Spatio-Temporal Analysis of Land Use Land Cover Changes and Spectral Normalized Difference Indices in Multan City, Pakistan

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Abstract: *The present study focuses the change in land use land cover along with the spectral normalized indices in Multan city for last three decades 1993 to 2023. The study years are 1993, 2003, 2013 and 2023. The land use land cover changes are evaluated through four specified classes including built-up area, agricultural land, barren land and water bodies while the spectral indices are NDVI, NDBI, NDBaI and NDWI. Urbanization dynamics requires quantitative descriptions and spatial distributions of urban areas, particularly in the face of rapid urban land-cover changes. To validate the method's accuracy, it was compared against ground truth data obtained from Landsat 5, Landsat 7, Landsat 8, and Landsat 9 images. The results of the accuracy assessments demonstrated the effectiveness of the method, with Overall Accuracy (OA) ranging from 0.854 to 0.913 and Kappa values ranging from 0.699 to 0.722. These findings affirm that the spectral normalized difference approaches can accurately describe spatial distributions and provide detailed information about urban extents. The findings showed considerable changes in all the four classes especially in built-up areas and agricultural areas. The built-up area increased in each study year along with decrease in agricultural land.*

Keywords: *Land Classification, Landsat images, Spatial Distribution*

I. Introduction

Population growth as well as the physical development of an urban area and cities are the dynamic causes of changes in land use land cover (Epstein et al., 2002). Human activities as well as quest for survival refer to change the land use to accommodate all types of population. Adaptation of urban infrastructure including urban settlements, commercial areas, industrialization and advanced agricultural practices becomes common. Change in LULC is the quantity of land that is developed and built-up for urban centers (Hasan et al., 2017). Urban growth is a major human activity that affects the urban environment significantly at different scales (Angel et al., 2010). As far as urban planning and sustainable management are concerned, this activity has become a serious managerial problem. LULC is sparked by socioeconomic progress and population growth (Benton et al., 2003).

It is well known that a variety of vegetation indices derived from satellite remote sensing pictures can be used to extract vegetation in both quantitative and qualitative ways. Several remote sensing indices have been quantitatively used to characterize land use and land cover for study on land surface temperatures (Gong et al., 2013). However, for urban land use planning and sustainable development, patterns from a qualitative research on the relationship between LST and LULC were used (Basse et al., 2014). Several vegetation indices derived from satellite thermal imagery can be used to quantify and qualitatively evaluate the assessment and amount of vegetation. The NDVI normalized difference vegetation index is the method used to measure plant growth that is most widely used(Xu & Guo, 2014a). The plant water content index, the normalized difference built-up index, the normalized difference bareness index, and the normalized difference water index (NDWI), (Özelkan, 2020).

Normative variation Additional indices called snow index (NDSI) are used to separate snow co e3ver from water bodies, snow cover, built-up territory, and vacant land, respectively(Zha et al., 2003a). These indices are calculated using a variety of algorithms based on various variables, such as the reflection of multispectral satellite image bands or intense absorption (J. Jensen, 2005). The vegetation's predicted output The Soil Adjusted Vegetation Index has been used in numerous metropolitan areas (Yuan & Bauer, 2007). The recommendation was made to use a Normalized Difference Built-Up Index based on the spectrum reflectance trait of synthetic exteriors (Zha et al., 2003b). The normalized variation for the quick certification of built-up buildings using satellite imagery, the Built-up Index (NDBI) was suggested (Xu & Guo, 2014b).

The Normalized Difference Water Index is used to represent water content quantitatively (Zha et al., 2003a). It is conceivable that the use of NDWI, IBI, NDVI, and SAVI in study on urban heat islands and climate could characterize and use categories through quantitative methods for recognizing correlation between dissimilar indices like NDVI, NDWI, and others (Zha et al., 2003a).An analysis of the region's spectral signature complements the development of an index for its information extraction from the satellite images (Fricke & Wachendorf, 2013). According to a number of factors affecting the morphology of towns and cities can be measured, approximated, and found using satellite remote sensing images (Næss & Jensen, 2004).

These characteristics include the size, shape, quantity, texture, density, and expansion of built-up territory in addition to the dwindling amount of vegetation in urban regions(Jat et al., 2008). Satellite remote sensing pictures are particularly crucial for spotting quick changes in land use and cover in cities where conventional surveying is labor- and time-intensive (Burke et al., 2021).

Controlling the amount, variety, and location of land use conversion is the main goal of monitoring urban growth and development (Gatrell & Jensen, 2008). Numerous research projects have focused on how to effectively use satellite remote sensing images in a variety of analysis and urban uses to support decision and policy making environments (Zeilhofer & Topanotti, 2008). Several studies have investigated municipal land use planning using satellite images, particularly spatial and temporal modeling of urban growth and urban change detection analysis Land use shift assessment, LST estimation, and observation of urban heat island phenomena are all connected ideas (Jensen & Im, 2007). Over a long period of time, the spatio-temporal dynamics of land use/land cover change (LULC) have an effect on the local environment and resources (Kayet et al., 2019). However, due to Pakistan's excessive population, the country's land use pattern has altered (Arsanjani et al., 2013).

2. Materials and Methods

2.1 Study Area

Multan, a historic city located in the province of Punjab, Pakistan, boasts a unique absolute location. Multan city is sited between 71.265° to 71.835° East Longitude and 29.792° to 30.457° North Latitude. Situated in the southern region of the country, Multan is strategically positioned at the crossroads of significant trade routes and has been a hub of commerce and cultural exchange for centuries. The city's absolute location places it on the eastern bank of the Chenab River. Multan's geographical position has contributed to its historical importance as a key center of trade and a melting pot of various civilizations and cultures (Figure 1).

The city is surrounded by vast agricultural plains, which are known for their fertile soils, making Multan a vital agricultural center and earning it the nickname "The City of Saints and Sufis" due to its rich agricultural bounty. To the north, the city is bordered by the districts of Khanewal and Vehari, while the districts of Lodhran and Bahawalpur lie to the south. To the east, the city shares its boundaries with the districts of Sahiwal and Mian Channu (Figure 1).

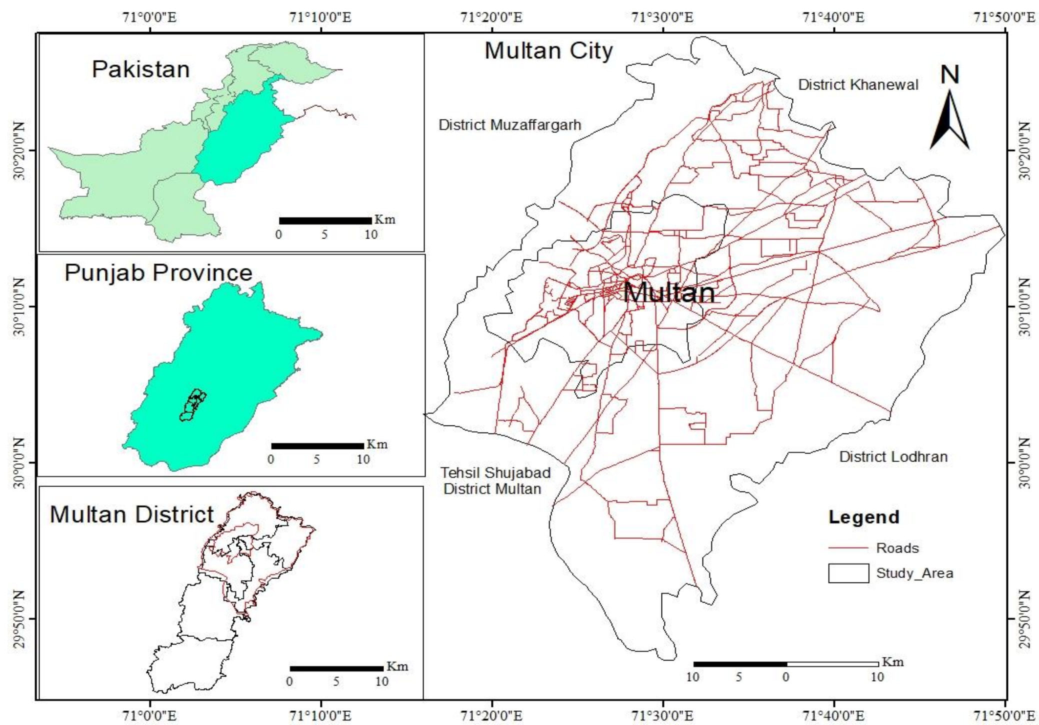


Figure 1 Location of the Study Area

2.2 Data Acquisition and Analyses

The current study used the spectral indices based on Land use Land cover changes for the last three decades from 1993 to 2023 in Multan city. For this purpose firstly the four Landsat images; Landsat 9 image of 2023, Landsat 7 image of 2013, Landsat 7 image of 2003 and Landsat 5 image of 1993 with SRTM 30m were downloaded from user section of Earth Explorer website (http:// earthexplorer.usgs.gov/).

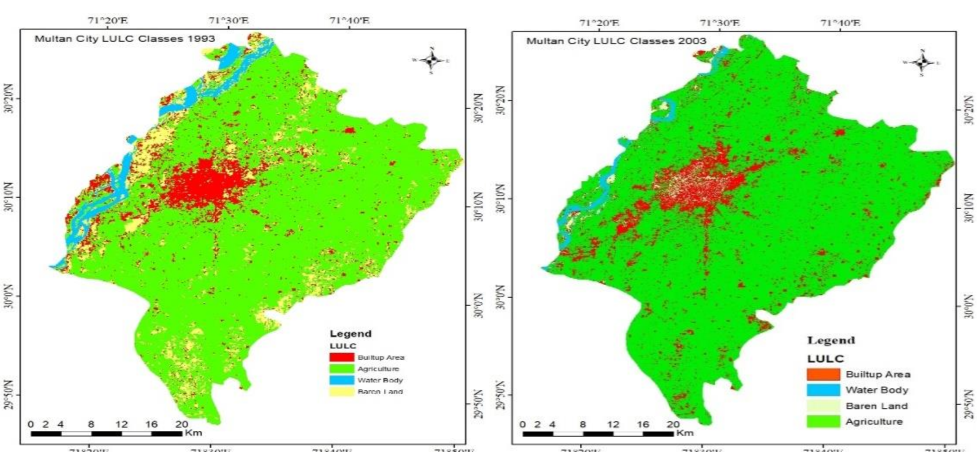
Landsat image classification as a powerful tool for monitoring changes in the study area over the specified time was the main target. Among the two major classification methods; supervised classification is carried out using the maximum likelihood classification method. After the band composite creates desired layers' built-up area, agricultural land, barren land and water bodies, the post-classification method is used for more data accuracy.

The remote sensing data utilized in this study originated from Landsat imagery. The data comprises spectral wavelength ranges and spatial resolution bands, which were utilized for analysis. The acquisition dates for the imagery were in March of 1993, 2003, 2013, and 2023, specifically in Path 150 and Row 39. The images obtained exhibited high-quality, with no cloud cover present over the study area.To ensure accuracy and consistency, the images were subjected to geometric correction at level 1T and projected into the World Geodetic System (WGS) 1984, utilizing the Universal Transverse Mercator (UTM) Zone_42N coordinate system. Subsequently, radiometric correction was applied, employing the atmospheric correction model. After the radiometric correction process, a subset image was extracted, focusing solely on the study area for further analysis.

3. Results and Discussions

3.1 Land use Land cover changes

Before heading towards the spectral normalized difference indices including NDVI (Normalized Difference Vegetation Index), NDBI (Normalized Difference Built Index), NDBaI (Normalized Difference Barren Index) and NDWI (Normalized Difference Water Index), the land use land cover changes is evaluated in the study area to monitor the urban growth during the study period 1993 to 2023. The study years are 1993, 2003, 2013 and 2023. The specified classes for LULC are four; built up area, barren land, agricultural and water bodies. The data witnessed that the built up area increased in the study area and the agricultural land along with the barren land and water bodies decreased and reduced in Multan city during the study period (Figure 2).



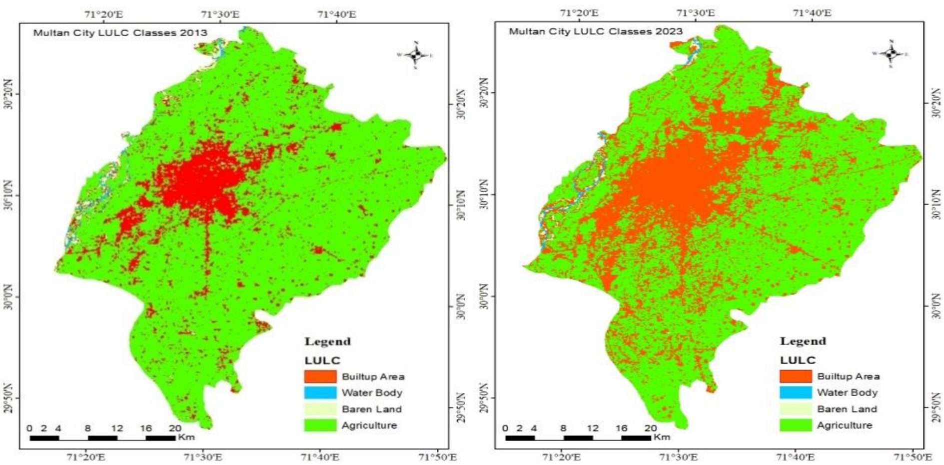


Figure 2 LULC of Multan city, 1993 – 2023

3.2 Spectral Indices with Normalized Differences

3.2.1 Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index (NDVI) is a widely used vegetation index that quantifies the amount of live green vegetation in an area based on satellite remote sensing data. NDVI is calculated from the ratio of the difference between the reflectance values of near-infrared (NIR) and red light wavelengths to their sum.

The vegetation index, which also makes use of the NDVI approach, gauges the condition of the vegetation. On how well plants reflect the electromagnetic spectrum, it is based. The dimensional index, which depicts the difference in vegetation cover's reflectance in the visible and near-infrared spectrum, is used to calculate the density of green on a piece of land. Using the raster calculator in ArcGIS, choose two bands for the NDVI calculation. NIR band 4 and red band 3 are used in the Landsat 5,7 photos to calculate NDVI. Similar to this, NIR band 5 and red are used to measure NDVI in Landsat 8.9 photos. Higher values on maps depict dense vegetation, whereas lower values depict shrubs. The NDVI number ranges from -1 to +1, with -1 standing for desolate land. Snow, sand, and bare rocks can be seen in the range of -1 to 0. Similar to this, 0.1 depicts grasses and shrubs, and 0.6 to 1 depicts extensive vegetation (Figure 3).

$$\text{NDVI} = \frac{(\text{NIR} - \text{Red})}{(\text{NIR} + \text{Red})}$$

$$\text{Landsat, 5 NDVI} = \frac{(\text{Band4-Band3})}{(\text{Band4+Band3})}$$

$$\text{Landsat 7, NDVI} = \frac{(\text{Band4-Band3})}{(\text{Band4+Band3})}$$

$$\text{Landsat 9,8NDVI} = \frac{(\text{Band5-Band4})}{(\text{Band5+Band4})}$$

NDVI values range from -1 to +1, with negative values indicating non-vegetated or non-photosynthetic areas such as water bodies, bare soil, or built-up areas, while positive values represent the presence of vegetation. The higher the NDVI value, the denser and healthier the vegetation covers.
NDVI has a broad range of applications in environmental monitoring, agriculture, forestry, and climate studies. It can be used to estimate vegetation growth, detect drought, monitor land use changes, assess soil moisture, and predict crop yield, among other things.

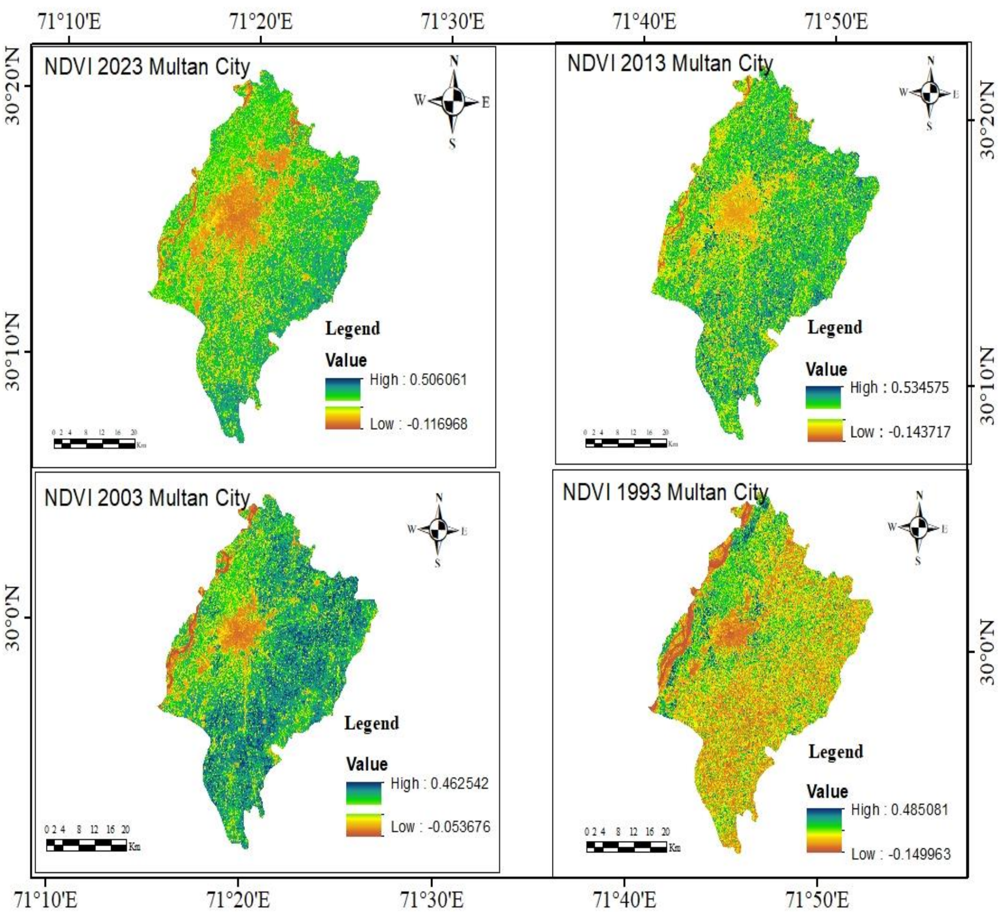


Figure 3 NDVI from (1993 to 2023)

3.2.2 Normalize Difference Built-up Index (NDBI)

Normalized Difference Built-up Index (NDBI) is a remote sensing index that is used to distinguish built-up areas from non-built-up areas in urban and peri-urban regions. It is calculated as the normalized difference between the near-infrared (NIR) and shortwave-infrared (SWIR) bands of a remote sensing image.
In this formula, NIR and SWIR are the spectral reflectance values of the near-infrared and shortwave-infrared bands, respectively. The NDBI values range from -1 to +1, with negative values indicating non-built-up areas such as vegetation, water bodies, and bare soil, and positive values indicating built-up areas such as buildings and roads.

$$NDBI = \frac{(SWIR - NIR)}{(SWIR + NIR)}$$

$$\text{Landsat 5 NDVI} = \frac{(Band5\text{-}Band4)}{(Band5+Band4)}$$

$$\text{Landsat 7 NDBI} = \frac{(Band5\text{-}Band4)}{(Band5+Band4)}$$

$$\text{Landsat 9, 8 NDBI} = \frac{(Band6\text{-}Band5)}{(Band6+Band5)}$$

Adjusted Difference The built-up area's state is determined by the built-up index, which likewise employs the NDBI methodology. It is based on how well structures reflect the electromagnetic spectrum. The high on a piece of urban is determined using the dimensional index, which illustrates the variation in built-up cover's reflectance in the visible and near-infrared spectrum. Choose two bands for the NDBI calculation using the raster calculator in ArcGIS. In the Landsat 5, 7 pictures, red band 4 and NIR band 5 are used to calculate NDBI. Similar to this, NDBI in Landsat 8.9 images is measured using NIR band 5 and band red 4.NDBI has a range of applications in urban planning, environmental monitoring, and disaster management. It is used to monitor urban growth, assess the spatial distribution of built-up areas, identify areas at risk of urban flooding, and estimate the urban heat island effect.

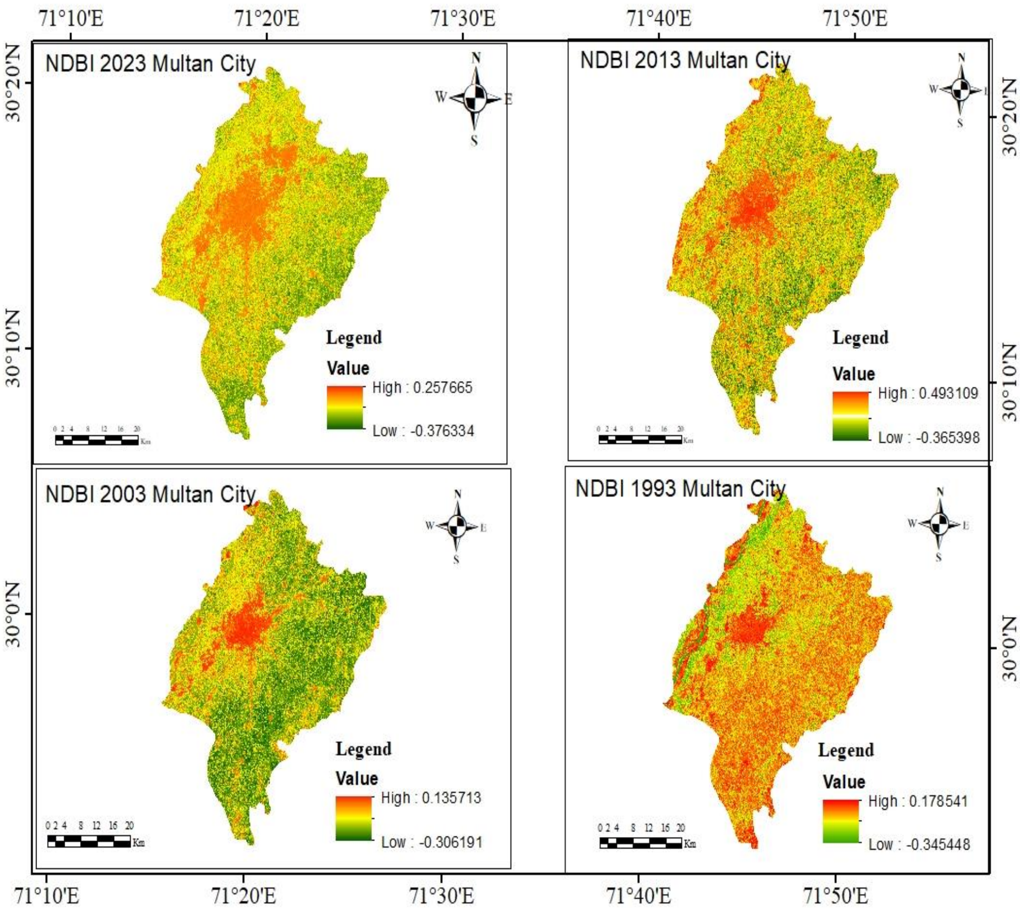


Figure 4 NDBI from (1993 to 2023)

3.2.3 Normalized Difference Barren Index (NDBaI)

Normalized Difference Barren Index (NDBaI) is a remote sensing index that is used to identify barren and sparsely vegetated areas from other land cover types. It is calculated as the normalized difference between the shortwave-infrared (SWIR) and the red bands of a remote sensing image.

It is illustrated that for the calculation of (NDBaI) first raster calculator is used in the ArcGIS environment. NDBaI was calculated using shortwave infrared and near-infrared bands. The range from -0.61 to -31 in 1993, -0.64 to -0.34 in 2003, -0.69 to 0.13 in 2013 and -0.68 to 0.44 in 2023. In the Landsat 5,7 pictures, red band 5 and NIR band 6 are used to calculate NDBaI. Similar to this, NDBaI in Landsat 8.9 images is measured using NIR band 6 and band red 5.

$$NDBaI = \frac{(SWIR1 - TIRS1)}{(SWIR1 + TIRS1)}$$

$$\text{Landsat 5,7} NDBaI = \frac{(Band5 - Band6)}{(Band5 + Band6)}$$

$$\text{Landsat 8,9} NDBaI = \frac{(Band5 - Band10)}{(Band5 + Band10)}$$

In this formula, SWIR and Red are the spectral reflectance values of the shortwave-infrared and red bands, respectively. The NDBaI values range from -1 to +1, with negative values indicating areas with dense vegetation cover, while positive values represent barren or sparsely vegetated areas such as deserts, rock outcrops, and dry riverbeds.

NDBaI has various applications in environmental monitoring, land use mapping, and natural resources management. It is used to monitor the expansion of desertification, identify areas with soil degradation, monitor the change in land cover, and detect the presence of mineral deposits in barren areas.

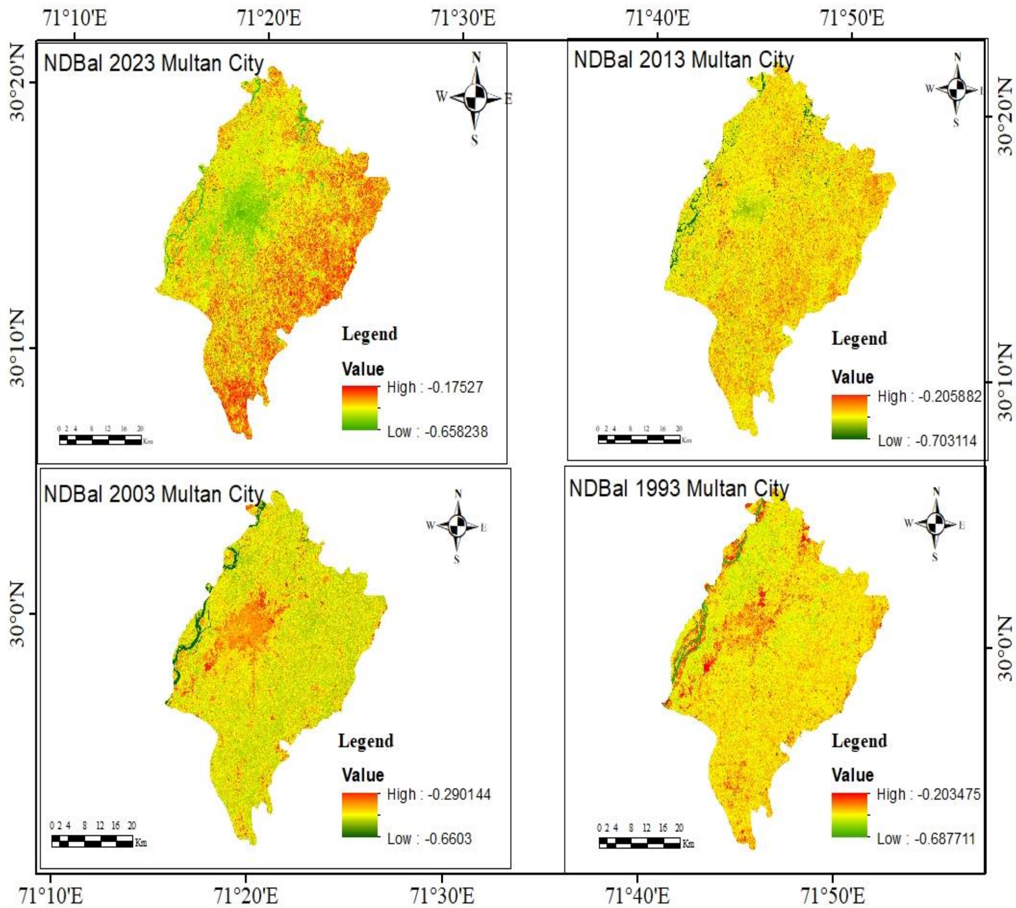


Figure 5 NDBaI from (1993 to 2023)

3.2.4 Normalized Difference Water Index (NDWI)

Normalized Difference Water Index (NDWI) is a remote sensing index that is used to detect and monitor the presence of water bodies in an area. It is calculated as the normalized difference between the green and near-infrared (NIR) bands of a remote sensing image.

An open body of water can "stand out" against the ground and vegetation by using the Normalized Differential Water Index (NDWI) to emphasize it in a satellite picture. The NDWI can improve the water bodies in a satellite picture by utilizing the NIR (near-infrared) and GREEN (visible green) spectral bands. The index's weakness is that it is sensitive to man-made structures, which might cause water bodies to be overestimated. The usual water surface reflect is maximized by the visible green wavelengths. The low reflectance of water features is minimum while the strong reflectance of terrestrial vegetation and soil characteristics is maximized by the near – infrared wavelengths. Positive values are obtained from the NDWI equation for water features, while negative values are obtained for soil and terrestrial vegetation.

$$\text{NDWI} = \frac{(\text{NIR} - \text{SWIR})}{(\text{NIR} + \text{SWIR})}$$

$$\text{Landsat 5 NDVI} = \frac{(\text{Band5-Band4})}{(\text{Band5+Band4})}$$

$$\text{Landsat 7 NDWI} = \frac{(\text{Band4-Band5})}{(\text{Band4+Band5})}$$

$$\text{Landsat 9,8NDWI} = \frac{(\text{Band3-Band5})}{(\text{Band3+Band5})}$$

In this formula, Green and NIR are the spectral reflectance values of the green and near-infrared bands, respectively. The NDWI values range from -1 to +1, with negative values indicating non-water features such as built-up areas, vegetation, and bare soil, while positive values represent the presence of water.
NDWI has a range of applications in environmental monitoring, hydrological studies, and water resource management. It is used to detect water bodies. It can be further used to monitor water quality, estimate the extent of flooding, assess the change in the water table, and identify wetlands and other areas with high water content.

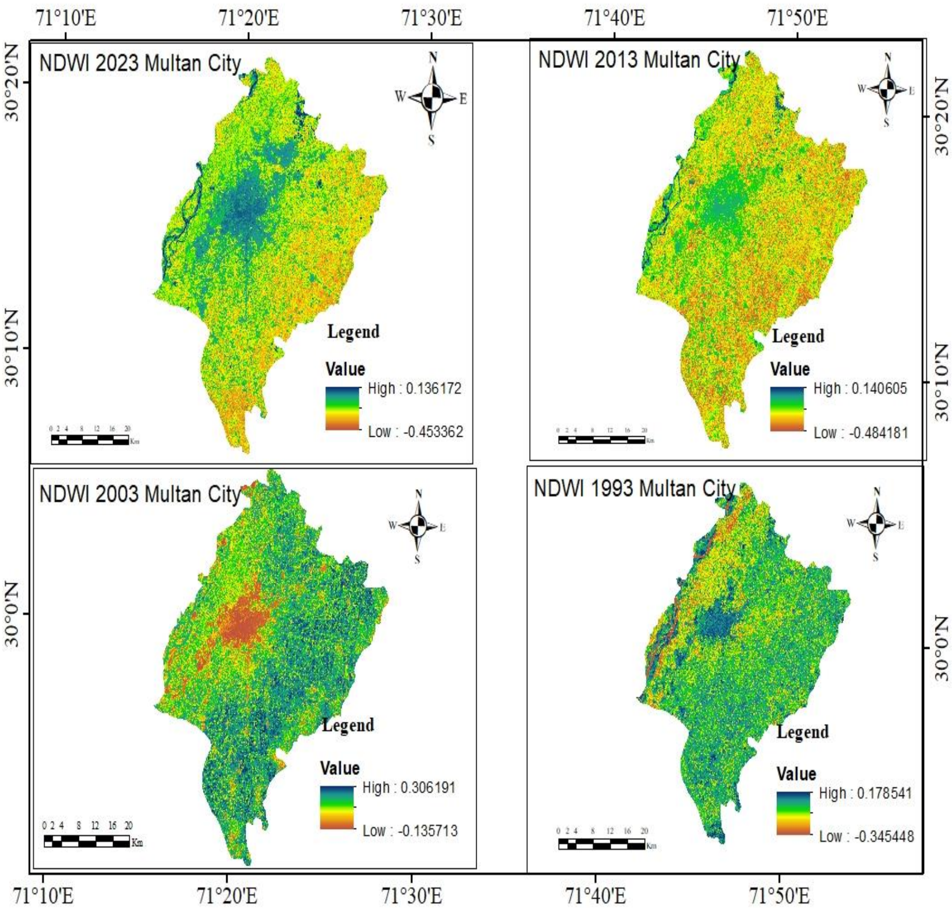


Figure 6 NDWI during 1993 to 2023

3.3 Accuracy Assessments

The classification process, based on the algorithms described earlier, may sometimes yield suboptimal results, leading to errors in the categorized image. These errors can be attributed to various factors such as incorrect labeling of training areas, flawed classification methods, and difficulties in distinguishing certain classes due to band correlation. Assessing the accuracy of the classified image becomes essential to understand the information quality derived from remotely sensed data. This assessment involves comparing the map created using remotely sensed data with another map obtained from a different source. Given the dynamic nature of landscapes, changes can occur rapidly, further complicating the accuracy evaluation. One prevalent method to express classification accuracy is through the creation of a classification error matrix, also known as a confusion matrix or contingency table. This involves locating ground reference test pixels or collecting samples to create the error matrix based on the classification results, employing various mathematical strategies for analysis and validation.

3.3.1 Omission error

Omission error, also known as a "false negative," occurs when pixels that belong to a specific class are not categorized correctly in that class during the classification process. This means that certain pixels, despite being part of the actual target class, are mistakenly classified into other classes. For example, if there are 12 pixels representing sand, but they are incorrectly labeled as water in the classified image, it results in an omission error. Such errors can arise due to the limitations of the classification algorithm, the complexity of the landscape, or the spectral similarity between different land cover types.

3.3.2 Commission error

Commission error, also known as a "false positive" or "inclusion error," occurs when pixels are classified into a specific class, but in reality, they belong to a different class. This means that certain pixels are mistakenly assigned to a particular land cover class during the classification process, even though they represent a different land cover type. For instance, if there are 20 pixels representing a forest, but they are incorrectly labeled as cultivated land in the classified image, it results in a commission error. Such errors can arise due to spectral confusion, limitations of the classification algorithm, or the complexity of the landscape, where certain land cover types may exhibit similar spectral signatures.

3.3.3 Overall Accuracy

Overall Accuracy is a widely used measure in classification accuracy assessment, calculated by dividing the total number of correctly classified pixels by the total number of reference pixels. While it provides an overall understanding of the classification performance, it does not offer insights into the accuracy of individual land cover classes. To gain a more detailed assessment, two additional measurements, namely producer accuracy and user accuracy, are commonly employed. Producer accuracy evaluates the ability of the classification to correctly identify pixels of a specific class, while user accuracy assesses the likelihood that a pixel classified as a particular class actually belongs to that class. By considering these additional measures, a more comprehensive evaluation of the classification's performance can be achieved, aiding in identifying potential sources of error and improving the reliability of land cover mapping results.

3.3.4 Producer accuracy

Producer accuracy is a metric used to assess the classification's ability to correctly identify pixels within a specific land cover category. It is calculated by dividing the total number of pixels correctly classified for a particular class by the total number of pixels representing that class within the sample. In essence, producer accuracy measures the classification's precision in accurately labeling pixels belonging to a specific land cover class. Higher producer accuracy values indicate a more reliable classification for that particular class, while lower values may suggest potential challenges in distinguishing that class from others. By analyzing producer accuracy for each land cover category, the strengths and weaknesses of the classification can be identified, leading to improvements in classification algorithms and techniques.

3.3.4 User accuracy

User accuracy, also known as user precision, is a crucial metric in classification accuracy assessment, as it evaluates the probability that a pixel labeled as a specific land cover class on the map truly belongs to that class. It is calculated by dividing the number of pixels correctly classified for a particular class by the overall number of pixels that were correctly identified within that specific class category. It is worth noting that producer accuracy and user accuracy may vary, as they represent different aspects of classification performance. While producer accuracy focuses on the classification's ability to correctly identify pixels of a specific class from the reference data, user accuracy assesses the likelihood that pixels classified as a certain class genuinely belong to that class. Analyzing both producer and user accuracy provides a more comprehensive understanding of the classification's strengths and weaknesses, allowing for targeted improvements and enhancing the reliability of land cover mapping results.

3.3.5 Kappa Coefficient

The Kappa Coefficient is a discrete multivariate method used to evaluate the accuracy of a classification. It takes into account the proportion of pixels that would be correctly classified by random chance alone. By incorporating statistical techniques that consider the role of random chance, the Kappa measure provides an indication of how much the classification outperforms random pixel allocation to their respective classes. In essence, the Kappa Coefficient measures the agreement between the classification's performance and what would be expected by chance, offering a more robust assessment of classification accuracy and aiding in understanding the classification's efficacy compared to random classification.

Accuracy Assessment of Land use Land Cover map 1993, 2003, 2013 and 2023

Years	Overall Accuracy %	User Accuracy %	Procedure Accuracy %	Kappa Coefficient
1993	90.49	93.35	92.26	0.93
2003	91.42	92.47	90.63	0.90
2013	92.22	90.43	90.28	0.89
2023	91.55	94.73	93.49	0.91

Overall Accuracy

$$\text{Overall Accuracy} = \frac{\text{Total Number of Correct Classified Pixel}}{\text{Total Number of Reference pixel}} \times 100$$

User Accuracy Calculation

$$\text{User Accuracy} = \frac{\text{Total Number of Correctly Classified Pixel}}{\text{Total Number of the Reference pixel}} \text{x}100$$

Producer Accuracy Calculation

$$\text{Procedure Accuracy} = \frac{\text{Total Number of Correctly Classified Pixel}}{\text{Total Number of Reference pixel}} \text{ x } 100$$

$$\text{Kappa coefficient Formula (T)} = \frac{(\text{TS X TCS}) - \Sigma\,(\text{Column total x Row Total})}{\text{TS}^2 - \Sigma\,(\text{Column total - Row Total})} \text{x}100$$

4. Conclusion

From the present research, it is concluded that land use land cover changes in the study area occurring at an evident pace. The each year of the study period; 1993, 2003, 2013 and 2023 witnessed changes in urban growth indicators in Multan city. The built up area increased and the agricultural land decreased during the last three decades in the study area. The increase in built up area is one of the main influencing factors towards growth of urban infrastructure. The barren land and water bodies in the study area also experienced radical changes as the area of both the classes decreased in the study area.

The results of the accuracy assessments demonstrated the effectiveness of the classification, with Overall Accuracy (OA) ranging from 0.854 to 0.913 and Kappa values ranging from 0.699 to 0.722. This assessment further authenticated that the changes in classes for built up area, agricultural land, barren land and water bodies along with the spectral normalized indices result are accurate and don't have any user or production error. The concern stakeholders in the study area direly needs to focus the unprecedented growth of built up area and reduction in agricultural land to adopt conducive mitigation strategies for coping the irregular and haphazard growth of the city along with the food shortage issues. By demonstrating great potential in mapping global urban information in a simple and precise manner, the classification offers valuable insights for addressing urban issues effectively.

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