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Comparative Analysis of Urban Sprawl through KNN and Random Forest Classification (RFC) ML Techniques

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The majority of optimization strategies fail to take into account the dynamic impact of urban sprawl on the spatial criteria that underlie decision-making processes. Furthermore, the integration of the existing simulation methodology with land use optimization techniques to arrive at a sustainable judgment regarding the appropriate site involves intricate procedures. The urban heat island phenomenon is a prominent consequence of urban expansion and human activities, leading to elevated temperatures within cities compared to their rural surroundings. The extent of sprawl was estimated through ML algorithms and it was revealed that RFC provided promising results that were near to statistics by various administrative authorities. Urban vegetation plays a crucial role in countering the urban heating effect by providing cooling mechanisms through evaporation and shading. In this context, a study was conducted in Allama Iqbal Town, Lahore, focusing on the assessment of land use changes, as well as the analysis of Normalized Difference Vegetation Index and Land Surface Temperature data for the years 2000, 2010, and 2023, obtained from Landsat 5 and Landsat 8 satellite imagery. The findings reveal significant land use changes of 7.52% (36.2 km^2) in the study area. The built-up areas expanded by 50.76%, while smart green spaces decreased by 48.30%. The relationships between NDVI and LST demonstrate a robust negative relationship ($R^2 = 0.99$). This research underscores the potential of utilizing GIS and remote sensing techniques to inform urban planning, decision-making, and policy formulation, ultimately contributing to the creation of sustainable urban environments in Allama Iqbal Town.

Keywords: Land Use Changes; Mitigation; Urban Hear Island; Urban Vegetation

Introduction:

In the past few decades, there has been a widespread occurrence of urban sprawl on a global scale, resulting in a rapid acceleration of Land Use Land Cover (LULC) change at an unprecedented pace. LULC has been significant in alterations to the planning criteria that determine the spatial distribution of diverse urban activities [1]. Hence, the process of selecting suitable locations for new industrial zones or communities requires the assessment of potential environmental risks in the future, which is contingent upon the dynamics of land use. Despite the ongoing efforts of several research communities to explore this subject, leading to the development of diverse approaches such as integration optimization and simulation land use strategies, additional study is required to advance this integration [2].

Land use optimization methodologies are a potent tactic for maximizing benefits in the realm of urban land use planning. Various methodologies exist to facilitate land use planning, including the utilization of a geographic information system (GIS) and Multi-criteria Decision Making (MCDM). MCDM is a prominent decision-making approach that aims to determine the most favorable choice by taking into account multiple factors during the selection process [3]. Nevertheless, both methodologies fail to account for the dynamics of LULC resulting from urban expansion when making judgments using a multicriteria approach. Hence, it is imperative to design a simulation technique that is compatible with the MCDM framework and can be effectively used in spatial contexts [4].

The examination of these characteristics and the investigation of LULC patterns have significant implications for the long-term viability of urban sustainability. The utilization of spatial analysis techniques facilitates the examination of driving factors that contribute to changes in LULC over time [5]. This analysis aids in the characterization of historical LULC patterns and enables the generation of potential transition pathways for future land use changes, specifically focusing on the conversion of non-urban land to urban land in each transition. The identification and prediction of urban growth and the factors that contribute to it would be beneficial in developing effective land-use practices and strategies that align with sustainability objectives [6][7].

Neighborhood variables encompass several elements such as the proximity to specific types of urban land, the proximity to important roadways, the proximity to an urban boundary, and the proximity to centers within the urban region. Socioeconomic factors encompass variables such as population size and Gross Domestic Product (GDP). Natural factors encompass several elements such as terrain and environmental parameters, specifically elevation, slope, and aspect [8]. Nevertheless, it is important to note that the driving factors influencing LULC as well as urban growth rates exhibit regional variations around the world. Consequently, distinct driving variables are employed to determine probable transition paths, taking into account the unique characteristics of each specific location [9]. Based on an extensive assessment of the existing literature and the insights provided by local experts, several driving forces have been identified as responsible for LULC changes [10].

The impact of proximity to urban centers, also known as Primary Central Cities (PCCs), on urban growth is significant. It effectively synchronizes with various forces and functions spatially and temporally to facilitate and propel urban expansion over the entirety of the metropolis [11][12]. Urban centers are highly desirable locations for establishing enterprises and developing new populations. Furthermore, the variable of road accessibility is frequently chosen as a spatial factor to predict urban expansion. The Proximity to Main Roads (PMRs) is a crucial determinant in the direction of urban development. Consequently, cities tend to expand in the direction of major roads [13]. In particular, development tends to concentrate near major roads, where access to urban infrastructure and amenities is readily available. Furthermore, primary thoroughfares contribute to the establishment of an urban framework characterized by advanced development, extending towards the periphery of the city. Hence, alterations in the configuration of road landscapes and the positioning of highway entrances and exits provide significant geographical implications in terms of proximity [14]. Contemporary architectural developments often tend to be situated near road networks. Consequently, this study posited that there exists a negative correlation between the land use change ratio and the distance from the aforementioned geographic characteristics [15].

The expansion of population leads to a rise in the demand for land, consequently resulting in significant impacts on LULC. Because a significant portion of the GDP originates from urban centers, it is observed that urban areas undergo more rapid growth and transformation as compared to rural regions [16].

Various machine learning techniques have emerged in the market that delineates a boundary around a residential area and provide statistics about expansion. These techniques include KNN and many others [17]. Despite its effectiveness in handling massive datasets and multiple variables, KNN provides easily interpretable signs. The K-Nearest Neighbors (KNN) algorithm employs a straightforward machine learning technique to accommodate the given dataset [18]. The KNN algorithm is a nonparametric machine learning method that is widely employed in a range of pattern recognition tasks. KNN-based approaches utilize the Euclidean distance metric to determine the similarity between a training and testing model. The KNN algorithm then assigns the output label of the testing model based on the majority vote among its KNN, as determined by the computed correlations. Moreover, it possesses the ability to undergo expedited training and provide swift predictions [19].

RFC based on ML is a suitable option as well. This method uses a linear equation to derive the optimal regression line, which is a straight line, for a given problem. This enables the visualization and prediction of the output of dependent variables. Furthermore, traditional machine learning methodologies, such as logistic regression, can produce prompt predictions [20]. In addition, logistic regression provides a straightforward yet efficient method for RFC based on ML. This work aims to utilize the regression technique to make long-term predictions of city expansion, leveraging its ability to foresee continuous outcomes over extended periods. The utilization of regression machine learning techniques enables the examination of the association between independent variables and dependent variable to make predictions about the spatiotemporal patterns of urban trends within the designated study area [21].

Urban neighborhoods located near factories that emit pollutants are susceptible to the adverse effects of environmental contamination. To address potential countermeasures, extensive scholarly investigation has put forth viable remedies, including various strategies for optimizing land utilization. The predominant techniques employed in spatial optimization include amalgamation of GIS and ML models, and the incorporation of RS data [22].

Urban green spaces play a crucial role in minimizing the Urban Heat Island (UHI) impact through the implementation of mechanisms such as evaporation and shading, as emphasized. scholars and researchers. The relationship between urbanization and landscape patterns plays a vital role in facilitating the effective management of urban ecosystems, as underscored by academic discourse. Across the literature, various elements related to urban green spaces have been identified as contributing to their cooling effects [9][23]. These considerations include the unique characteristics of plant life present in these places, the cooling impact that individual parks can have, and the broader cooling influence that these green spaces exert on the surrounding regions. These aspects have been extensively studied in scholarly works. It is worth noting that there exists an inverse relationship between the extent of vegetation coverage and NDVI, which is a metric that reflects plant photosynthetic activity, and the UHI impact [24]. The primary aim of this study is to evaluate the influence of urban green spaces on temperature variations in Allama Iqbal Town through ML techniques and to evaluate the effectiveness of

KNN and RFC based ML techniques. The study specifically aims to emphasize the correlation between vegetation and temperature in this urban environment [25].

Material and Methods:

The Study Area:

Allama Iqbal Town is situated within the geographical coordinates of approximately 31.51° N and 74.28° E as shown in Figure 1.

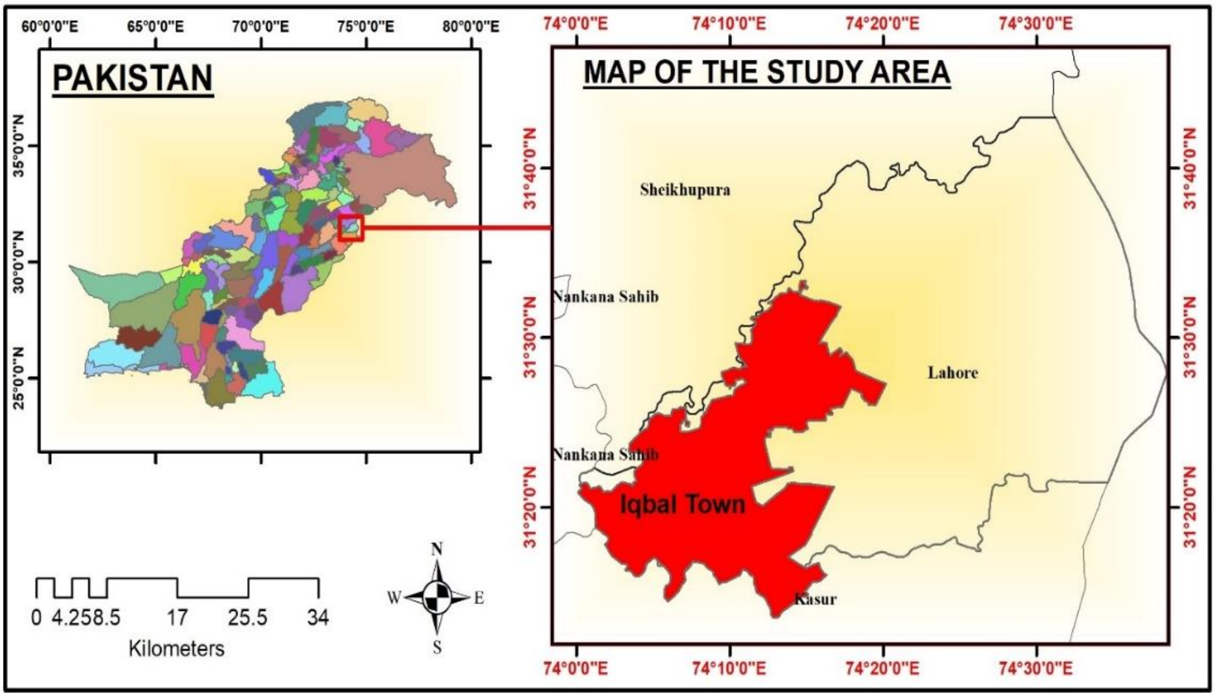

Figure 1. Map of the Study Area

The LULC, NDVI, and LST maps were prepared in ArcGIS 10.8 software however the processing of satellite images was carried out through ML techniques [26]. The details of satellite images that participated to carry out this research are given in Table 1.

Table 1: Detail of Landsat Images used by the Study.

Years	Satellite	Sensor	Path/Row	Row	Resolution (m)	Acquisition Day
2000	Landsat-7	ETM	149	38	30	19th March 2000
2010	Landsat-7	ETM	149	38	30	07th March 2010
2023	Landsat-8	OLI	149	38	30	18th March 2023

Normalized Difference Vegetation Index (NDVI):

The Normalized Difference Vegetation Index was measured using Equation 1.

$$NDVI = (NIR - R) / (NIR + R) \quad (1)$$

NDVI ranges between -1 to +1 where +1 indicates the lush green vegetation and vice versa.

Land Surface Temperature:

LST refers to the radiative temperature of the Earth's surface. LST plays a pivotal role in influencing how energy is distributed between the ground and vegetation and ultimately determines the surface air temperature, using the following equations:

Firstly, the radiation was calculated by using Equatio.iance =

$$\frac{LMAX-LMIN}{QCALMAX-QCALMN}(QCAL-QCALMIN)+LMIN \quad (2)$$

Secondly, the study calculated the LST in Kelvin through Equation 3.

$$T= K2 / (In (K1 / L\gamma + 1)) \quad (3)$$

To convert the 'Kelvin (A)' temperature values into 'Degree Celsius (B)' using equation 4.

$$B = A - 273.15 \quad (4)$$

KNN algorithm to compute pixel-based temperature and Classification

```
import numpy as np
from sklearn.neighbors import KNeighborsRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
'thermal_band_data'
# and the corresponding temperature values in a numpy array called 'temperature_values'
# Flatten the thermal band data and temperature values
X = thermal_band_data.reshape(-1, 1)
y = temperature_values.flatten()
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Initialize the k-NN regressor
knn_regressor = KNeighborsRegressor(n_neighbors=5)  # You can adjust 'n_neighbors' as needed
# Train the regressor
knn_regressor.fit(X_train, y_train)
# Predict temperature values for the test set
y_pred = knn_regressor.predict(X_test)
# Calculate the Mean Squared Error (MSE) as a measure of performance
mse = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error: {mse}")
```

RFC algorithm to compute pixel-based temperature and Classification

```
import numpy as np
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Step 2: Initialize and train the Random Forest Classifier
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42) # You can adjust hyperparameters as needed
rf_classifier.fit(X_train, y_train)
# Step 3: Predict the labels for the test set
y_pred = rf_classifier.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)
print(f"Accuracy: {accuracy}")
print(f"Classification Report:\n{report}")
```

Results and Discussion:

The LULC classification executed through KNN indicates that in 2000, approximately 36.04% (173.5 km^2) of the area was built up, while 63.31% (304.9 km^2) was categorized as green spaces, and 0.65% (3.1 km^2) consisted of water bodies. RFC based ML technique was used to classify the satellite image of 2010, the built-up area had increased to about 43.24% (208.2 km^2), while green spaces decreased to 55.84% (268.9 km^2), and water bodies made up 0.92% (4.4 km^2) of the land cover. This data reveals a 7.2% (34.6 km^2) increase in built-up areas, a -7.47% (35.9 km^2) decrease in green spaces, and a 0.27% (1.3 km^2) increase in water bodies during this period.

In 2023, the built-up area further expanded to approximately 50.76% (244.4 km^2), while green spaces decreased to 48.30% (232.6 km^2), and water bodies slightly increased to 0.94% (4.5 km^2). This indicates a 7.52% (36.2 km^2) growth in built-up areas, a -7.54% (36.304 km^2) decrease in green spaces, and a minimal change of 0.02% (0.041 km^2) in water bodies.

Figure 2 and Table 2 clearly illustrates these significant changes observed in LUCL patterns over the years 2000, 2010, and 2023.

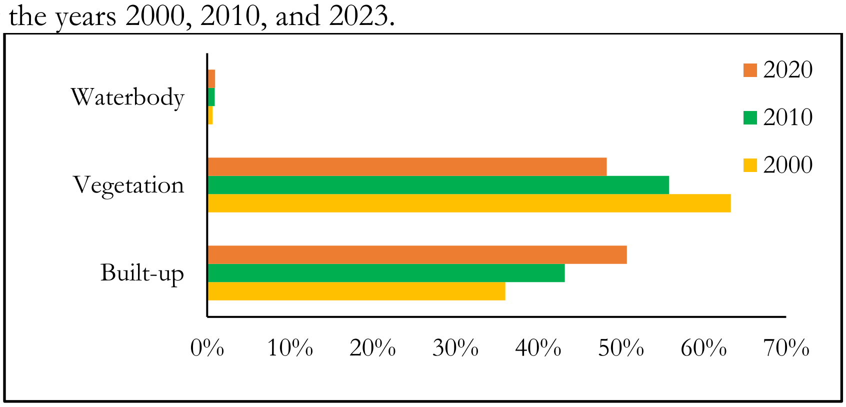

Figure 2. Land Use Land Cover Changes from 2000 to 2023

Table 2. Comparison of KNN and RFC Technique

Years	Built Up (km^2)		Vegetation (km^2)		Water (km^2)	
	RFC	KNN	RFC	KNN	RFC	KNN
2000	166.7	173.5	310.5	304.9	4.3	3.1
2010	193.6	208.2	283.5	268.9	5.4	4.4
2023	234.9	244.4	241.5	232.6	5.1	4.5

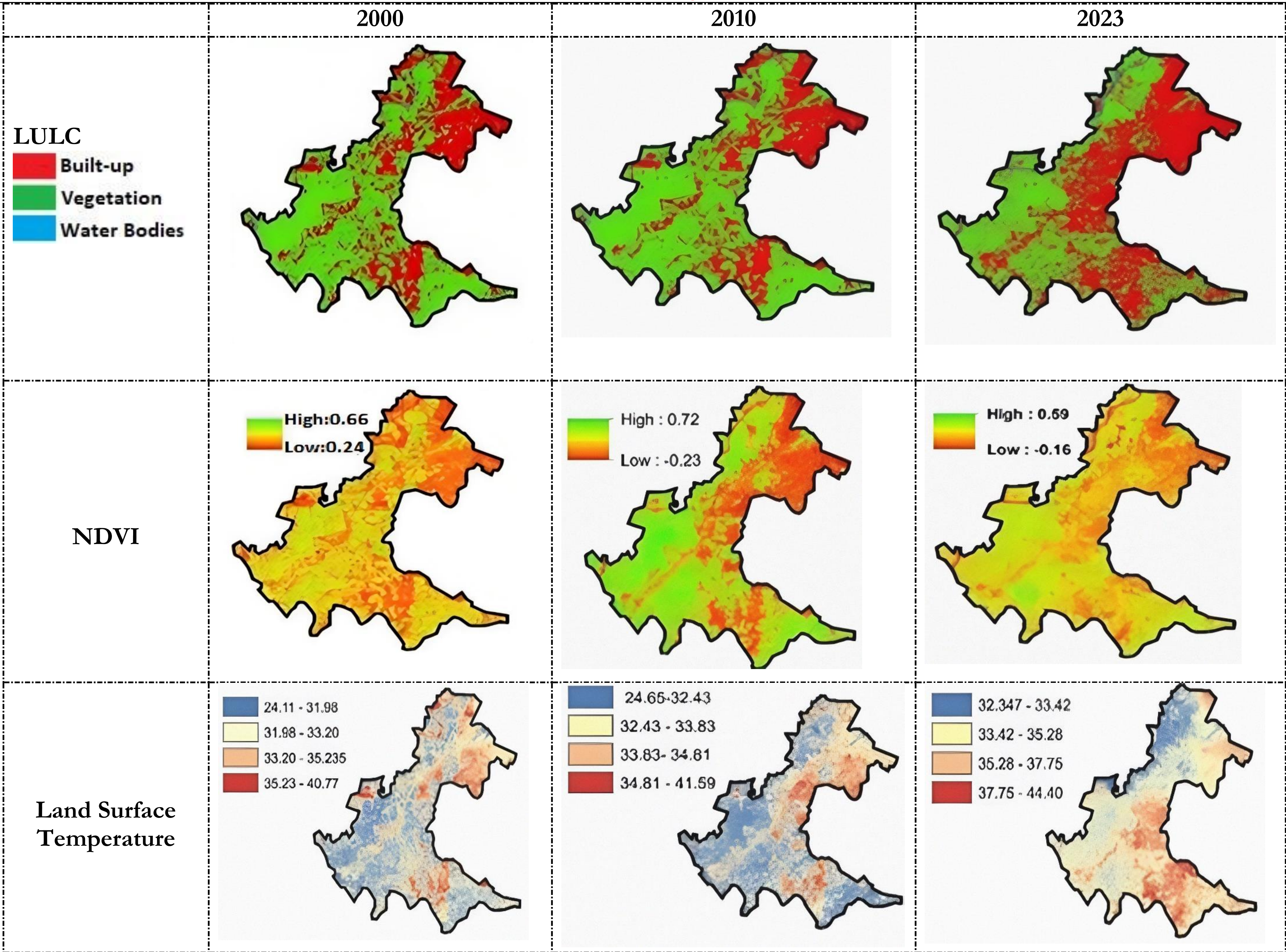

Figure 3. Spatio-temporal variation in LULC/NDVI and Temperature from 200-2023

The comparison map of LULC shows that the built-up area increases with a high ratio, the green spaces decrease, and water bodies have an insignificant change, as shown in Figure 3. The extent of sprawl was estimated and it was appraised that RFC based ML technique provided promising results that were near to statistics by various administrative authorities.

NDVI

In the year 2000, the NDVI ranged from a maximum value of 0.6687 to a minimum of -0.246. In 2010, the NDVI values spanned from a maximum of 0.729 to a minimum of -0.230. Conversely, in 2023, the NDVI exhibited a maximum value of 0.595 and a minimum value of 0.161, indicating a gradual decline in vegetation cover. It is worth mentioning that the maximum and minimum NDVI values experienced changes from 2010 to 2023. The overall trend observed over the 20 years clearly demonstrates a significant reduction in NDVI in these areas. This reduction can be attributed to notable alterations in the coverage of water bodies and built-up areas, as detailed in Table 3.

Table 3: Values of NDVI and Temperature

Years	Maximum	Minimum	Built-up	Green Spaces
2000	0.6687	-0.246	35.23 - 40.77°C	24.11 - 31.98°C
2010	0.729	-0.23	34.81 - 41.59°C	24.65 - 32.43°C
2023	0.595	-0.161	37.75 - 44.40°C	32.34 - 33.42°C

The comparative analysis of NDVI, as depicted in the comparison map, clearly indicates a reduction in both the maximum and minimum values, as illustrated in Figure 4.

Land Surface Temperature (LST):

The LST distribution for the year 2000 has been mapped in Figure 3, with corresponding mean temperatures for built-up and green spaces outlined. As indicated in the figure, the highest temperature range for 2000 falls within the range of 35.23°C to 40.77°C (observed in built-up areas), while the lowest temperature ranges between 24.11°C and 31.98°C (noted in green spaces). In 2010, the maximum LST values spanned from 34.81°C to 41.59°C, with the minimum temperature range falling between 24.65°C and 32.43°C. For 2023, the maximum temperature range extended from 37.75°C to 44.40°C, and the minimum temperature ranged from 32.34°C to 33.42°C. Notably, the highest mean temperatures were consistently observed within the built-up areas, while the lowest mean temperatures were consistently within the green spaces and water bodies.

The transformation of natural vegetation, such as forests and green spaces, into built-up surfaces composed of concrete, stone, metal, and asphalt can result in elevated surface radiant temperatures. However, despite the significant increase in built-up areas, the surface temperatures remain relatively lower. This could be attributed to the substantial presence of green spaces in the study area. Table 3 underscores that the maximum LST value has experienced an increase from 2000 to 2023, indicating a rise in temperature over this period. The comparison map of Land Surface Temperature unmistakably reveals an increase in both the maximum and minimum values, as evidenced in Figure 5.

Relationships between LST and NDVI:

Figure 4 presents the correlation between LST and NDVI within the specific study area for the years 2000, 2010, and 2023. The data clearly illustrates a robust correlation between land surface temperature and NDVI, implying that NDVI values can be employed to estimate surface temperatures effectively. The calculated correlation coefficient stands at an impressive 0.9964. This signifies a strong and negative correlation, indicating that regions with lower vegetation cover tend to exhibit higher land surface temperatures.

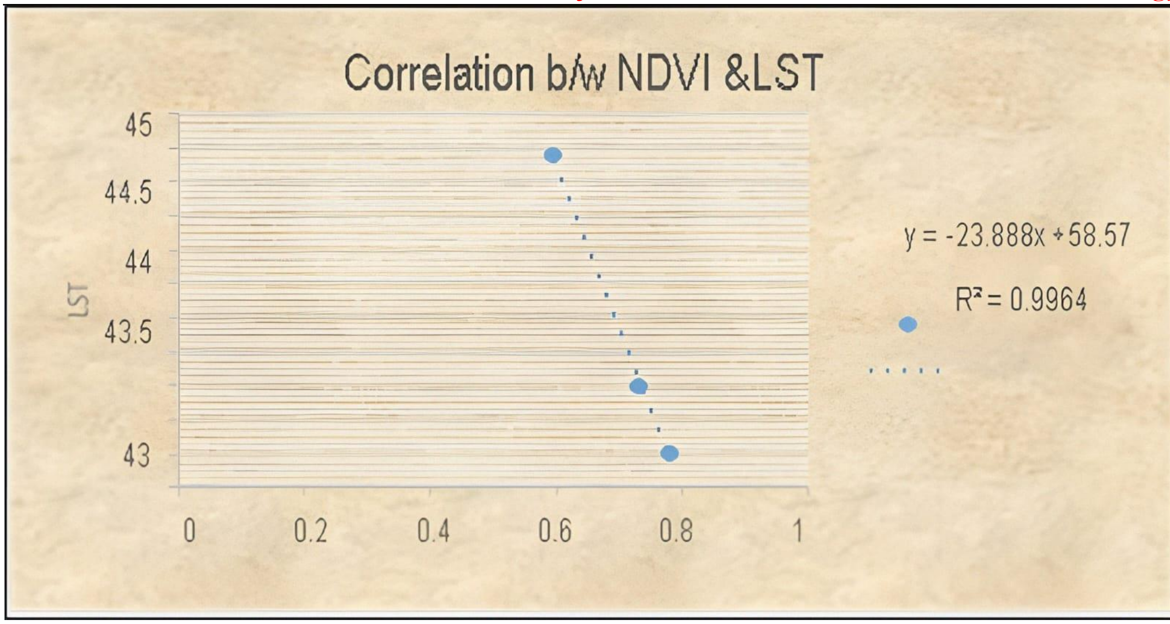

Figure 4. Correlation between LST and NDVI

Discussion.

The results of this study demonstrate that both the ML techniques are remarkably effective in proactively predicting probable long-term effects of Urbanization on environmental consequences. Consequently, this has led to detrimental consequences on natural systems. The expansion of urban development would persist in the direction of the region where existing or planned industrial ventures contravene local environmental standards, which are designed to safeguard urban communities against environmental contamination.

ML offers a valuable contribution to the field of land use planning by providing an effective means of validating and supporting decision-making processes, particularly in the context of long-term land use planning. This stands in contrast to traditional and contemporary techniques for LULC optimization and simulation. However, it is important to acknowledge the merits of these advantages, even though their outcomes are frequently linked to a certain degree of ambiguity. Nevertheless, the majority of these criteria are subject to dynamic spatial elements that undergo temporal fluctuations as a result of the influence of urban development. The omission of this change in land use optimization methodologies results in a gradual weakening of choices made based on multicriteria.

While KNN has provided recognition from numerous scholars as the most efficient technology however in case of urban area mapping RFC is proved efficient, the integration of this approach with land use optimization methods to arrive at a sustainable decision for identifying a suitable site for diverse activities is a complicated task. The selection of an appropriate site for a certain activity necessitates the execution of many activities in a sequential manner. Although key industrial projects, like oil refineries, power plants, and wastewater treatment plants, are often built to operate for several decades, existing prediction methodologies have limitations in accurately forecasting beyond a three-decade timeframe. To address these disparities, a novel methodology was devised, utilizing ML and GIS. The findings of this study confirm that the utilization of this innovative methodology can effectively mitigate the likelihood of erroneous judgments that incur substantial expenses when their repercussions necessitate rectification.

The methodology has capability to identify planning issues encountered in previously completed projects, as well as forecast prospective environmental challenges in ongoing construction projects and even planned planning project sites. Hence, the utilization of Decision

Support Tools (DSTs) holds significant potential in the context of land use optimization, particularly in the identification of suitable locations for projects that may contribute to pollution. This technique is deemed essential for scholars and urban planners with an interest in the pursuit of Sustainable Development Goals (SDGs).

The findings substantiate that random forest classifications approach is viable that should be incorporated into Multi-Criteria decision-making processes to facilitate informed decision-making and validate prior decisions. The process of urbanization often leads to an increase in temperatures within cities due to factors such as reduced natural surroundings, higher heat emissions, greater impermeable surfaces, and increased surface roughness. This phenomenon is commonly represented as the Urban Heat Island (UHI) effect. The consequences of UHI extend beyond altering the urban thermal environment; they encompass a heightened risk of dangerous heat events, elevated air pollution levels, increased energy utilization, and threats to human health.

The utilization of remote sensing and geospatial technology has played a pivotal role in classifying satellite data through RFC based on ML classification. This approach has enabled the tracking of changes over time, particularly the expansion of built-up areas and the decline of vegetation. The analysis of land use change types has underscored the significant impact of different land cover types on both NDVI and LST. It has been observed that built-up areas consistently exhibit higher LST compared to areas with vegetation and water bodies. Moreover, a robust negative correlation has been identified between NDVI and LST, indicating that an increase in vegetation leads to a decrease in surface temperature. This highlights the crucial role of vegetation in mitigating the UHI effect.

Conclusion.

Remote sensing and Geographic Information Systems have proven to be effective tools for assessing UHI in urban areas. The transformation of green areas into residential and commercial zones has notably contributed to increased LST, emphasizing the importance of preserving mature trees to alleviate the UHI effect. Therefore, the Iqbal Town Council must embark on tree-planting initiatives, involving the public and students in these efforts. Additionally, awareness campaigns should be initiated to promote the significance of green spaces and sustainable urban planning. This study provides valuable insights into the systematic planning of the urban environment.

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