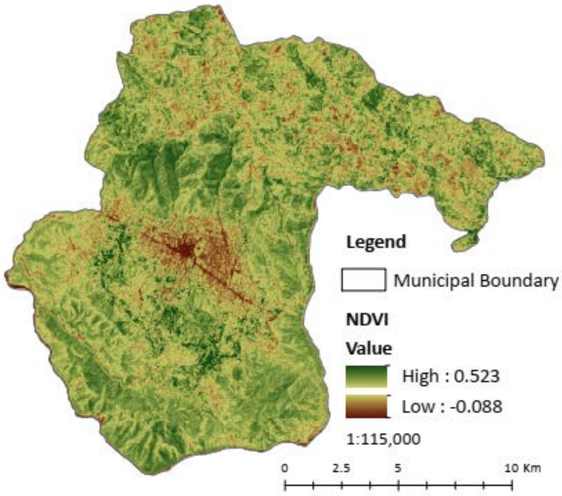

Figure 5. Normalize Difference Vegetation Index map

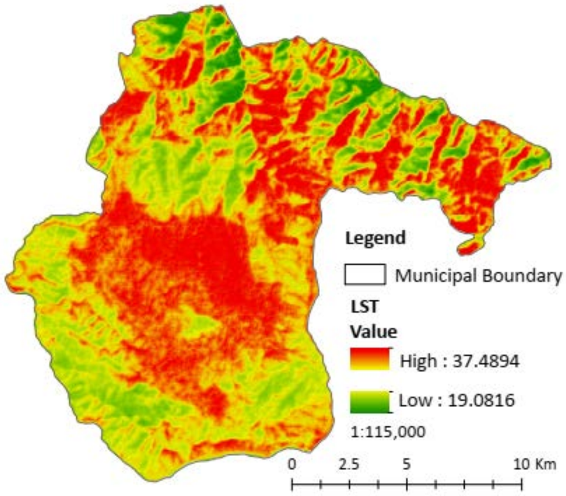

Figure 6. Land Surface Temperature Map

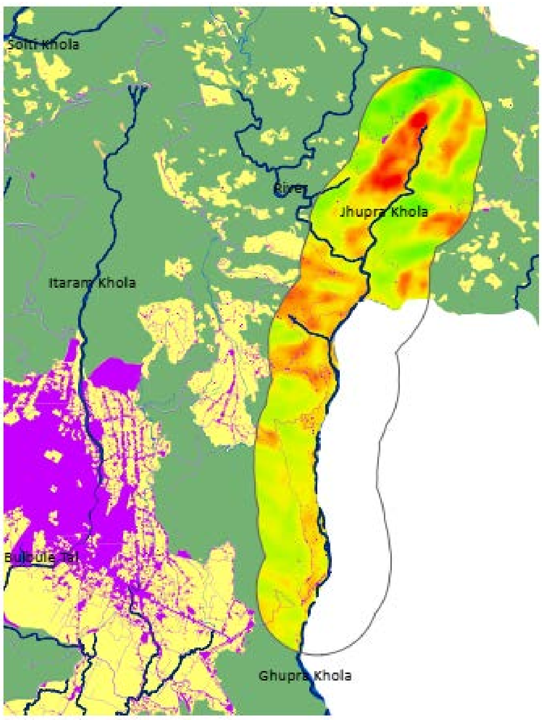

Figure 7. Land surface temperature of small sample area

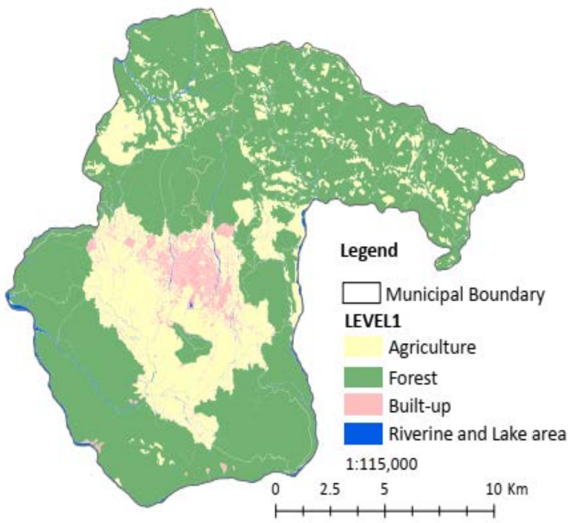

Figure 8. Land use Map 2022

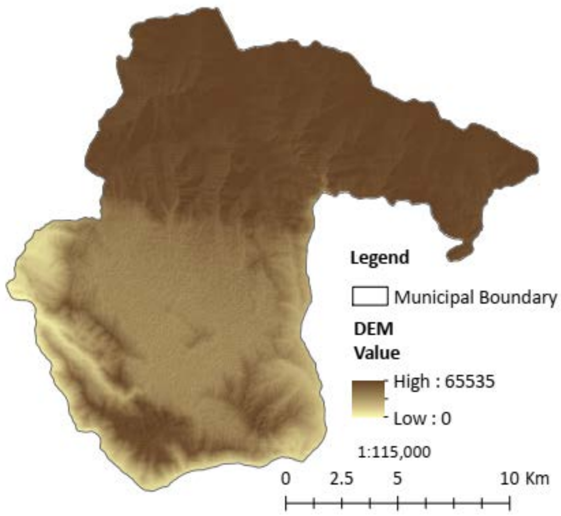

Figure 9. Digital Elevation Model Map (meter)

3. Results

3.1. Distribution Pattern of LST and LULC

The number of samples is 3832; among them, the LST points with agricultural land use are 267, with built-up land use are 229, and with forest land use are 2736 sample points.

The interpretation of box plot and whisker data (Figure 10):

The centre of distribution of the forest is the lowest of the three distributions (the median is 26.03). The distribution is positively skewed. Generally cooler, likely due to shading and evapotranspiration. Agriculture has a median of 28.51, which is a moderate temperature, potentially due to open fields. The distribution of agriculture is nearly symmetric. Built-up (the median is 29.99) is the highest of the three distributions and is negatively skewed. Indicating that urban areas are hotter.

The interquartile range for agriculture is 1.70, where 50% of the data are found; it is the most concentrated distribution. The upper outlier limit is 26.85, and the lower outlier limit is 25.15. The interquartile range for built-up is 2.08, the upper outlier limit is 27.67, and the lower outlier limit is 25.59. Similarly, the interquartile range for the forest is 2.62, the upper outlier limit is 23.63, and the lower outlier limit is 21.01. Outliers might indicate unusual heating or cooling events that warrant further investigation.

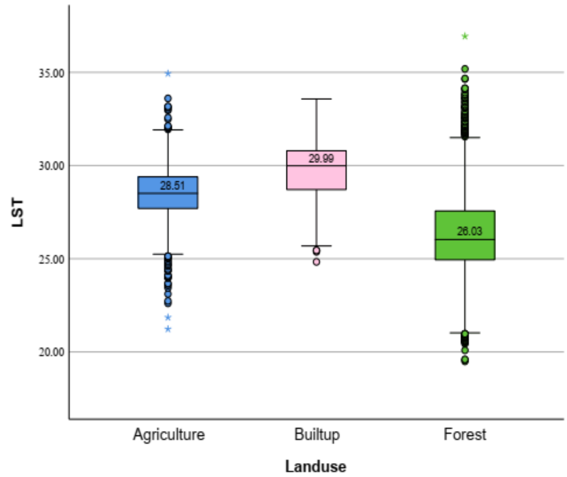

Figure 10. Box and Whisker plot of Land use vs LST

Outliers based on the "1.5 * IQR rule." All three distributions include potential outlier, which represent values that are unusually high or low compared to the rest of the dataset.

Whisker represents the range of the data. The top of the whisker of agriculture is 7.54, and the bottom is 6.47; this suggests that the temperatures are relatively clustered within this range. The top of the Whisker of built-up is 2.78, and the bottom is 3.88, but since it is higher than the top whisker value, this suggests a possible error. Normally, the bottom whisker should have a lower value than the top whisker. This could be due to a typographical error. The top of the whisker of the forest is 9.37, and the bottom is 5.45; this suggests a greater range of temperatures, perhaps due to differing shade and canopy cover levels.

3.2. Relationship between LST with NDVI, Proximity to Water and DEM for Large Sample Area

Pearson correlation matrices were conducted in Excel, and SPSS to examine the relationship of the independent variables: vegetation, NDVI, distance to waterbodies (Nearest distance), and elevation vs the dependent variable (LST).

Table 1. Relation between LST with NDVI, Proximity to Waterbodies and DEM

Variables	Correlation	LST
NDVI	Pearson Correlation	-0.237**
	Sig. (2-tailed)	<0.001
Near_Distance/ proximity to water bodies	Pearson Correlation	0.033*
	Sig. (2-tailed)	0.041
DEM	Pearson Correlation,	-0.128**
	Sig. (2-tailed)	<0.001
	N	3832

**. Correlation is significant at the 0.01 level (2-tailed)
*. Correlation is significant at the 0.05 level (2-tailed)

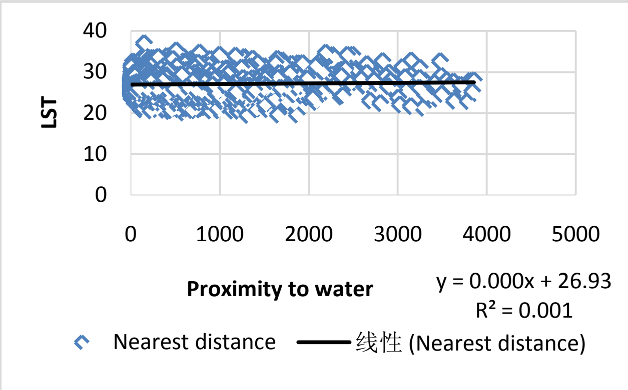

Figure 11. LST vs Distance to water (near distance)

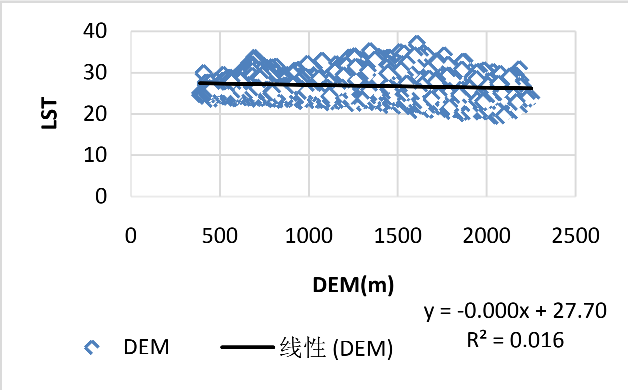

Figure 12. LST vs DEM

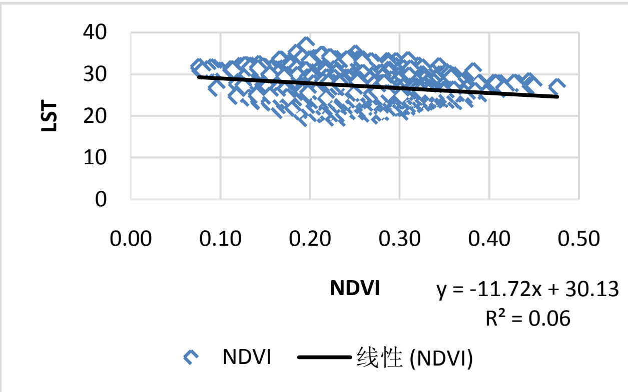

Figure 13. LST vs NDVI

The relation between LST and NDVI, proximity to water bodies (nearest distance to water), and DEM was comprehended using Pearson's correlation. The values of correlation coefficients of NDVI and DEM were found to be -0.237 and -0.128 at the 0.001 level (2-tailed) significance level, and PW was 0.33 at the 0.05 level (2-tailed) significance level (Table 1).

Relation between LST and Proximity to Water:

There is a significant positive correlation between LST and proximity to water (r=0.33, p=0.041) (Figure 11). The relationship between LST and PW is weakly positive and negligible. This suggests that as the distance to water increases, LST tends to increase. It also means that the other factors might have larger influences on LST more than the distance to water bodies. The significance level of p=0.041 indicates that this weak association is statistically significant at the 0.05 level (two-tailed test). In other words, there is a 4.1% chance of seeing a correlation coefficient as significant as r=0.033 or higher because of random sampling variability if there is no connection in the sample. As a result, caution should be applied when evaluating the practical importance of such a low correlation value. So, the small area sample points are also calculated to compare which component is creating an unusual statistic.

Relation between LST and NDVI, LST and DEM:

There is a significant negative correlation between LST and NDVI (r = -0.237, p < 0.001) and LST and DEM (r = -0.128, p < 0.001). The result showed that the relationships between LST and NDVI (Figure 13), and LST and DEM (Figure 12) are weakly negative and negligible. This suggests that as LST increases, NDVI and DEM tend to decrease. It also means that other factors might have larger influences on LST more than NDVI and DEM. The correlation is statistically significant at a very high level (p < 0.001), indicating the probability of observing the given correlation coefficient if there is no correlation in the sample (i.e., the null hypothesis is true). Here, "Sig. (2-tailed) <0.001" indicates that the correlation coefficient is statistically significant at a level of less than 0.001.

3.3. Relationship between LST, and Proximity to Water for Small Sample Area

Sample result from the buffer zone of the Jhopra River: A 1000-meter buffer was used along the river to select the area of study. The same sample points were correlated; the result is below (Table 2).

Table 2 Relation between LST and Proximity to Water

Variables	Correlation	LST
NDVI	Pearson Correlation	-.231**
	Sig.(2-tailed)	<0.001
	N	228

**. Correlation is significant at the 0.01 level (2-tailed).

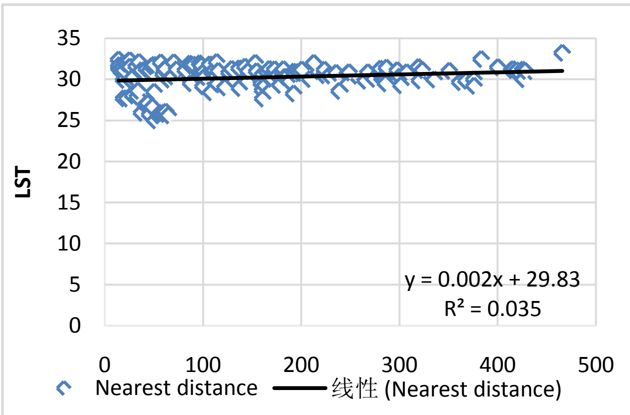

Figure 14. LST vs Distance to water (near distance)

There is a significant negative correlation between LST and PW (r = -0.231, p < 0.001). The result showed that the relationship between LST and PW (Figure 14) is weakly negatively correlated and negligible. This suggests that as LST increases, proximity to water tends to decrease. However, it also means that the other factors might have larger influences on LST than PW. The significance level

(p) represents the chance of seeing a correlation coefficient if there is no correlation in the population (i.e., the null hypothesis is true). "Sig. (2-tailed) <0.001" means the correlation coefficient is statistically significant at a level less than 0.001.

This demonstrated that using the same data but a different sample size has a significant impact on statistical data output.

3.4 Coefficient of Determination of Large Sample Area

Table 3. Regression from Large Sample

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.290 a	0.084	0.083	2.2850308

a. Predictors: (Constant), DEM, NDVI, NEAR_DIST

Interpretation (Table 3):

An R-value of 0.290 indicates a moderately positive correlation between the variables.

An R square value of 0.084, which is quite low, means that 8.4% of the variance in LST can be explained by the independent variables. The independent variable(s) included in the model do not explain the remaining 91.6% of the variation in the dependent variable. Suggesting that the model does not provide a very good fit to the data does not explain much of the variability in the data, and other factors may be influencing the dependent variable. This unexplained variance might be attributed to components not included in the model, random fluctuation or noise in nature, measurement error, or other unknown variables.

An adjusted R square value of 0.083 means that 8.3% of the variance in LST close to R square indicates that adding more predictors hasn't significantly improved the model's fit.

Table 4. Coefficient from Large Sample

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
	(Constant)	30.964	0.229		135.448	<.001
1	NDVI	-12.112	0.767	-0.245	-15.783	<.001
2	NEAR_DIST	0	0	0.094	5.575	<.001
3	DEM	-0.001	0	-0.18	-10.735	<.001

a. Dependent Variable: LST

Standard Error of the Estimate 2.28 indicates, on average, that the dataset's actual values differ from the projected values by about 2.28 units. It serves as a measure of the model's predictive accuracy and precision, with the lower values indicating better model fit and higher confidence in the predictions.

Analysis suggests that both NDVI, DEM, and proximity to water have a statistically significant effect on LST, with NDVI and DEM having a negative effect and proximity to water having a positive effect.

However, the model only explains 8.4% of the variance in LST, indicating that other factors such as sample size, the nature of the relationship, and the presence of outliers can influence the interpretation of the correlation coefficient.

Interpretation (Table 4):

Constant: The model's intercept, denoted by B (unstandardized coefficient), is 30.964. It denotes the expected value of the dependent variable when all independent variables are set to zero.

The t-value: is 135.448, a very high t-value, indicating that the intercept is statistically significant.

Sig.: <0.001, the p-value for the constant is less than 0.001, indicating that the intercept is highly significant. This value is almost certainly not zero.

NDVI: B (Unstandardized Coefficient): -12.112 indicates that each unit increase in NDVI reduces the dependent variable by 12.112. This is a negative relationship.

The NDVI coefficient's standard error is 0.767, indicating variability.

The standardized coefficient (beta) is -0.245 and measures the strength of the relationship between NDVI and the dependent variable in standardized units (z-scores). The value of -0.245 indicates that NDVI has a moderately negative impact on the dependent variable. The t-value: is -15.783, this t-value is extremely large (in magnitude), indicating that the NDVI coefficient is highly statistically significant.

A p-value less than 0.001 indicates that NDVI is a strong predictor of the dependent variable.

NEAR_DIST (Distance to nearest water feature):

B (Unstandardized Coefficient): 0; changes in the independent variable do not result in changes in the dependent variable.

Std. Error: The coefficient is still significant based on the t-value.

Beta (Standardized Coefficient): 0.094, the standardized coefficient is 0.094, suggesting a weak positive effect of NEAR_DIST on the dependent variable.

The t-value: is 5.575, this t-value is also large, indicating that NEAR_DIST is a statistically significant predictor.

Sig.: <0.001, the p-value is less than 0.001, showing that NEAR_DIST is highly significant.

DEM (Digital Elevation Model):

B (Unstandardized Coefficient): -0.001. This indicates that each unit increase in DEM decreases the dependent variable by 0.001, indicating a very slight negative effect.

The standard error shows the value of the coefficient is still statistically significant based on the t-test.

Beta (Standardized Coefficient): -0.18, the standardized coefficient indicates a moderately negative effect of DEM on the dependent variable.

The t-value of -10.735 indicates that DEM is statistically significant in predicting the dependent variable.

The p-value of less than 0.001 indicates that DEM is highly statistically significant.

3.5. Coefficient of Determination of Small Sample Area

Table 5. Regression from Small Sample

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.231[a]	0.053	0.049	2.3496026

a. Predictors: (Constant), NEAR_DIST

Interpretation (Table 5):

An R-value of 0.231 indicates a weak positive correlation between the variables.

An R square value of 0.053, which is quite low, means that 5.3% of the variance in LST can be explained by the independent variables. The independent variable(s) included in the model do not explain the remaining 94.7% of the variation in the dependent variable. Suggesting that the model does not provide a very good fit to the data. That does not explain much of the variability in the data, and other factors may be influencing the dependent variable. This unexplained variance might be attributed to components not included in the model, random fluctuation, measurement error, or other unknown variables.

An adjusted R square value of 0.049 means that 4.9% of the variance in LST close to R square indicates that adding more predictors haven't significantly improved the model's fit.

Standard Error of the Estimate 2.35: on average, the dataset's actual values differ from the projected values by about 2.35 units. It measures the model's predictive accuracy and precision, with lower values indicating better model fit and increased confidence in the predictions.

Analysis suggests that proximity to water has a statistically significant effect on LST. The LST with proximity to water has a negative effect. However, the model only explains 5.3% of the variance in LST, indicating that other factors such as sample size, the nature of the relationship, and the presence of outliers can influence the interpretation of the correlation coefficient.

Table 6. Coefficient from Small Sample

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	28.075	0.289		97.187	<.001
	NEAR_DIST	-0.002	0.001	-0.231	-3.569	<.001

a. Dependent Variable: LST

Interpretation (Table 6)**:**

(Constant): B (Unstandardized Coefficients): 28.075. This is the model's intercept, indicating that if all predictor variables are set to 0, the dependent variable should be 28.075.

Std. Error: 0.289, the standard error of the intercept indicates the estimate's precision.

t: 97.187, The t-statistic for the intercept is used to determine whether it is significantly different from zero.

Sig.: <0.001, the p-value indicates the significance level. Because it's less than 0.001, the intercept is extremely significant.

NEAR DIST (Distance to nearest water feature):

B (Unstandardized Coefficients): -0.002. This is the slope of the predictor variable "NEAR_DIST." It suggests that for every one-unit increase in NEAR_DIST, the dependent variable decreases by 0.002 units.

Std. Error: 0.001, the standard error of the slope, indicating the precision of the slope estimate.

Beta (Standardized Coefficients): -0.231, this is the standardized coefficient, which allows comparison between variables measured on different scales. It shows the relative impact of NEAR_DIST on the dependent variable.

t: -3.569, The t-statistic for NEAR_DIST testing whether the coefficient is significantly different from 0.

Sig.: <0.001, the p-value, showing that NEAR_DIST is a significant predictor of the dependent variable.

4. Discussions

4.1. Distribution Pattern

Larger forest regions are shown by the positively skewed distribution, which implies that there are more outliers on the top end of the distribution. Larger forest areas are further confirmed by the longer whisker and half-box on the top side of the median. The study area's forest cover varies significantly, as indicated by the broad interquartile range (2.62), with some regions having dense forests and others having scant vegetation or deforested land. The agriculture distribution is the most concentrated among the three, so there is less variability in agriculture compared to forest and built-up areas. Out of the three distributions, the built-up area distribution has the highest centre, suggesting a larger percentage of built-up land in comparison to the forest and agricultural land. There may be more outliers on the lower end of the distribution, which might indicate places with smaller built-up footprints, according to the negatively skewed distribution. Larger built-up regions are further confirmed by the longer whisker and half-box on the bottom side of the median, which may indicate urban centres or places with extensive infrastructure. The interquartile range (2.08) is narrower than in forests but broader than in farmland, indicating significant heterogeneity in built-up land cover throughout the research region.

4.2. Relationship Patterns

The study suggests a positive correlation between land surface temperature (LST) and the distance from water sources/proximity to water (PW), indicating that LST generally increases as one moves farther from water. However, this relationship is weak and influenced by multiple factors in urban environments, such as vegetation density, land cover, and infrastructure. Additionally, microclimatic effects, including heat retention and release from urban structures, can reduce the cooling impacts of nearby water bodies, particularly in densely populated areas. The previous research showed that the surrounding area near the water bodies has a lower LST than the farther areas [21].

In the current study, a weakly negative relationship exists between LST and NDVI and LST and DEM, suggesting that as LST increases, NDVI and DEM decrease. However, the relationship is negligible, suggesting other factors may have larger influences on LST than NDVI and DEM. At a high level, the link is statistically significant. Similar results were obtained by previous studies. The study also revealed that the vegetation index had a cooling effect that alleviated the UHI effect [22]. Another previous study was not entirely consistent, where the study showed that LST was positively correlated to DEM [23].

This study found a weakly negative correlation between LST and PW for a small sample area, suggesting that LST decreases as one moves toward the water sources. However, the relationship is weak and negligible, suggesting other factors may have larger influences on LST than PW. Urban design strategies that use water features can help to improve environmental quality, lessen heat stress, and create more livable communities. One of the studies demonstrated that the distance to water bodies has greatly influenced the LST, particularly in cities; the negative correlation gradually disappeared as the distances increased from the water bodies [21].

4.3. Assessing the Proportion of Total Variation in Outcomes

In the case of a large sample area, this study revealed that the model shows a moderate positive correlation with variables; with an R-value of 0.290, the strength is weak. The R square value of 0.084 explains 8.4% of the variance in LST, the proportion of variance in the dependent variable that is predictable from the independent variables. While an adjusted R square value of 0.083 explains 8.3%, it makes adjustments for the model's total number of independent variables. The standard error of the estimate is 2.29 units, indicating predictive accuracy and precision in the differences between the observed and predicted values of the dependent variable for the large sample area between the variables NDVI, distance to water, and DEM.

In the case of a small sample area. The model shows a weak positive correlation with an R-value of 0.231. The R square explains 5.3% of the variance in LST but not 94.7% of the dependent variable's variation. The adjusted R square value is 0.049, indicating that 4.9% of the variance can be explained by independent variables. The model's predictive accuracy and precision are measured by the standard error of the estimate of 2.35.

For a large sample area, NDVI has a significant negative effect on the dependent variable.

NEAR_DIST has a weak positive effect, but it is still highly significant.

DEM has a small but significant negative effect on the dependent variable.

All predictors in the model have p-values of less than 0.001, indicating that they are all highly statistically significant. The model shows that both NDVI and DEM have a negative effect on the dependent variable, whereas NEAR_DIST has a positive effect, though weaker than the other predictors.

For a small sample area, the model suggests that NEAR_DIST has a small but statistically significant negative impact on the dependent variable, with a standardized effect size of -0.231.

The constant (intercept) is also highly significant, and the overall model appears to be quite strong.

The NEAR_DIST has p-values < 0.001, meaning they are highly significant predictors of the dependent variable.

5. Conclusion

The study aimed to estimate the factors influencing land surface temperature (LST) through remote sensing, revealing a maximum of 37°C and a minimum of 19°C. It analyzed LST distribution in relation to land use, vegetation indices, proximity to water bodies, and elevation using a data-driven approach.

The analysis of temperature variations between urban land, forest, and vegetation areas in the Birendranagar Municipality confirmed the presence of the distribution pattern of the LST effect. The temperature in the built-up area was higher temperature than in agricultural land, than in the forest. Forests hold the lowest surface temperature.

The study in Birendranagar Municipality shows lower temperatures near water bodies, with land surface temperature increasing with distance. However, near the Jhupra River, temperatures rise by the banks and decrease further away, influenced by forests, agriculture, and urban areas. This counterintuitive result contrasts with the overall negative correlation previously observed between land surface temperature and distance to water bodies. It emphasizes that water sources impact the water table, affecting wells and rivers, with permeable soils aiding groundwater replenishment and cooler temperatures. The findings highlight the need to conserve riverbank recharge areas and maintain green spaces.

Similarly, LST tends to be lower at higher altitudes and greater at lower altitudes. Higher elevations have cooler air due to decreased atmospheric pressure and reduced absorption of solar energy. Topographic features, such as slopes and aspects, can impact local climatic patterns and contribute to changes in LST with elevation. Healthy vegetation absorbs more red light and reflects more near-infrared light, which leads to higher NDVI readings, where vegetation acts as a natural cooler via transpiration and shadowing.

The study does acknowledge some limitations. These include data availability and cleaning, data representativeness, and the complexity of the relationship between LST and other factors such as population density, built-up density, LULC changes, precipitation and humidity, human activities, climate change, urban pattern/design, and green spaces. Long-term monitoring and broader geographical coverage might help future researchers better understand these issues.

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Declaration of Author

The authors declare no conflicts of Interest.

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