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Using GIS tools to detect the land use/land cover changes during forty years in Lodhran District of Pakistan

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Abstract

Land use/land cover (LULC) change has serious implications for environment as LULC is directly related to land degradation over a period of time and results in many changes in the environment. Monitoring the locations and distributions of LULC changes is important for establishing links between regulatory actions, policy decisions, and subsequent LULC activities. The normalized difference vegetation index (NDVI) has the potential ability to identify the vegetation features of various eco-regions and provides valuable information as a remote sensing tool in studying vegetation phenology cycles. Similarly, the normalized difference built-up index (NDBI) may be used for quoting built-up land. This study aims to detect the pattern of LULC, NDBI, and NDVI change in Lodhran district, Pakistan, from the Landsat images taken over 40 years, considering four major LULC types as follows: water bodies, built-up area, bare soil, and vegetation. Supervised classification was applied to detect LULC changes observed over Lodhran district as it explains the maximum likelihood algorithm in software ERDAS imagine 15. Most farmers (46.6%) perceived that there have been extreme changes of onset of temperature, planting season, and less precipitation amount in Lodhran district in the last few years. In 2017, building areas increased (4.3%) as compared to 1977. NDVI values for Lodhran district were highest in 1977 (up to + 0.86) and lowest in 1997 (up to − 0.33). Overall accuracy for classification was 86% for 1977, 85% for 1987, 86% for 1997, 88% for 2007, and 95% for 2017. LULC change with soil types, temperature, and NDVI, NDBI, and slope classes was common in the study area, and the conversions of bare soil into vegetation area and built-up area were major changes in the past 40 years in Lodhran district. Lodhran district faces rising temperatures, less irrigation water, and low rainfall. Farmers are aware of these climatic changes and are adapting strategies to cope with the effects but require support from government.

Keywords Farmers' perception · Normalized difference vegetation index · Climate change · Remote sensing · Geographic information system · Normalized difference built-up index

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Introduction

Global surface average temperature will upsurge about 1.1–6.4 °C by the end of this century, according to the fourth assessment report published by IPCC (Saud et al. 2017). So climate change is a major challenge for food security, agriculture, and the rural livelihoods of billions of people in the whole world (Ateeq-Ur-Rehman et al. 2018; Adnan et al. 2018; Aziz et al. 2017a, b; Fahad and Bano 2012; Fahad et al. 2013, 2014a, b, 2015a, b, 2016a, b, c, d, 2017, 2018; Hafiz et al. 2016, 2019; Kamarn et al. 2017; Saud et al. 2013, 2014, 2016, 2017; Shah et al. 2013; Sönmez et al. 2016; Turan et al. 2017, 2018; Qamar-uz et al. 2017; Wajid et al. 2017; Yang et al. 2017; Zahida et al. 2017; Muhammad et al. 2019). In the recent past, global change in climate has had great impacts on the vegetation (Zoungrana et al. 2018). The Pakistan economy is mostly agrarian, so it is highly sensitive to climate change (Ladd and Suvannunt 2010; Ateeq-Ur-Rehman et al. 2018). Land degradation is reduction in the ability of the land to produce benefits from a land use (LU) under a specified management of land (Ozesmi and Bauer 2002; Lorencová et al. 2013; Hammad et al. 2018). Land cover (LC) defines the physical properties on the land's surface such as forest, water, crops, and urban infrastructure; however, LU is the modification of LC as per human requirements and actions. Land cover (LC) is the best indicator of LU (Udin and Zahuri 2017; Zaidi et al. 2017). Land use/land cover (LULC) mapping has been done most effectively through satellite images of various spectral, spatial, and temporal resolutions (Friedl et al. 2010; Solaimani et al. 2010; Jia et al. 2011; Sahana et al. 2016; Aredehey et al. 2018). On the other hand, in semi-arid and arid environments, multi-temporal satellite images have been less used for planning and monitoring of LULC changes (Jia et al. 2014; Udin and Zahuri 2017; Aredehey et al. 2018; Teka et al. 2018). Change of LULC should be monitored regularly as it causes irreversible impacts on the environment, especially causing urban micro-climate warming (Hahs et al. 2009; Niyogi et al. 2010; Nagendra et al. 2012; Ahmed et al. 2013; Dewan 2015; Heinl et al. 2015; Policelli et al. 2018).

In the previous few decades, the normalized difference vegetation index (NDVI) (Ouyang et al. 2012; Liang et al. 2017) has been widely used for describing the spatiotemporal characteristics of LULC, with percent vegetation cover (Barraza et al. 2013; Reddy and Reddy 2013; Rahman et al. 2017). The NDVI values range from − 1.0 to 1.0; low NDVI values are for common surface materials, and higher NDVI values are for green vegetation (Ahmad 2012a, b; Forkel et al. 2013). Negative NDVI values represent the water bodies (Lambin et al. 2003; Ahmad 2013a). Closest to 0 NDVI values are represented by bare soil (Ahmad 2013b; Olmanson et al. 2016). The NDVI values show photosynthetic activity and are related to plant water stress, biomass, biodiversity, and carbon sequestration (Pettorelli et al. 2012; Gillespie et al. 2018). In remote sensing (RS) studies, the NDVI has been widely used because it provides useful information for interpreting and detecting vegetation (Ahmad 2012a, b; Harris et al. 2014). The NDVI has been a useful tool to couple vegetation and climate distribution and performance at large temporal and spatial scales (Ahmad 2012a, b, 2013c) as vegetation productivity as well as vigor are linked to temperature, evapotranspiration, and precipitation (Zoran and Anderson 2006; Omran 2012; Usman et al. 2015; Nayak and Fulekar 2017). Vegetation area was extracted using NDVI; a water body's area was extracted by using the normalized differences water index (NDWI) and the built-up area was extracted by using the normalized difference built-up index (NDBI). In addition to the reflectance bands of TM, ETM+, and OLI sensors, another 3 spectral indices can be constructed by band recombination: these are the NDVI, the NDWI, and the NDBI (Kaptué et al. 2015; Pal and Ziaul 2017).

The geographic information system (GIS) and remote sensing (RS) are powerful tools (Bansod and Dandekar 2018) for studying urban dimensions, with LULC mapping and urban density (Pozzi and Small 2002), urban modeling (Herold et al. 2003), and environmental effects of urban development (Milesi et al. 2003) over time intervals (Peng et al. 2012a, b; Kumar et al. 2016; Bansod and Dandekar 2018). Data from RS provides timely, reliable, and accurate information on degraded lands at definite time periods in a cost-effective manner (Ahmad 2013; Chen et al. 2017). According to the requirement of the case study, one can manage and analyze the spatial data with the help of GIS technology (Tan et al. 2016; Ali et al. 2018) (Ahmad et al. 2009; Tan et al. 2016; Roy et al. 2017). Remote sensing data are useful for LULC inventory and mapping (Li et al. 2011; Ayele et al. 2018). For LULC planners, Landsat sensor with Landsat-5 Thematic Mapper (TM), Landsat-7 Enhanced TM Plus (ETM+) (Moody et al. 2017), and Landsat-8 Operational Land Imager (OLI) (Cheema and Bastiaanssen 2010) provide various satellite data that play a key role in detecting changes in NDBI, NDVI, and LULC (De Fries and Belward 2000; Ahmad 2012a, b; Aboelnour and Engel 2018). Change detection involves applying RS information to analyze the previous effects of an occurrence quantitatively and therefore help in indenting the changes related to LULC properties with reference to the various satellite datasets (Ahmad 2012a, b; Seif and Mokarram 2012; Arora and Wolter 2018). Supervised classifications require a priori knowledge of the scene regions and area containing a material of interest (Butt et al. 2015), training sites, and are stored and delineated for use in the supervised classification algorithm (Masood et al. 2012; Pal and Ziaul 2017; Orimoloye et al. 2018).

Pakistan is one of the most climate change-susceptible countries among the climate-affected countries, making the livelihood of small landholders and agriculture highly vulnerable to damage. Small-scale farmers in Pakistan are mostly affected by the climate change because they completely depend on agriculture for securing their livelihood. Southern Punjab is famous for cotton production in comparison to the entire province of Sindh (Pakistan), but now, the climatic variations mostly affect cotton production in this region (Amin et al. 2017). Lodhran is situated in Southern Punjab (Pakistan); there are no previous studies on the spatiotemporal changes in the landscape of the district of Lodhran, which is reportedly among the most susceptible parts in Pakistan to climate change. Lodhran is well connected to Bahawalpur, Multan, and Khanewal through a network of inter-city roads. The mixture of slow- and fast-moving traffic causes traffic jams, delays, congestion, accidents, and pollution. Due to fast urbanization, the district of Lodhran is growing in a haphazard manner, without any expansion control. The existing infrastructure in towns is deteriorating as the population pressure is not keeping pace with the available resources for the extension of the infrastructure. These towns face many problems such as loss of amenities, unhealthy environment, and incompatible land uses.

In this paper, a long time series LULC change monitoring has been studied in Lodhran district based on remote sensing and GIS technology. The aims of our study were (1) to delineate and identify various LULC categories and patterns of LULC changes for 40 years; (2) thereafter conduct NDVI and NDBI analysis, mapping, and change detection by using satellite data; and (3) conduct comparisons of various factors like temperature, rainfall, LULC, and NDVI for the last few years.

Materials and methods

Study location

The study area is bounded by Lodhran district of Southern Punjab (Pakistan). It is situated on the northern side of river Sutlej. This area lies between latitude 29° 19′ 11″ N to 30° 28′ 16″ N and longitude 70° 58′ 34″ E to 71° 43′ 25″ E approximately (Fig. 1). The district of Lodhran is situated on a smooth plain and consists of three tehsils: Dunyapur, Kahror Pakka, and Lodhran (district headquarters). The district of Lodhran is bounded on the east by Bahawalpur and Vehari districts; on the west by the district of Multan; on the north by Vehari, Khanewal, and Multan districts; and on the south by the district of Bahawalpur. The underground water is brackish in the Dunyapur area. The climate of the district of Lodhran is cold during the winter but dry and hot during summer season.

Data collection

For identification of LULC, NDBI, and NDVI changes, images of Landsat 4, 5 Thematic Mapper (TM), Landsat 7 Enhanced TM Plus (ETM+), and Landsat 8 Operational Land Imager (OLI) were used. For this study, Landsat satellite images were acquired for 5 years: 1977, 1987, 1997, 2007, and 2017 downloaded freely from the United States Geological Survey (USGS) obtained by NASA's Earth Observing System distribution website (earthexplorer.usgs.gov) shown in Table 1.

Survey data

A survey of 60 farms was conducted in the district of Lodhran to collect information about LULC changes and climate change. A total of 20 union councils were selected, and from each union council, 3 villages were selected by simple random technique. GPS Essential software was used to collect georeferenced data. It is a mobile-based application which allows collecting the digital and georeferenced field data. Survey data included climate change data (temperature, rainfall, rainfall intensity, and duration) and LULC changes.

Image classification

The Landsat image must be composed because it comprised many bands, i.e., 11 bands. Layer stacking was fulfilled to get an image with band combination. The process of subsetting was conducted in Arc GIS 10.1 software by using the extract by mask tools of the image based on the study area (Iqbal and Khan 2014). Digital LULC classification through the supervised classification method (maximum likelihood algorithm), based on the field knowledge, was employed to perform the classification for years (1977 to 2017 for the district of Lodhran). To make LULC maps, we have used supervised classification by taking care of the study area of interest as well as field survey measurements together for training and validation parts. These LULC images were then reclassified by using software Arc GIS 10.1 to compare the changes found in these years. ERDAS Imagine 15 and Arc GIS 10.1 are powerful tools for extracting the LULC, from satellite imageries. The methodology for classification is shown in Fig. 2.

The LULC classes included vegetation (natural vegetation, forest, crop fields, agricultural lands, parks, and vegetated lands), built-up area (all infrastructure, commercial and residential; road networks; and settlements), bare soil (unused lands, empty lands, open space, fallow lands, earth/sand fillings, bare soil, and others), and water bodies (river, lakes, ponds, canals, low-lying areas, marshy lands and swamps, etc.) (Aboelnour and Engel 2018).

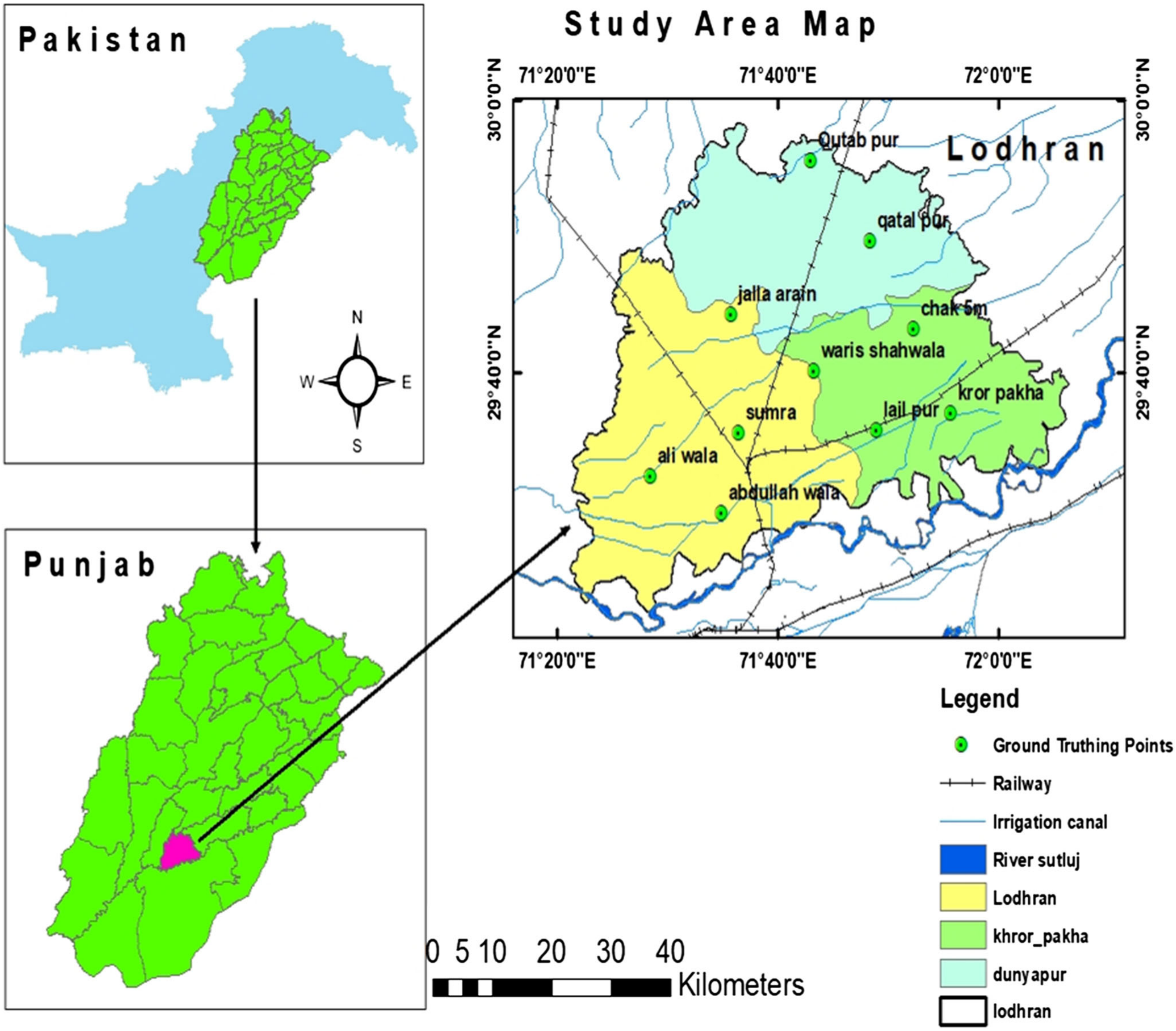

Fig 1 Location of the study area (Lodhran)

Table 1 Specification of Landsat satellite images

S. no.	Data type	Date of production	Scale	Sensor	Path/row
1	Landsat image	1977	30 m	TM	150/039 150/040
2	Landsat image	1987	30 m	TM	150/039 150/040
3	Landsat image	1997	30 m	TM	150/039 150/040
4	Landsat image	2007	30 m	ETM+	150/039 150/040
5	Landsat image	2017	30 m	OLI	150/039 150/040

TM Thematic Mapper, *ETM*+ Enhanced TM Plus, *OLI* Operational Land Imager

Estimation of NDVI and NDBI

The vegetation characteristic like NDVI was estimated for mentioned vegetation area duration for every study year. To calculate the vegetation indices, NDVI is estimated as follows (Huyen et al. 2016):

$$\mathrm{NDVI} = \frac{\mathrm{NIR}-\mathrm{RED}}{\mathrm{NIR}+\mathrm{RED}} \quad (1)$$

where NIR is near-infrared band (TM and ETM band 4, OLI band 5) and R is the red band (TM and ETM band 3, OLI band 4).

The NDBI was used to calculate built-up lands. NDBI was calculated by using Arc GIS 10.1 software following Pal and Ziaul (2017).

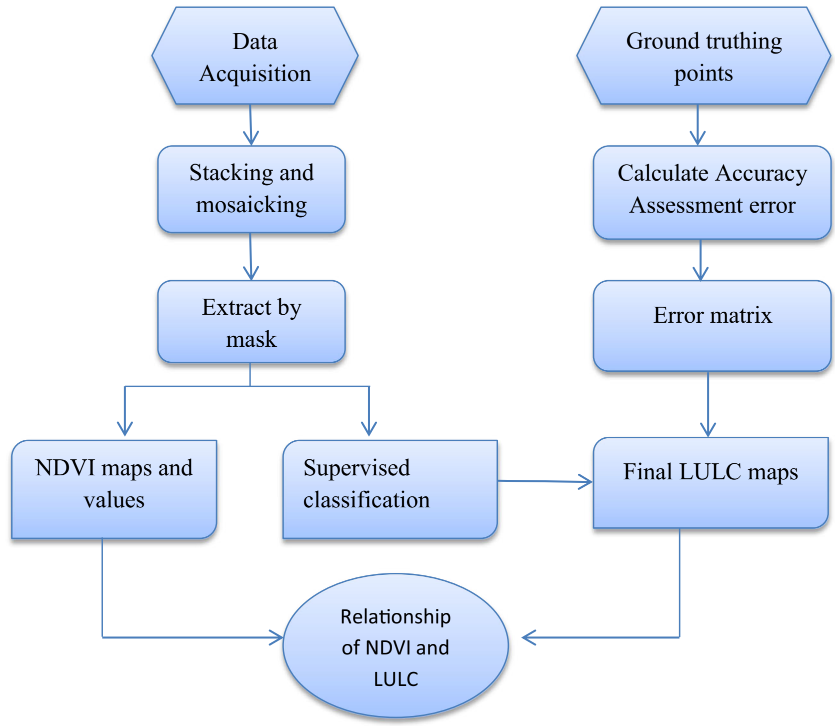

Fig. 2 Flow chart for methodology

$$\mathrm{NDBI} = \frac{(\mathrm{MIR}-\mathrm{NIR})}{(\mathrm{MIR}+\mathrm{NIR})} \tag{2}$$

where MIR is the middle infrared band (TM and ETM band 5, OLI band 6) and NIR is the near-infrared band (TM and ETM band 4, OLI band 5). The indices such as NDVI and NDBI were calculated from satellite imageries and have characteristic values between − 1 and 1.

Accuracy assessment

Accuracy is considered a significant step in the assessment of various image-processing procedures in the classification of images (Lin et al. 2015; Ibharim et al. 2015). The error matrix is the maximum general and mutual means to current accuracy outcomes (Lu et al. 2013). Various statistical processes of accuracy assessment can be drawn from the error matrix with % of producer's accuracy user's accuracy as well as overall accuracy which address the error produced by chance (Zhang et al. 2016).

Overall accuracy

$$= \frac{\text{number of sampling classes classified correctly}}{\text{number of reference sampling classes}} \tag{3}$$

For any acceptable research findings, there must be a high level of confidence in the result which is what accuracy assessment is all about.

The KHAT values below are measures of how well RS classification agrees or is accurate with the reference data (Usman et al. 2015). Mathematical representation of KHAT is as follows:

$$K = \frac{\text{observed accuracy}-\text{chance assessment}}{1-\text{chance agreement}} \tag{4}$$

Results and discussion

Farmers' perceptions about LULC and temperature

The respondents observed different degrees of climate change and the effects based on their resilience, adaptive capacities, and exposure levels (Limantol et al. 2016). As is evident in Fig. 3, 97.3% of the farmers contend that the climatic effects were notable or observed in the district of Lodhran. Most farmers (46.6%) observed that there were extreme changes of poor rainfall amount and the onset of the planting season, as well as the distribution in the cropping period and intermittent drought situations that sometimes occur during the crop growth stage. Over 25.9% of farmers also perceived that their livelihoods faced many changes due to an increase in temperature (that occurred in the study area). Only 2.7% observed that there was no change in the district of Lodhran in the last few years.

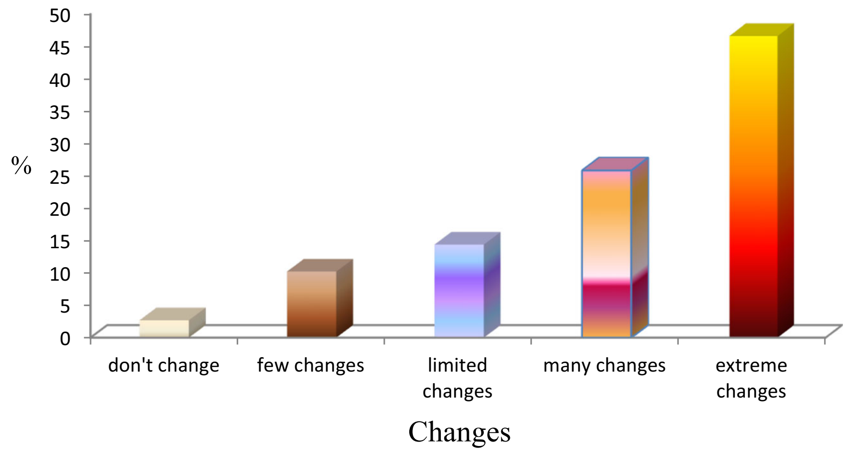

Fig. 3 Farmers' view of extent of changes in climate variables over the last few years

In response to the change in temperature, 67% of the farmers described that they used various varieties of crop types over the last few years, 28% used a mix of crop varieties, and only 5% of them did something else. However, most respondents also believed that precipitation decreased over the equivalent time period in all measures regarding duration, amount, intensity, and number of precipitation events.

In Table 2, 67.7% of the farmers perceived that irrigation has decreased over the last few years in the district of Lodhran, while only 45% of the rainfall area would harvest irrigation water for irrigation. Conversely, 55% of the rain-fed group would utilize groundwater, while 68% of the irrigation group would increase their use of fertilizer: 32% of the irrigation group acknowledged an intention to vary crop types without the use of fertilizer. Different analyses conducted on the perception of precipitation (rainfall duration, number of events of rainfall, and density) (Table 3) showed that only 33.4% of the respondents perceived rainfall increase while 63.3% perceived rainfall decrease. Farming practices studied across 2 groups of farmers include their adjustment to rainfall and temperature and frequency of fertilizer application, as well as planned capitalization on observed opportunities. As an adjustment to precipitation during the last few years, 43% of the farmers showed they use fertilizer, 36% use various crop types, and only 21% do something else.

Table 2 Farmers' response about temperature and LULC changes

No.	Climate variables	Response	Percentage (%)
1	LULC changes	Yes	76.7
		No	23.3
2	Temperature	Increase	96.7
		Decrease	3.3
		No change	0
3	Irrigation water	Increase	23.3
		Decrease	67.7
		No change	9

Climate factors of the study area

Climate change has a maximum impact on the adaptability of LULC classes in various portions of the biosphere. Also, change in climate affects the terrestrial in world closely related with hydrological and energy series therefore affecting the vegetation index (VI) to a maximum amount (Xu et al. 2010, 2016; Adnan et al. 2018; Aziz et al. 2017a, b; Fahad and Bano 2012; Fahad et al. 2013, 2014a, b, 2015a, b, 2016a, b, c, d, 2017, 2018; Hafiz et al. 2016, 2019; Kamarn et al. 2017; Saud et al. 2013, 2014, 2016, 2017; Shah et al. 2013; Sönmez et al. 2016; Turan et al. 2017, 2018; Qamar-uz et al. 2017; Wajid et al. 2017; Yang et al. 2017; Zahida et al. 2017; Muhammad et al. 2019). In the recent past, global change in climate has had great impacts on the vegetation (Zoungrana et al. 2018). Between various climatic factors, temperature and rainfall were more linked with LULC. The temperature data collected from field surveys along with coordinates were fed to software Arc GIS 10.1; next, interpolation using IDW was performed and the spatial map of temperature was obtained. This map showed the variation of temperature throughout the district of Lodhran and gave an idea about the cool and hot areas existing in the study area.

Table 3 Farmers' perceptions about rainfall

No.	Climate variables	Response	Percentage (%)
1	Rainfall duration	Increase	33.4
		Decrease	63.3
		No change	3.3
2	Number of events of rainfall	Increase	20
		Decrease	73.3
		No change	6.7
3	Rainfall density	Increase	31.7
		Decrease	50
		No change	18.3

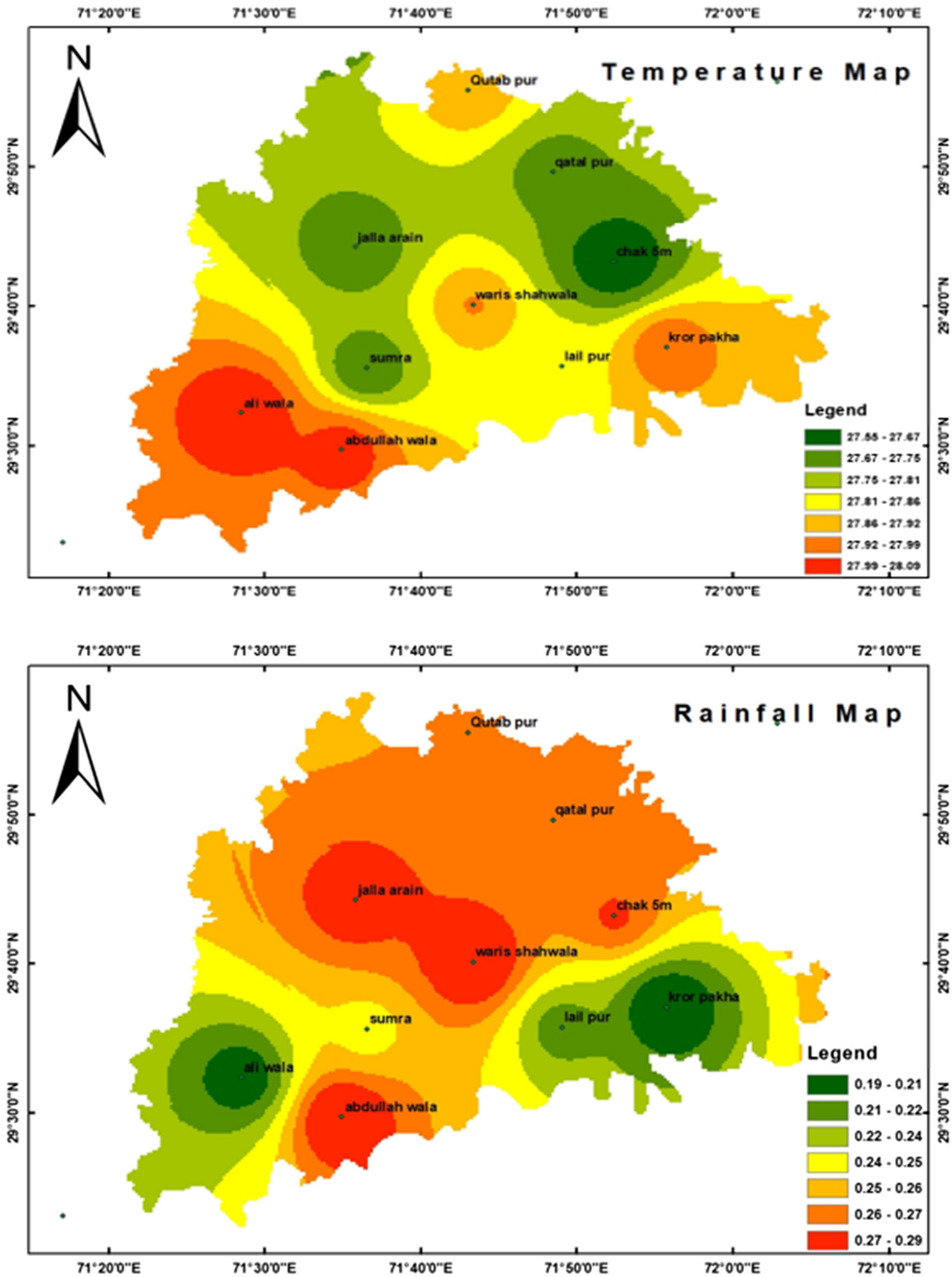

Fig. 4 Maps of climate factors (temperature and rainfall) in the study area

Figure 4 represents the average temperature and rainfall maps of the district of Lodhran. From the temperature map (showing the spatiotemporal difference of temperature), the principal area was extracted. The high temperature rose to 28.09 °C, and the low temperature noted was 27.55 °C. From Fig. 4, it is clearly understood that 2 survey points, Ali wala and Abdullah wala, held high temperatures. Similarly, in study area Chak No. 5M, minimum temperature was

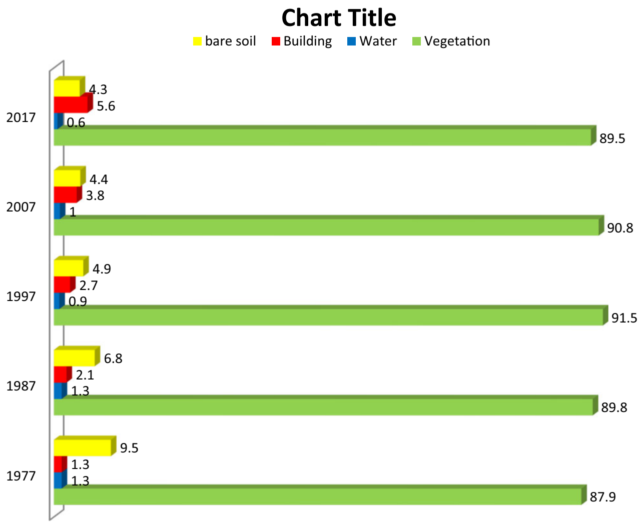

Fig. 5 Land use/land cover areal distribution of the district of Lodhran

observed. The average temperature in the district of Lodhran was calculated at 27.81 °C to 27.86 °C at Lail pur. From this, it is understood that less temperature was noted in water bodies and vegetation areas, and the average temperature was recorded in the barren area and open area. Maximum temperature was observed in built-up areas. Average maximum and minimum rainfall in our study area is shown in Fig. 4. The maximum rainfall rises up to 0.19 mm, and the minimum rainfall value recorded is 0.29 mm. From the rainfall map, it is clearly understood that Jalla arain, Waris shahwala, and Abdullah wala recorded maximum rainfall. Similarly, in Lodhran, Ali wala and Kror pakha showed minimum temperature. Average rainfall in district Lodhran was found 0.24–0.26 mm at Sumra.

Land use/land cover classification

The analysis by using supervised classification between 1977 and 2017 showed that the study area was covered with various land features (water body, vegetation, built-up, and bare soil). A classification scheme of LULC was employed by using survey and GIS information for the district of Lodhran. In year 1977 (Fig. 5), vegetation was 87.9% followed by water (1.3%); the area covered by the built-up area was 1.3% while bare soil covered about 9.5%. In year 1997, vegetation was 91.5% followed by water (0.9%); the area covered by the built-up area was 2.7% while bare soil covered about 4.9%. But in year 2017, the vegetation area was 89.5% followed by water (0.6%); the area covered by the built-up area was 5.6% while bare soil covered about 4.3%, as shown in Fig. 5.

The "built-up area" in 1977 occupied 1.3% of all the classes. But in 2017, the building area increased (5.6%) as compared to 1977. However, the "building area" has experienced a significant increase between 1977 and 2017 (Fig. 6). "Bare soil" in 1977 occupied the class with 9.5%, but in 1997, bare soil decreased (4.9%) as compared to 1977, and similarly bare soil in 1997 occupied the class with 4.9%. In 2017, bare soil decreased (4.3%). This result showed that bare soil was converted to residential and commercial areas, and road. "Water bodies" occupied the minimum class among all the classes in Lodhran district (1.3%, 1.3% 0.9%, 1%, and 0.6% in 1977, 1987, 1997, 2007, and 2017, respectively). According to Ali et al. (2018), during the last few years, the built-up area had increased, while the rate of increase for the populated area was a bit less. This directly establishes that a rapid increase in urbanization in the approaching years is expected which would ultimately cause loss in vegetation area.

Change detection

Various studies about LULC change detection considers two well-separated years for this process (Usman et al. 2015). In this study, LULC classes with maximum and minimum changes under a LULC were selected as lower and upper baselines to identify the maximum relative change during 40 years in Lodhran District.

In 1977, the "vegetation area" occupies the greatest class, with 87.9% in Lodhran District. LULC change, from Table 4, "vegetation" areas had been increased (3.6%) during 1977 to 1997 by a significant portion, but vegetation areas had been decreased (2%) during 1997 to 2017 by a significant portion. From the LULC change analysis, it has been found that bare soil is decreasing day by day. In 1977, 9.5% of the area was covered by bare soil which decreased to 4.6% in 1997 and 5.2% during 1997 to 2017. "Water" occupied 1.3% in 1977, but the water area decreased (0.4) between 1977 and 1997 and decreased to 0.7% during 1977 to 2017 (Table 4). In 1977, 1.3% of the area was covered by "building" which increased to 1.4% in 1997 and 2.9% during 1997 to 2017; however, 4.3% increase was observed during 1977 to 2017. It is worth observing that for 40 years almost 6% of the water and bare soil have been transformed to built-up areas and roads. Construction of more than 60 colonies along different roads increased the urban area by wiping out agricultural land. The sparsely and densely populated areas are along Multan Road, Jaat Wala Road, Koudhi Road, Haveili Nasir Khan Road, Bhatti Wala Road, Bypass Road, Super Chowk, and Bahawalnagar Road. The city of Lodhran is growing in two main directions, i.e., in the northern and southern directions. In the north, the city is growing along the national highway towards Multan. In the south, the expansion is towards Bahawalpur.

There are a number of small colonies developed along the main highway, i.e., from Ali Wah Minor Bridge to Super Chowk. The total number of these colonies is 37 in tehsil Lodhran. The approximate area of

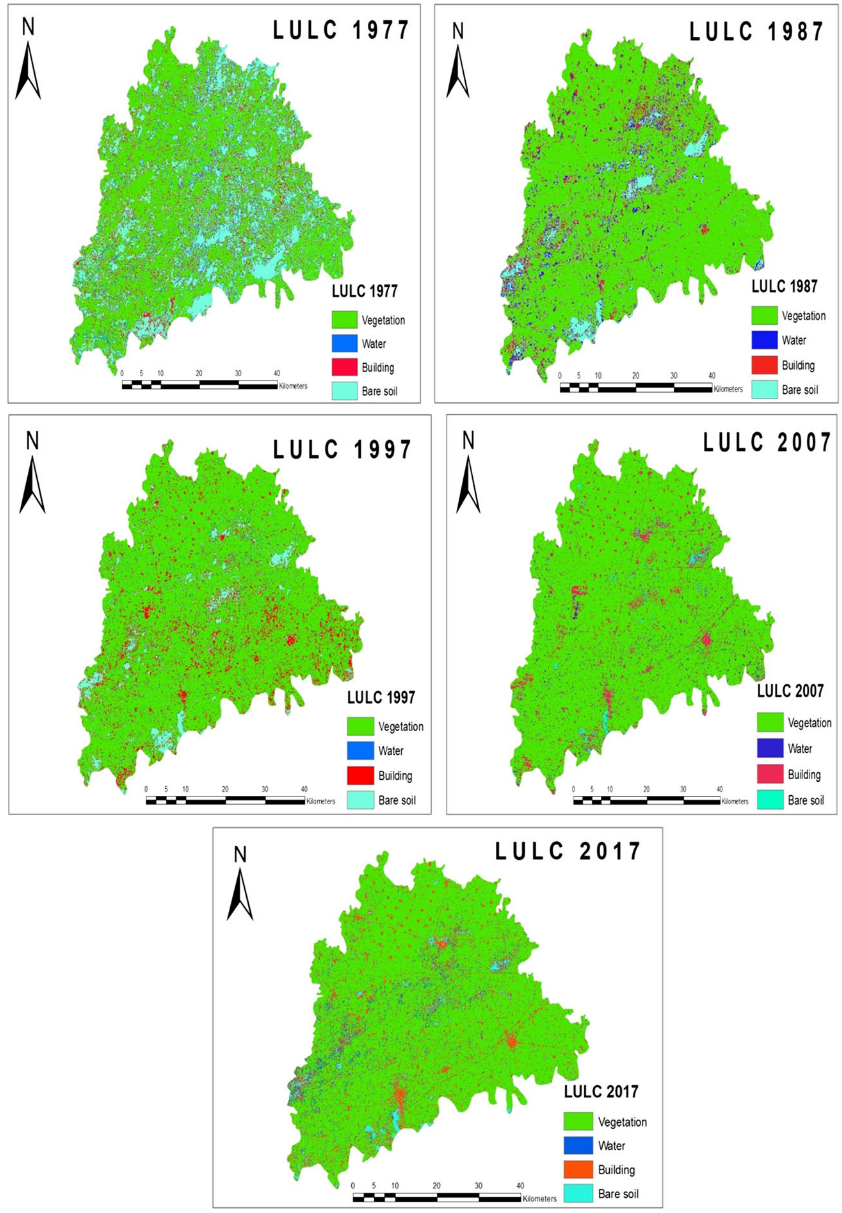

Fig. 6 Land use/land cover maps of the study area

these colonies ranges from 4 to 6 acres. These were small individual plots which were then subdivided and sold in plots. Many agricultural areas have turned into residential colonies. The commercial area is also growing with the densification of the residential area. Growth of residential areas along major routes shows the ribbon development in the study area. The purpose of change detection is to know which land use was

Table 4 LULC changes, 1977 to 1997, 1997 to 2017, and 1977 to 2017

LULC categories	1977–1997 Area (%)	Annual rate of change	1997–2017 Area (%)	Annual rate of change	1977–2017 Area (%)	Annual rate of change
Vegetation	3.6	0.72	-2	-0.4	1.6	0.64
Water	− 0.4	− 0.08	− 0.3	− 0.06	− 0.7	− 0.28
Building	1.4	0.28	2.9	0.58	4.3	1.72
Bare soil	− 4.6	− 0.92	− 0.6	− 0.12	− 5.2	− 2.08

Table 5 Maximum and minimum NDVI values of the district of Lodhran

Years	NDVI max.	NDVI min.	NDVI avg.	NDBI max.	NDBI min.	NDBI avg.
1977	0.86	− 0.12	0.37	0.43	− 0.29	0.07
1987	0.6	− 0.29	0.15	0.39	− 0.43	− 0.02
1997	0.67	− 0.33	0.17	0.35	− 0.45	− 0.05
2007	0.72	− 0.05	0.33	0.26	− 0.42	− 0.08
2017	0.55	− 0.17	0.19	0.12	− 0.39	− 0.135

increased or decreased for 40 years and which land use has been converted into other land use types. Change detection gives clear information about the rate at which an area is changing in terms of LU. From the classification maps of the district of Lodhran, it has been seen that Lodhran has witnessed a change in terms of urban land use during the last 40 years.

The NDVI and NDBI

The values of NDVI show the amount of chlorophyll content present in vegetation, where the greater NDVI value shows healthy and dense vegetation, but a lower MDVI value shows sparse vegetation. In the case of the district of Lodhran, NDVI values in 1977 ranged from − 0.86 to + 0.12; in 1987, the

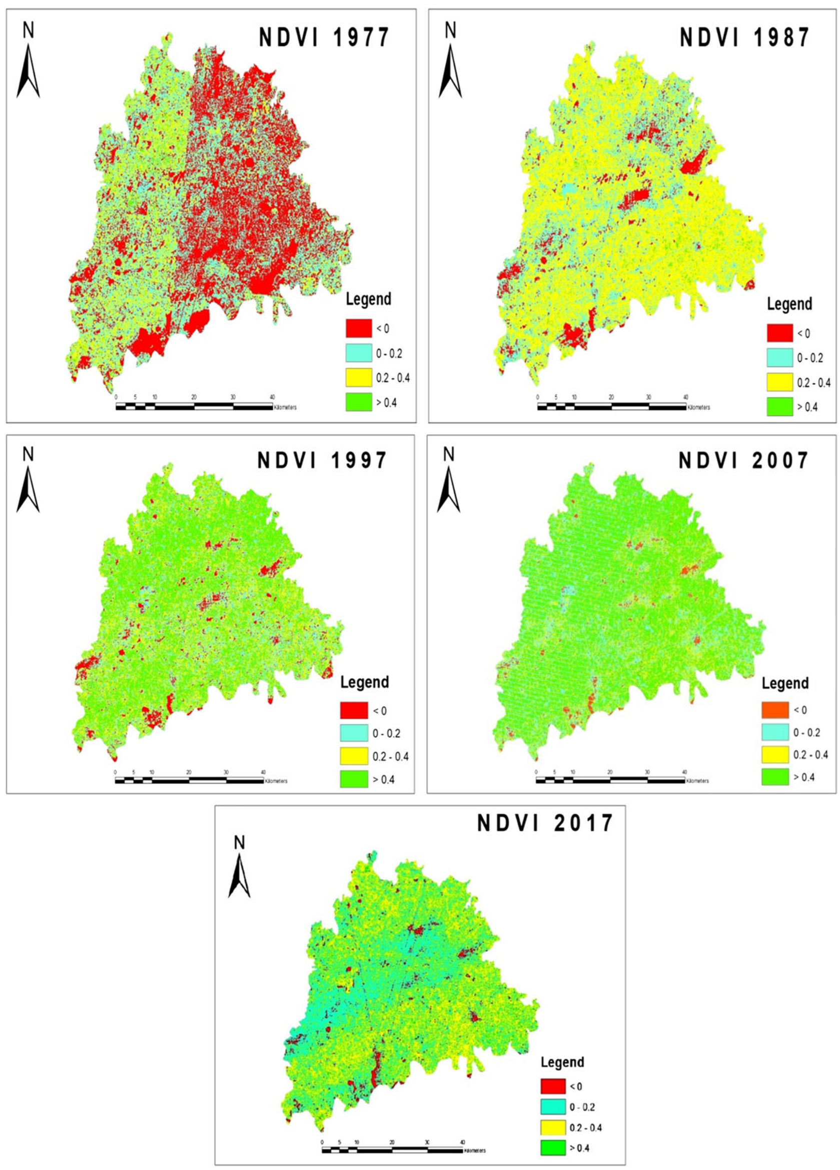

Fig. 7 Normalized difference vegetation index maps of the study area

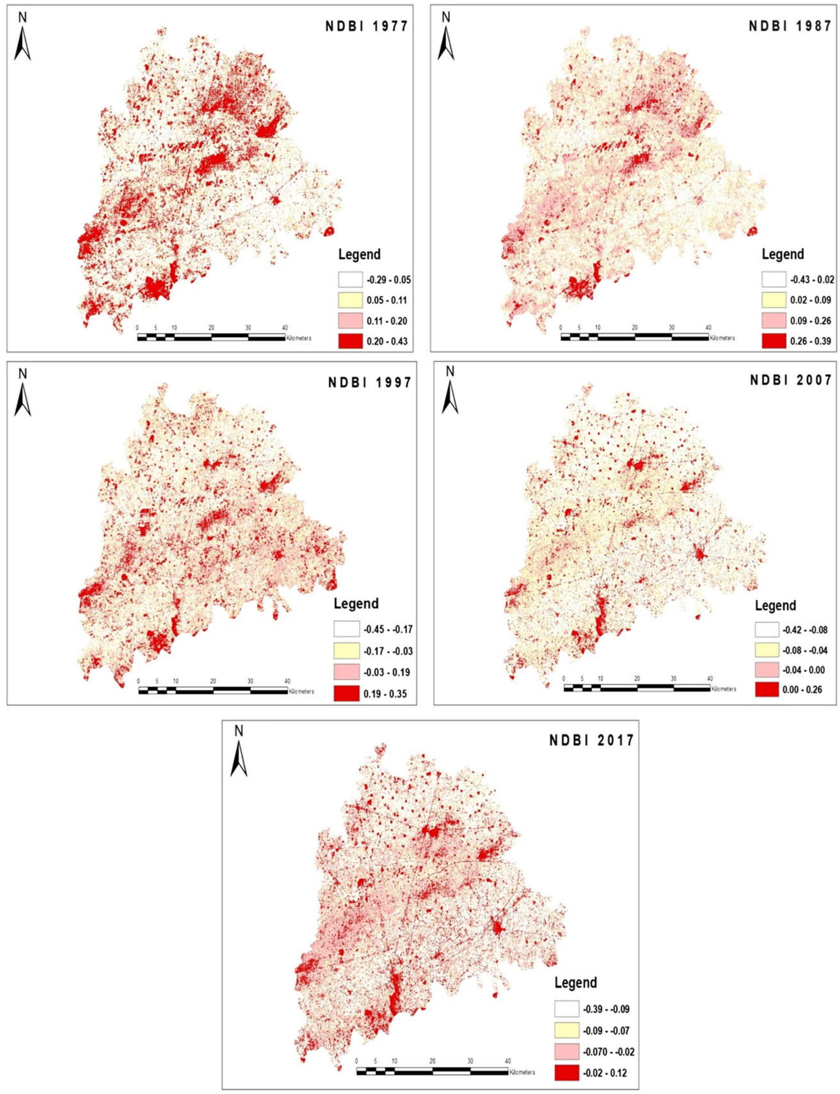

Fig. 8 Normalized difference built-up index maps of the study area

NDVI value indicated the minimum value that is − 0.29 and maximum + 0.6. In 1997, it slightly increased from − 0.33 to + 0.67, while in 2007, the NDVI value indicated the minimum value that is − 0.05 and maximum + 0.72. In 2017, NDVI shows the minimum value that is − 0.17 and maximum + 0.55 (Table 5). Average NDVI values were observed at 0.37, 0.15, 0.17, 0.33, and 0.19 for 1977, 1987, 1997, 2007, and 2017, respectively. Also, NDVI for the district of Lodhran was highest in 1977 at + 0.86 and lowest in 1997 at − 0.33 which shows that NDVI classes indicating a spatial pattern of vegetation and green area in the map show the productive and most productive areas for agriculture like forest and vegetation area. Similarly, in Fig. 7, the red portion shows the less productive areas like buildings and bare soil. The NDVI is mostly used in all vegetation indices tested and its performance is due to non-systematic difference as described by Ahmad et al. (2014).

Average NDBI values were observed at 0.07, − 0.02, − 0.05, − 0.08, and − 0.13 for 1977, 1987, 1997, 2007, and 2017, respectively. Similarly, NDBI values for the district of Lodhran were higher in 1977 at + 0.43 and lowest in 1997 at − 0.45. Figure 8 shows the extracted NDBI classes indicating the spatial pattern of impervious land and built-up area for 1977, 1987, 1997, 2007, and 2017. Expansion in the urban area with time can be seen in Fig. 8. Major growth has taken place in the south and east as well as in the central part. Moreover, a main road from Vehari to Bahawalpur and a railway line also pass through the city. Three main railway lines which are coming from Vehari, Multan, and Khanewal combine at Lodhran District. In the south, the built-up area has grown along the River Sutlej, which passes through the southern part of the study area. Population data also indicate an increase in population. In 1998, the total population was 1,171,800 which increased up to 1,700,620 in 2017, showing a rise of more than 0.6 million inhabitants in district Lodhran that has resulted in urban expansion. More than 60 new colonies have been built in the study area during the last 40 years,

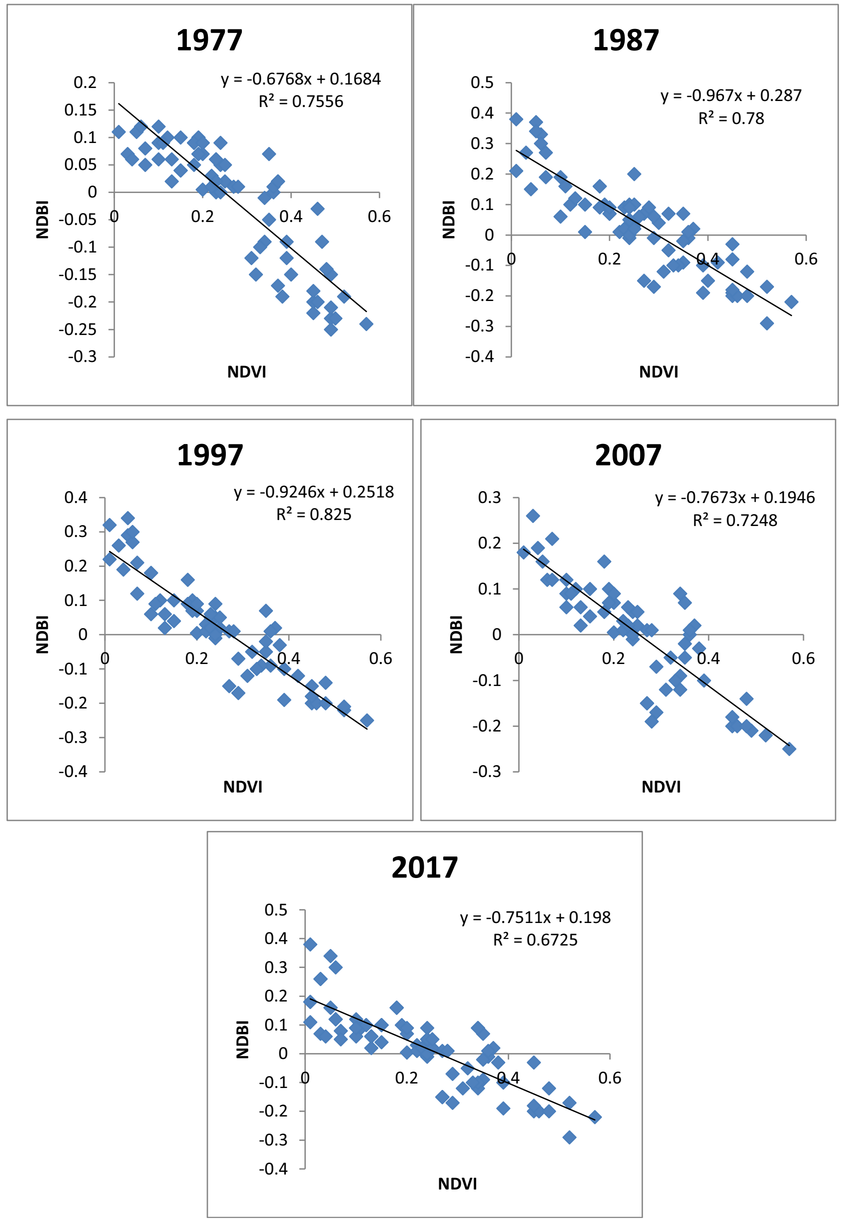

Fig. 9 Regression analyses between NDVI and NDBI in the study area

Table 6 Summary of the producer's and user's accuracy and kappa coefficients

LULC classes	Season and class										Overall accuracy	*K*
	Producer's accuracy (%)					User's accuracy (%)						
	1	2	3	4	Avg.	1	2	3	4	Avg.		
1977	96.7	55	80	100	82.9	78.9	100	92.3	95.3	89.1	0.86	0.77
1987	93.3	75	83.3	84	83.9	84.8	75	8.2	91.3	84.3	0.85	0.74
1997	90	85	83.3	84	85.5	84.4	94.4	78.1	91.3	87	0.86	0.77
2007	96.7	80	90	84	87.7	87.8	94.1	90	87.5	89.8	0.88	0.79
2017	96.7	90	96.7	96	87.5	93.5	90	96.7	100	95	0.95	0.84
Avg.	94.7	77	86.7	89.6	85.5	85.9	90.7	88.7	91.1	89	0.88	0.78

1 vegetation, *2* water, *3* building, *4* bare soil which mainly contributed to urban expansion. In Fig. 8, maps show that the red portion was observed as the least productive area, for example water bodies, bare soil, and built-up area. NDBI was also correlated with temperature, for example, areas where NDVI values were greater were the areas having the greatest temperature. From certain driving factors like temperature in the local scale, it is being identified that association of NDBI strongly controls land surface temperature (LST) followed by major roads and LU (Pal and Ziaul 2017).

Linear regression analysis was used to generate relationships between NDBI and NDVI. Regression analysis (R^2) is done to find out how changes of LU intensity within LULC unit varies over space and brings intra LU variation of NDBI. However, a negative relationship between NDVI and NDBI existed, with a correlation coefficient of R^2 = 0.75 for 1977, 0.78 for 1987, 0.82 for 1997, 0.72 for 2007, and 0.67 for 2017 indicated in all images, between vegetation index (NDVI) and NDBI-derived built-up fractions, as shown in Fig. 9. Regression analysis shows that in such area where NDBI values were greatest, NDVI values were lowest.

Accuracy assessment

The accuracy of the classification was described in terms of both user's accuracy and producer's accuracy. Producer's accuracy is defined as the amount of a land category correctly classified on the classification image, while user's accuracy is defined as the probability that a category on the classification image will be correct when used on the ground. Table 6 presents the results of the producer and user accuracy, while it also indicates overall accuracy and KHAT (k) values in the years 1977, 1987, 1997, 2007, and 2017. Average producer and user accuracy of vegetation were 94.7 and 85.9, respectively. Similarly, average producer and user accuracy of water were 77 and 90.7, respectively.

Average accuracies for producer as well as user are 82.9% and 89.1% for 1977, 83.9% and 84.3% for 1987, 85.5% and 87% for 2007, 87.7% and 89.8% for 2007, and 85.5% and 95% for 2017, respectively (Table 6). Overall accuracy for classification is 86% for 1977, 85% for 1987, 86% for 1997, 88% for 2007, and 95% for 2017. Kappa coefficients for 1977, 1987, 1997, 2007, and 2017 are 0.77, 0.74, 0.77, 0.79, and 0.84, respectively.

Conclusion

This study was conducted in the district of Lodhran in Southern Punjab (Pakistan) to study the effect of climate change on rural livelihood. Rural livelihood farmers totally depend on agricultural activities that directly depend on the natural temperature, but changes in natural temperature cause less rain, shortage of irrigation water, and drought that directly affect the agricultural activities and agricultural yield. The district of Lodhran faces rising temperature, less irrigation water, and low rainfall. Farmers are aware of these climatic changes and are adapting strategies to cope with the effects but require support from government. The results revealed that the vegetation fraction gives a more grounded positive connection with NDVI for all over the levels, but open surface and built-up area give negative relationship of NDVI and LULC during 40 years.

Average NDVI and NDBI values were observed between 0.37 to 0.19 and 0.07 to − 0.13 during 1977 to 2017, respectively. Average accuracies for producer as well as user are 82.9% and 89.1% for 1977, 83.9% and 84.3% for 1987, 85.5% and 87% for 2007, 87.7% and 89.8% for 2007, and 85.5% and 95% for 2017, respectively. Kappa coefficients for 1977, 1987, 1997, 2007, and 2017 are 0.77, 0.74, 0.77, 0.79, and 0.84, respectively. Bare soil has decreased by 4.6% during the period 1977 to 1997 and 5.2% during the period 1977 to 2017 as bare soil was transformed to built-up and roads. Water consisted of 1.3% in 1977 but water area decreased (0.7) during 1977 to 2017 in the district of Lodhran. As an outcome, LULC changes are vital for a wide range of applications, including temperature, erosion, and land plan activities. There was a significant change in bare soil, water bodies, and cultivated areas across the slope due to enhanced human impact as well as subsequent need for arable areas. The result of our study provides a vital monitoring basis for continuous studies of changes in the land management and will help policy makers to develop policies to effectively manage the land resources.

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