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ANALYSIS OF URBAN SPRAWL IN CHINIOT DISTRICT USING GEOINFORMATICS TECHNIQUES

MAHNOOR[1], REHAN AHMAD PARVAIZ*[2] AND MIRZA NASEER AHMAD[3]
Abdul Salam School of Sciences, Nusrat Jahan College, Rabwah, Pakistan

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Abstract: Fast urban growth in developing countries often spreads into farmland and puts pressure on land and infrastructure. Medium-sized districts in Pakistan, such as Chiniot, have received little attention, where planning often depends on old or incomplete data. This study maps and measures urban sprawl in Chiniot District between 1990 and 2025 using geoinformatics. Landsat images from 1990, 1999, 2013, 2020 and 2025 were corrected for radiometric and geometric errors and classified into built-up, vegetation, water and barren land with the Maximum Likelihood Classifier. Accuracy was checked with confusion matrices and Kappa statistics, and the Normalized Difference Built-up Index (NDBI) was used as a second, independent check on the built-up class. Kappa values rose from 0.78 in 1990 to 0.91 in 2025. Built-up area grew from 210.29 km² to 512.10 km², an increase of about 144% (8.62 km² per year), and growth was fastest before 2013. Vegetation fell by about 310 km², while water and barren land changed from year to year, probably because of season and rainfall. NDBI patterns agreed with the classified maps. The results show steady, scattered and mostly unplanned expansion at the cost of vegetation, which give planners in Chiniot a factual base for zoning and land management.

Keywords: Urban sprawl, LULC classification, NDBI Landsat, Chiniot, Pakistan.

Introduction

Urbanization is the process by which more and more people live and work in towns and cities (UN DESA, 2019). In many developing countries it happens without much planning, and the result is urban sprawl: cities spread outward in a scattered way and use land inefficiently (Brueckner, 2000; World Bank, 2020). In Pakistan, population growth, migration from villages and weak planning rules have pushed cities to expand sideways, and medium-sized cities are no exception.

Urban sprawl is usually described as the unplanned spread of built-up land into surrounding rural and peri-urban areas. It breaks up land-use patterns, damages the environment and raises the cost of providing roads, water and other services (Ewing, 1997; Galster *et al*., 2001; Bruegmann, 2005). Studies from different regions link this kind of growth to heavy land consumption and ecological stress (Angel *et al*., 2011; Seto *et al*., 2012). Sprawl also affects rural land around cities, as shown for Colombo District in Sri Lanka (Antalyn & Weerasinghe, 2020).

Tracking urban growth needs spatial tools that can cover large areas over long periods. Geoinformatics, which combines remote sensing and Geographic Information Systems (GIS), is well suited to this job. It has been used to follow urban expansion in India, Ghana, Nigeria and Ethiopia (Jat *et al*., 2008; Kpienbaareh & Luginaah, 2020; Koko *et al*., 2021; Fenta *et al*., 2017). Land use/land cover (LULC) classification and spatial analysis have been used to detect growth patterns and landscape change (Mundia & Aniya, 2005; Weber *et al*., 2005; Onur *et al*., 2009), and multi-date satellite images have been used to study the speed, direction and structure of urban growth (Ward *et al*., 2000; Bhatta, 2009; Yu, 2009 and Yuan, 2010).

Other work has focussed on applied geospatial methods to the environmental and social effects of sprawl in both developed and developing regions (Murayama *et al*., 2021; Shao *et al*., 2021; Manesha *et al*., 2021), and change-detection studies with Landsat data have shown that long-term land-use change can be captured reliably (Muttitanon & Tripathi, 2005; Tewabe & Fentahun, 2020; Donatien *et al*., 2024). In Pakistan, remote sensing studies of Faisalabad have documented the spread of built-up land into the surrounding area (Naeem *et al*., 2021).

Studies on Lahore, the provincial capital, show the same trend on a much larger scale. Built-up land there grew by about 114% between 1994 and 2024, while vegetation and farmland shrank, and the value of ecosystem services fell by roughly 37% (Jabbar *et al*., 2026); green cover declined from 1,292.8 km² to 754 km² between 1990 and 2020 as built-up area rose from 262 km² to over 550 km² (Sattar *et al*., 2025).

Mean land surface temperature in Lahore rose by 6.82 °C between 2000 and 2025 (Nasar-u-Minallah *et al*., 2025a), and urban heat and air pollution reinforce each other, with CO and NO_2 correlating positively with night-time surface heat island intensity (Nasar-u-Minallah *et al*., 2025b). In Punjab, the built-up area of Faisalabad grew from about 223 km² in 2000 to 281 km² in 2010 (Naeem *et al*., 2021).

*Corresponding author e-mail: rehanparvaiz@njc.edu.pk

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Most urban studies in Pakistan have looked at large cities. Chiniot District, which became a separate district in 2009, has been paid little attention, even though its furniture trade, local commerce and farming are changing quickly. Planning decisions in such districts are often made with outdated maps and limited data. Present study aims to fill this gap, and covers the whole district, instead of only the main city, so growth around smaller towns and along roads is included. Secondly, in this study five dates have been considered over 35 years (1990, 1999, 2013, 2020 and 2025), which allows the pace of change to be compared between periods. Thirdly, it checks the classified built-up area against NDBI and reports user's accuracy, producer's accuracy and Kappa for every year, so readers can judge how far the results can be trusted.

The aim of this study is to assess the spatial and temporal pattern of urban sprawl in Chiniot District from 1990 to 2025 using Landsat images, supervised LULC classification and NDBI. The specific objectives are:

1. To map LULC in Chiniot District for 1990, 1999, 2013, 2020 and 2025 using the Maximum Likelihood Classifier;
2. To measure the change in built-up, vegetation, water and barren land between these years;
3. To use NDBI to check the extent and spread of built-up areas;
4. To test the accuracy of each classified map with confusion matrices and Kappa statistics; and
5. To discuss what the observed growth means for land-use planning in the district.

Study Area

Chiniot District lies in central-eastern Punjab, Pakistan, between 31°43′ and 32°05′ N and between 72°58′ and 73°40′ E (Fig. 1) It was created as a district in 2009 and has three Tehsils: Chiniot, Lalian and Bhowana. The River Chenab forms its eastern boundary and shapes both the physical and economic setting of the district.

The district is a fertile plain with a semi-arid climate. Farming is the main occupation and depends on irrigation. The furniture industry of Chiniot and local trade also draw people to the area and add to population growth and urbanization (Govt. of Punjab, 2017). In recent years the district has seen fast, poorly regulated development, with agricultural land being turned into built-up land, which is typical of urban sprawl. Chiniot was chosen because of its fast urban growth, the availability of many Landsat scenes, and the lack of earlier studies of the district.

Materials and Methods

Data and Sources

Landsat images from several sensors were used to follow urban expansion from 1990 to 2025. Only cloud-free scenes were selected. The sensor, year and resolution of each image are given in Table 1. Training samples and reference data came from the satellite images, existing maps and high-resolution Google Earth imagery. All image processing and spatial analysis was done in ArcMap 10.8.

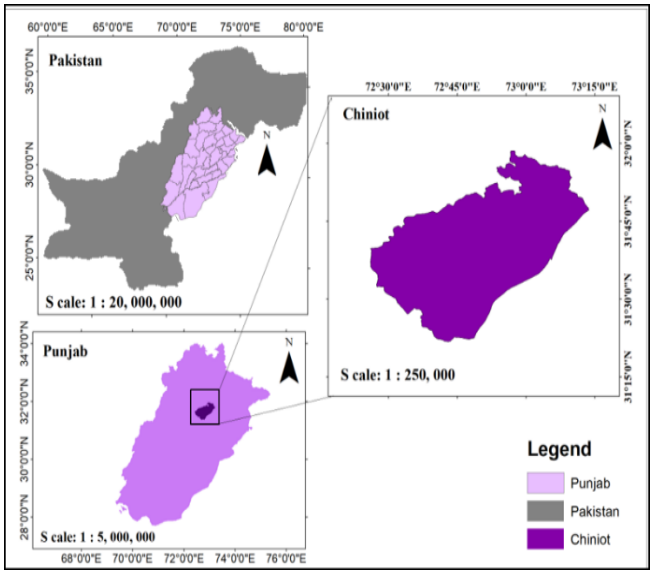


Fig. 1 Study area map of Chiniot District.

Table 1. Landsat data used for Chiniot District.

Sensor	Year	Resolution	Purpose
Landsat TM	1990	30 m	Baseline for urban expansion
Landsat ETM+	1999	30 m	Growth in the middle of the study period
Landsat OLI	2013	30 m	Recent growth, better radiometric quality
Landsat OLI	2020	30 m	Recent growth, better radiometric quality
Landsat OLI	2025	30 m	Current extent of built-up land

Methodological Flow Chart

The work followed the steps shown in Figure 2: image acquisition, pre-processing, supervised classification, accuracy assessment, NDBI calculation, and change detection between the five dates. The LULC maps and NDBI maps were then used to measure the amount, rate and pattern of urban growth.

Image Pre-Processing

Pre-processing was done so that images from different years could be compared without false differences. It included radiometric and geometric correction, sub-setting to the district boundary, and projection to UTM Zone 42N (WGS 84) (Jensen, 2016).

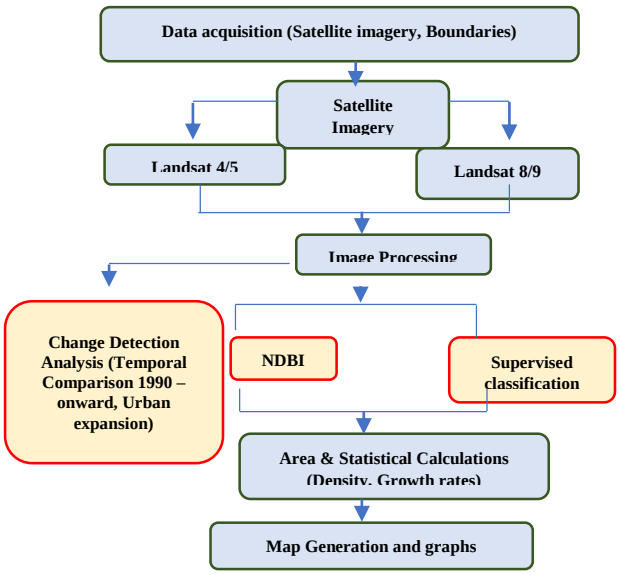


Fig. 2 Methodological flow chart of the study

Supervised LULC Classification

Each image was classified into four classes: built-up area, vegetation, water body and barren land. Training sites were chosen using the images themselves, existing maps and Google Earth.

The Maximum Likelihood Classifier (MLC) was used because it handles urban data well, and is widely applied for this purpose (Lillesand *et al*., 2015). One LULC map was produced for each year.

Normalized Difference Built-up Index (NDBI)

NDBI was calculated from the shortwave infrared (SWIR) and near-infrared (NIR) bands:

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

The index gives higher values to built-up surfaces and lower values to vegetation and water, so it works as a second check on the classified built-up area (Zha *et al*., 2003; Xu, 2008). NDBI was calculated for all five years.

Accuracy Assessment

Each classified map was compared with reference points taken from high-resolution imagery and Google Earth using a confusion (error) matrix. Overall accuracy and the Kappa coefficient were then worked out:

Overall Accuracy (%)

$$= \frac{\text{Correctly classified pixels (Diagonal)}}{\text{Number of reference pixels}} \times 100$$

Here N is the total number of reference samples, x_ii is the number of correctly classified samples in class i, x_i+ is the row total and x_+i is the column total, with sums taken over all classes (Congalton & Green, 2009).

Kappa values were read as follows: below 0.40 is poor, 0.40–0.60 is moderate, 0.60–0.80 is substantial, and 0.80 or more is almost perfect. User's accuracy (UA) and producer's accuracy (PA) were also calculated for each class.

Change Detection

Class areas were calculated in square kilometres for each year, and the change between dates was worked out by comparing the LULC maps. The annual rate of built-up growth for each period was calculated as the change in area divided by the number of years in that period.

Result and Discussion

Four LULC classes were mapped for every year (Figs. 3-7). Built-up land increased over time, mostly around the main urban centre and along the *larger* roads. The area of each class is given in Table 2.

Built-up Area Expansion

Built-up land grew from 210.29 km² in 1990 to 512.10 km² in 2025. This is a gain of 301.81 km², or about 144%, and an average of 8.62 km² per year. The built-up share of the district rose from about 8% in 1990 to about 20% in 2025. Growth was fastest before 2013 and slower afterwards (Table 3).

The rate was about 11.7 km² per year in 1990–1999 and 10.0 km² per year in 1999–2013, then fell to 3.1 km² per year in 2013–2020 before rising again to 7.0 km² per year in 2020–2025. The maps show that the new built-up land is scattered and spreads outward in all directions rather than filling gaps inside existing settlements, which is the pattern expected of sprawl.

Vegetation, Water and Barren Land

Vegetation fell from 2,045.39 km² in 1990 to 1,735.44 km² in 2025, a net loss of about 310 km² (roughly 15%). The change was not steady. Vegetation dropped to 1,478.86 km² in 1999, recovered to 1,984.82 km² in 2013 and then declined again. The 2013 recovery is probably linked to the season of the image or re-cultivation.

Water bodies decreased from 104.29 km² in 1990 to 32.95 km² in 2013, and then increased to 74.68 km² in 2025. Barren land was very variable. It rose from 242.47 km² in 1990 to 650.29 km² in 1999, fell to 129.46 km² in 2013, and was 280.49 km² in 2025. These swings are more likely to come from season, river flow, fallow fields and land waiting for construction than from direct urban growth.

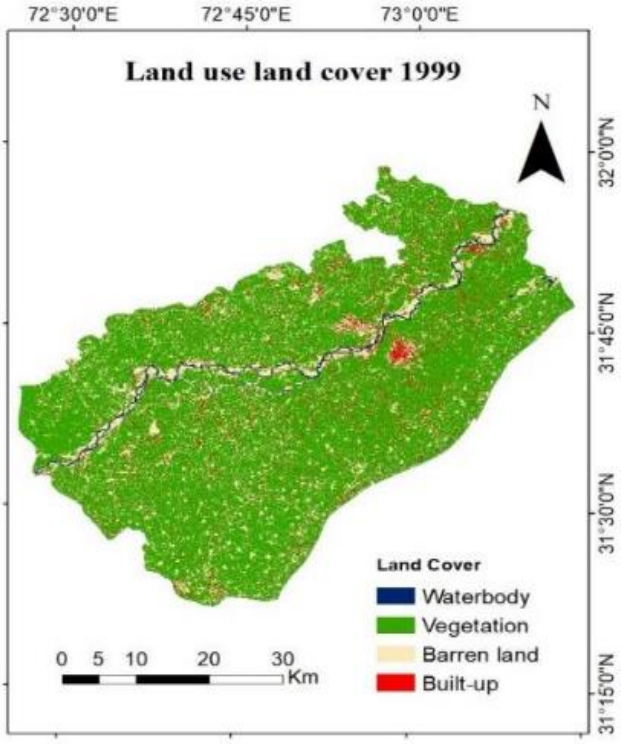


Fig. 3 LULC map of Chiniot District, 1990.

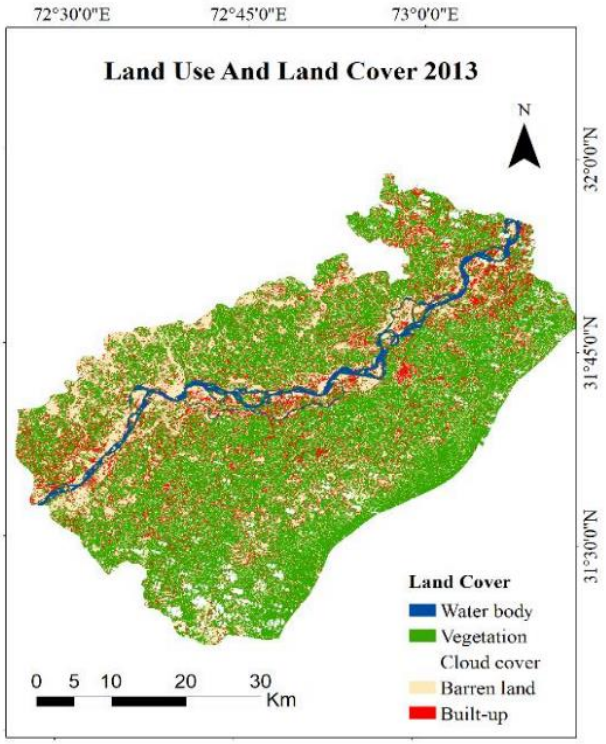


Fig. 5 LULC map of Chiniot District, 2013.

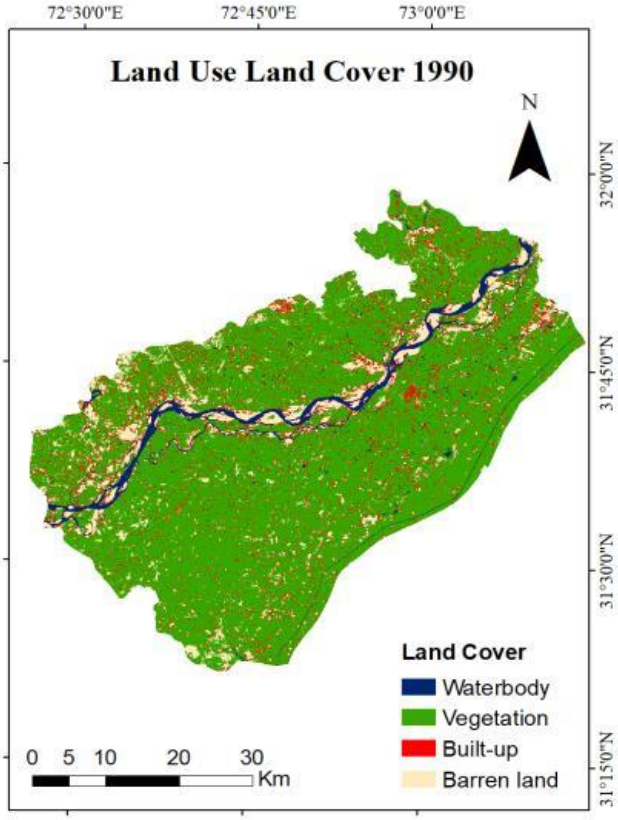


Fig. 4 LULC map of Chiniot District, 1999.

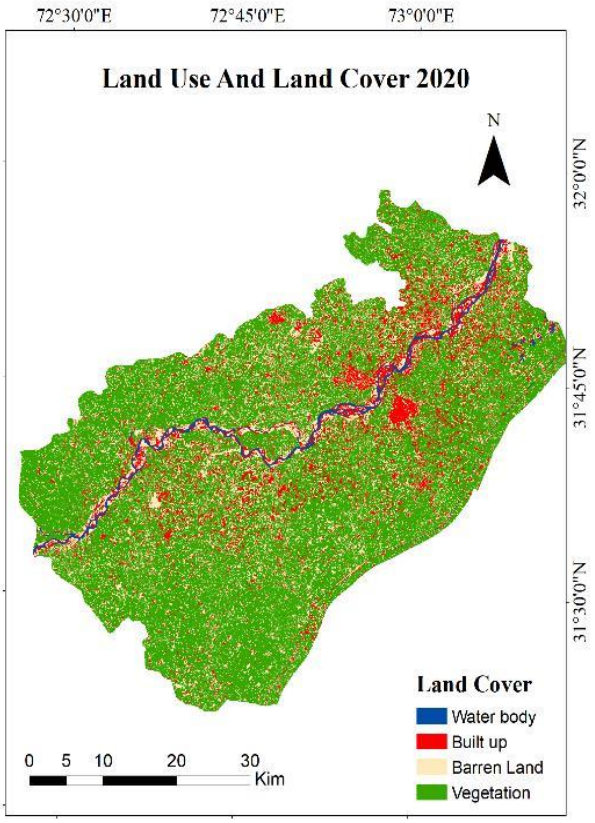


Fig. 6 LULC map of Chiniot District, 2020.

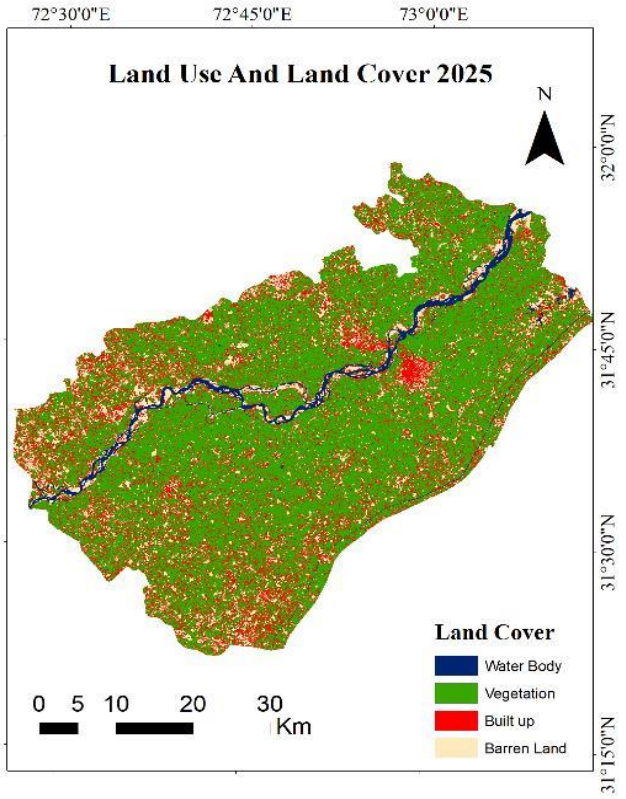


Fig. 7 LULC map of Chiniot District, 2025.

Accuracy Assessment

User's and producer's accuracy are given in Tables 4 and 5. Built-up and water classes were classified well in most years. Vegetation and barren land had lower accuracy in the early years (1990–1999), mainly because of spectral confusion and the coarse resolution of the older sensors.

Table 2. Land use/land cover (LULC) area statistics (km²).

Class	1990	1999	2013	2020	2025
Built-up	210.29	315.41	455.18	476.88	512.10
Vegetation	2,045.39	1,478.86	1,984.82	1,770.05	1,735.44
Water body	104.29	67.97	32.95	39.55	74.68
Barren land	242.47	650.29	129.46	316.27	280.49

Table 3. Change in built-up area by period.

Period	Change (km²)	Years	Rate (km² per year)
1990–1999	+105.12	9	11.68
1999–2013	+139.77	14	9.98
2013–2020	+21.70	7	3.10
2020–2025	+35.22	5	7.04
1990–2025	+301.81	35	8.62

Table 4. User's accuracy (UA) by class and year.

Year	Built-up	Vegetation	Water body	Barren land
1990	66.66%	83.33%	100%	66.66%
1999	100%	83.33%	100%	66.66%
2013	100%	83.33%	100%	83.33%
2020	100%	100%	83.33%	66.66%
2025	100%	66.66%	100%	100%

Table 5. Producer's accuracy (PA) by class and year.

Year	Built-up	Vegetation	Water body	Barren land
1990	100%	83.33%	85.71%	100%
1999	85.71%	83.33%	100%	100%
2013	100%	71.42%	100%	83.33%
2020	100%	100%	71.42%	80%
2025	100%	100%	100%	100%

The Kappa coefficient rose from 0.78 in 1990 to 0.91 in 2025 (Table 6). Agreement with the reference data was therefore substantial in 1990, and almost perfect from 1999 onward. The improvement is probably due to better sensors and cleaner images in the later years.

Table 6. Kappa coefficient and agreement level.

Year	Kappa	Agreement level
1990	0.78	Substantial
1999	0.83	Almost perfect
2013	0.87	Almost perfect
2020	0.88	Almost perfect
2025	0.91	Almost perfect

NDBI Results

NDBI values were high and positive in urban zones in every year, and the area covered by these values grew from 1990 to 2025 (Figs. 8-12, Table 7). This agrees with the growth of built-up land in the LULC maps.

Table 7. NDBI statistics for Chiniot District.

Year	NDBI max	NDBI min	Mean
1990	0.585	−0.366	0.585
1999	0.684	−0.218	0.684
2013	0.585	−0.366	0.585
2020	0.632	−0.373	0.632
2025	0.630	−0.296	0.630

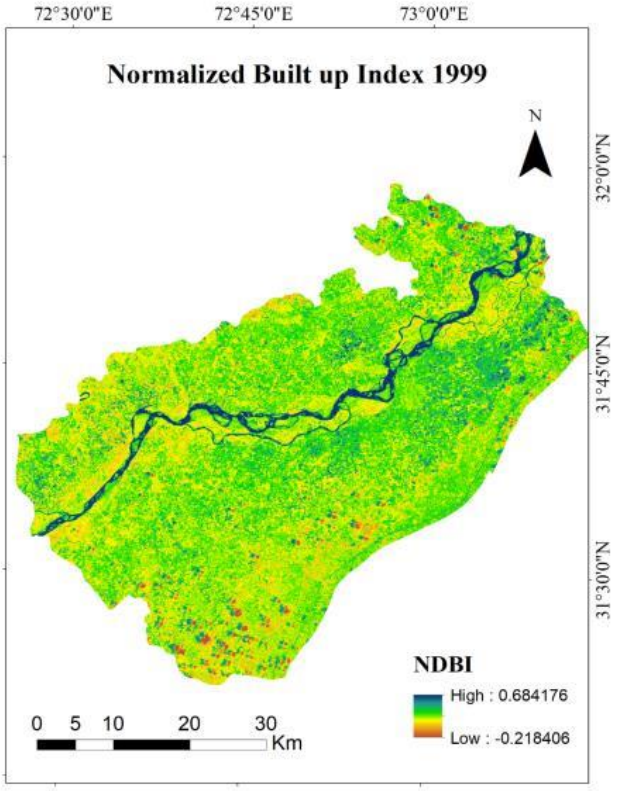


Fig. 8 NDBI map of Chiniot District, 1990.

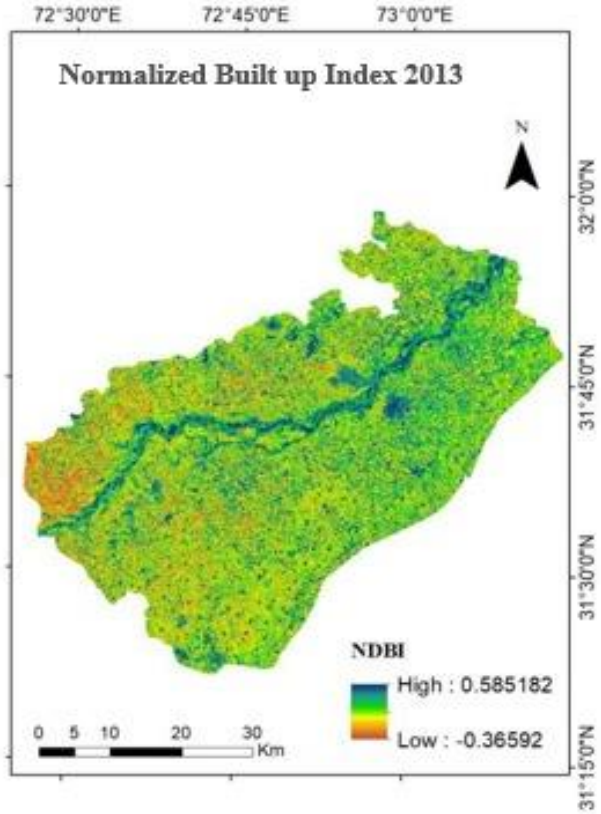


Fig. 10 NDBI map of Chiniot District, 2013.

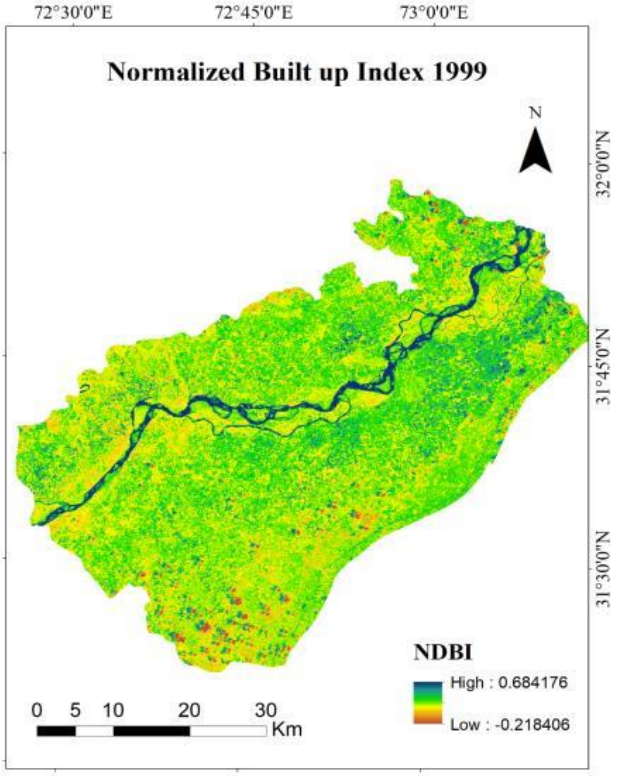


Fig. 9 NDBI map of Chiniot District, 1999.

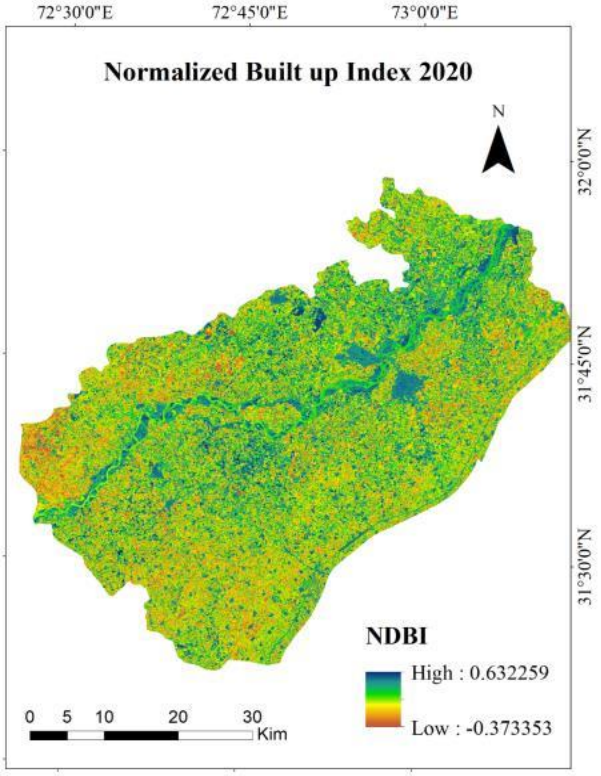


Fig. 11 NDBI map of Chiniot District, 2020.

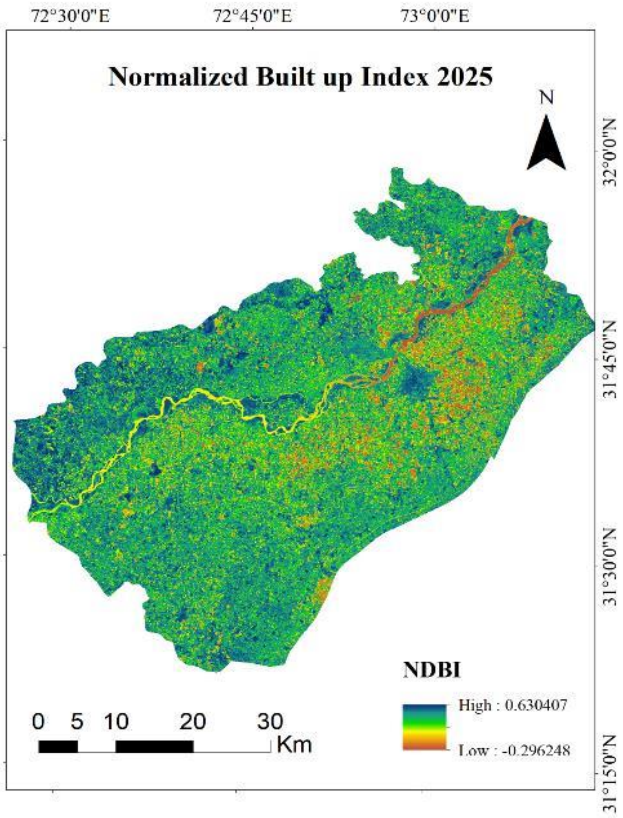


Fig. 12 NDBI map of Chiniot District, 2025.

Pace and Pattern of Urban Growth

The built-up area of Chiniot District more than doubled in 35 years. Growth was quickest between 1990 and 2013, at around 10 to 12 km² a year, and slowed between 2013 and 2020, before picking up again after 2020 (Table 3). Because the share of built-up land is still only about 20% of the district, which is far from fully urbanized, yet the new land is spread out and not compact (Figs. 3-7).

Dispersed, outward growth of this kind is how sprawl is usually described (Ewing, 1997; Galster *et al*., 2001; Sudhira *et al*., 2004). A single set of area figures cannot show whether the slower years reflect a real slowdown or only differences between images, and this is one reason why a fuller measure of sprawl, such as Shannon's entropy or landscape metrics, would be worth adding in later work.

What Happened to Farmland and Vegetation

Vegetation, which here is mostly irrigated cropland, shrank by about 15% between 1990 and 2025. The land-cover maps and the area figures, both suggest that new built-up land has mostly replaced cropland and barren land. The same pattern has been reported for other fast-growing cities in the developing world, for example Nairobi (Mundia & Aniya, 2005), Kolkata (Bhatta, 2009), Mekelle in Ethiopia (Fenta *et al*., 2017) and Lagos (Koko *et al*., 2021).

Seto *et al*. (2012) also expect much of the future urban growth in Asia and Africa to take place on farmland. For Chiniot this matters because farming is the main occupation in the district, so every square kilometre of cropland that is built over affects local food production and rural income.

The vegetation curve is not a smooth decline, the sharp fall in 1999 and the recovery in 2013 are too large to be explained by building alone. A likely reason is that the images were taken in different seasons or crop stages, so that fields lying *by building alone.* A likely reason is that the images were taken in different seasons or crop stages, so that fields lying fallow appear as barren land in some years and, as vegetation in others. The barren-land peak in 1999 (650.29 km²), which falls at the same time as the vegetation low, supports this reading.

Water bodies and barren land

Water showed no steady trend. It fell until 2013 and then recovered. Surface water along a river such as the Chenab changes with rainfall, flood events and the date of the image, and satellite studies of other water bodies have shown similar year-to-year swings (Rai & Nair, 2013). For this reason, the changes in water area should not be read as a result of urban growth. Barren land is a mixed class that holds river sand, fallow fields, degraded land and plots cleared for building, so its swings are hard to link to one cause.

Comparison with other Studies

The results fit the general picture from other studies in South Asia, Africa and Pakistan. Studies of Faisalabad, another Punjab city with a strong industrial and trade base, also report a steady spread of built-up land into surrounding areas (Naeem *et al*., 2021). Work on Colombo District found that sprawl pressed on rural land around the city (Antalyn & Weerasinghe, 2020), and the Ajmer study in India showed that modelling of growth with spatial tools can pick up the same outward pattern (Jat *et al*., 2008).

Chiniot differs from these larger cities in one respect: a district of this size has had least planning, so the growth we see is likely to be driven more by local trade, the furniture industry and road building than by a formal city plan. Built-up area in Chiniot grew by about 144% between 1990 and 2025 (8.62 km² per year), compared with about 114% in Lahore between 1994 and 2024 (Jabbar *et al*., 2026) and more than 110% (262 to over 550 km²) between 1990 and 2020 (Sattar *et al*., 2025). Lahore's absolute gain is larger, about 362 km² in 30 years or roughly 12 km² per year, but the relative growth in Chiniot is similar or higher.

In Faisalabad, built-up land rose from 222.81 km² in 2000 to 281.01 km² in 2010, a gain of about 26% (Naeem *et al*., 2021), which is a slower relative rate than the long-term average in Chiniot, although the periods are not the same. Vegetation loss shows a different picture: green cover in

Lahore fell by about 42% (1,292.8 to 754 km²) (Sattar *et al*., 2025), against about 15% in Chiniot. This may be because Chiniot has a large share of cropland that is still intact, although the seasonal differences between image dates also affect the Chiniot figure.

Agreement between NDBI and the classification

NDBI and the supervised classification point the same way. High NDBI values are found in the same zones where the LULC maps show built-up land (Figs. 3-7 compared with Figs. 8-12), and the area with high values grows over time (Table 7). Two different methods giving the same trend makes it less likely that the result is only an error of one method.

Still, NDBI can confuse bare soil and dry sandy land with built-up surfaces, and this is a known weakness in dry regions (Zha *et al*., 2003; Xu, 2008). Chiniot has a semi-arid climate and large areas of barren land, so some of the high NDBI values outside the towns may come from bare soil and not from buildings.

Drivers of Growth

The main factors are population growth, the furniture industry, local trade and better roads (Govt. of Punjab, 2017). This study did not test these drivers with data, so they remain likely explanations and not proven causes. Population census data, road networks and economic data could be linked to the LULC maps in later work to measure how much each factor adds.

Meaning for Planning

If the present pattern continues, more cropland will be lost and services will have to be stretched across a wider area. Chiniot has room to guide growth now, while built-up land is still a small part of the district. The first steps would be to set urban growth boundaries around the main towns, to keep the best irrigated farmland out of development, and to encourage building on land that is already served by roads and utilities. Regular satellite monitoring, using the same methods as this study, would show whether such rules are working.

Limitations and Future Aspects

This study has several limits. First, the images come from different Landsat sensors with different spectral and radiometric properties, which can cause small differences between years that are not real change. Second, the early images have limited quality, and the 30 m pixel size mixes land-cover types in small settlements and narrow roads. Third, seasonal differences between image dates affect vegetation, water and barren land. Fourth, vegetation and cropland have similar spectral signatures, and this lowered the accuracy of the vegetation class in some years.

Fifth, the number of reference samples is small, which is visible in the accuracy values that move in steps of 16.67%, so the accuracy figures should be treated with some care. Sixth, the 1999 class areas add up to about 90 km² less than the other years, and the 2013 map has a cloud class that is not in Table 2. Finally, the study measures area and not the form of the growth, and it does not test the drivers.

Future work could use more reference samples collected in the field, images from the same season in every year, higher-resolution data such as Sentinel-2, and sprawl metrics such as Shannon's entropy. Adding population, road and economic data would make it possible to test the drivers of growth, and a land-change model such as CA-Markov could be used to project growth to 2040 or 2050.

Conclusion

This study measured urban sprawl in Chiniot District from 1990 to 2025 using Landsat images, supervised classification and NDBI. The classified maps were reliable, with Kappa values from 0.78 to 0.91, and NDBI gave the same picture of growth. Built-up land grew from 210.29 km² to 512.10 km², an increase of about 144%, and its share of the district rose from about 8% to about 20%. Growth was fastest before 2013, slowed between 2013 and 2020, and picked up again after 2020. The new built-up land is scattered, which is the typical form of sprawl. Vegetation, which is mostly cropland, declined by about 310 km², and the maps suggest that most of the new built-up land replaced farmland and barren land. Water and barren land changed from year to year, most likely because of season, river flow and fallow cycles, and not because of building.

Taken together, the findings show steady and largely unplanned growth in a district that depends on farming. This has consequences for food production, land quality and the cost of services. The study also shows that free satellite data and GIS can give planners in medium-sized districts a clear record of how their land has changed. The main limits are the mix of sensors, seasonal differences between images and the small reference sample, and these should be dealt with in later work.

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