

Original Research

Iterative Cellular Automation Approach to Analyze Spatial Dynamics of Urbanization and Population Growth

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Abstract

Population measurement and its spatial distribution are required to understand the urban pattern of any city. We have used a methodology for measuring urban spatial morphology, infill, outlying expansion, and compactness over a decade. The aims of this research are related to data-driven categorization of large cities of Punjab and its correlation with urban attributes by identifying relative disparities in expansion and vertical growths; instead of city portfolios exerted and/or perceived by various groups of relevant urban stakeholders. Urban extents and sprawls were identified by using Geospatial data and techniques by applying supervised parameter optimization. The analytical tool was employed to highlight and better understand the relative (hierarchical) position of selected cities of Punjab, Pakistan. The results depict that the total urban area of selected cities has increased in ten years (2008-2018) from 914 km² to 1649 km². The cities' saturation level helped to identify highly densified and the cities where the potential of infill is available. This study provides an effective and efficient way to monitor and evaluate the morphology of the cities and addresses the issues of mismanaged urban sprawl and decreasing densities.

Keywords: cities morphology, remote sensing, landsat, population density, sustainable urbanization

Introduction

Cities are the magnets and engines of urban growth [1], about 44 M (million) people are being added every year to Asian cities, generating the need for more infrastructure [2]. The world has experienced a high population growth rate after the industrial revolution [3], which adds great pressure on resources, the

environment, and sustainable development [4]. It is estimated that in the urban areas of Pakistan almost 50 million people will be lived between 2014 to 2050. Moreover, the urban sprawl generally includes changes in land use of outer peripheries in an urban area [5]. Population density, urban sprawl, and land-use conversion shall be taken into account to estimate urban patterns [6]. These indicators are key to stipulate the decisions of the governments [7]. To estimate the population, census is the key, but the conventional door-to-door evaluation is costly and also time-consuming [8]. The restraining fact for using population data in the

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urban demographic study in Pakistan is the long-awaited census in Pakistan [9]. The latest population survey took place after two decades in 2017 [10]. The recent studies identified the multi-temporal Landsat satellite images with socio-economic data to observe the urban growth focus on urban sprawl detection and estimating directional changes using Markov algorithm [11]. the population and urban growth patterns could be utilized as baseline for planning and development [12]. Landsat satellite imagery with the help of multivariate statistical analysis are used to map landscape imperviousness indexes [13].

Multispectral images for estimation of population density with the help of statistical measures and regression models are key elements for population estimations [14, 15]. In recent studies Landsat Thematic Mapper (TM) for image interpolation method [16], night light imagery [17]. [18] are also used to determine urban population density. Satellites are used to observed the earth from an orbit variables [19] and also to produce 30'' high-resolution population databases for the globe [20]. Landsat and LandScan proved to be cost-effective, time-efficient, and multi-temporal datasets, for identification of patterns by comparing compactness and expansion of the major cities along with population dynamics between 2008 and 2018. In Pakistan, the cities are administrated with demarcation limits such as areas of the metropolitan corporation, municipal corporation, and town committees, or cantonment boards [21]. However, the city administrations do not follow the notified boundaries, of which lack of land use planning is a vital issue that results in expansion beyond their administrative boundaries. Urbanized areas are mostly overcrowded and densely clustered in city centers [22]. In a recent study [23], Lahore metropolitan of Pakistan was selected and observed that the urban growth patterns which highlighted 100% increase in the urban area from 1999 to 2011. Also, with the help of GIS, the urban expansion and socio-economic development was analyzed in Bahawalpur, Pakistan and concluded that the population density of the city increased mainly due to the migration of people from rural to the urban areas for better lifestyle [24]. Furthermore, LandScan utilized for modeling approach and its principles for attaining the temporal dynamics of population by evaluating night time and day time population at 3 arc second resolution [25]. Calka and Bielecka, [26] observed that the population of Poland using LandScan dataset and compared its accuracy with the official polish population grid. In another study, urban expansion with the help of change vector analysis (CVA) extracted and analyzed the transformation of barren land, vegetation, and water into urban areas using the temporal segmentation approach [27].

The concepts of population distribution and density are different, as distribution is based on location, while density is a ratio. For equitable urban and rural development of Punjab (most populated province of Pakistan), accurate data on urban expansion,

cities' saturation, and the population density trends were missing, and a dire need was felt at various platforms during planning and management. The study circumscribes spatio-temporal urban growth modelling to extrapolate the past and future urban growth patterns and its impact on various land-use classes integration geospatial techniques including cellular automata (CA) [28]. The study focused on the reliability of cellular automata algorithm for extraction of urban growth patterns with best model calibration approach [29]. In this study, an integrated approach has been used to cater to the cross-linkages between both the factors. This study also tracks the vibrant characteristics and spatio-temporal morphology with population distribution across ten major cities of Punjab, for sustainable spatial planning and management of cities.

Study Area

Punjab is the most populous among the five provinces of Pakistan and covers an area of 205,344 km² (79,284 mi²) with a population of more than 100 million. Moreover, the concentration of the urban population is confined to a few cities in Punjab. The study discusses urban morphology of ten larger cities given in in Fig. 1. Lahore is the provincial capital and also known as 'city of gardens' and Faisalabad is the industrial hub of Punjab. Gujranwala city called the 'city of wrestlers' and also known as rice producer and Sialkot is the hub of small and medium industries and give the highest per capita income in the country. Sahiwal is good in cotton goods manufacturers and woodwork. Sargodha is famous for orange production. Bahawalpur is a city of monuments and forts. Dera Ghazi Khan is the junction for all four provinces of Pakistan. Moreover, Rawalpindi is famous for its landscape and historical monuments. Punjab province climate conditions are diverse and multiple weather conditions such as, foggy winter, summer, spring and monsoon.

Material and Methods

Data Acquisition and Processing

The LandScan data was acquired from LandScanTM for 2008 and 2017 [30], and later it was projected to the year 2018. We acquired Landsat TM and Operational Land Imager (OLI) images (30 m resolution) from the United States Geological Survey because of excellent price-quality ratio, spectral bands coverage, and spatial characteristics.. The multilayer images were downloaded from the USGS website [31]. Radiometric calibration and correction processes were used for the conversion of digital number (DN) to reflectance, also baptized as the top of atmospheric correction [32]. The change in brightness values denotes the rate of change in the surface condition of the area of interest [33]. The subsets of all satellite images were produced using

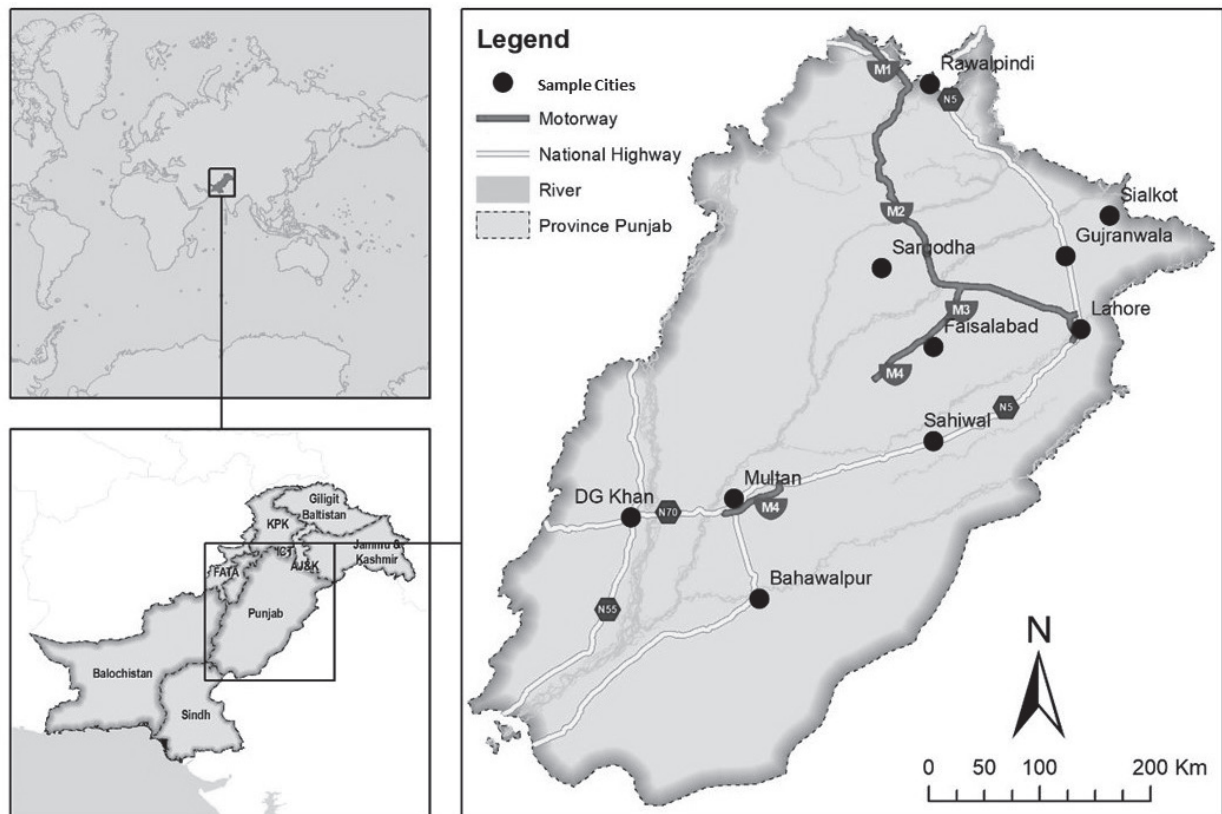


Fig. 1 Map of the study area.

a 10 km buffer on the city boundary as cities' expansion above the buffer was not observed through multi-temporal satellite images. The sub-setting minimized the file size and provided accuracy in classification as only the histogram of the Area of Interest (AOI) was available for spectral classification.

Urban Expansion and Saturation

The built-up areas were extracted by classifying satellite images using the Maximum Likelihood

Classifier (MLC) [34]. The MLC algorithm identified the neighborhood pixel of the same intensity in the raster data set and spectral rules defined the classified layer [35]. Fig. 2 shows the maximum likelihood of cluster samples. MLC estimates exponential models for dependent data by using Markov model's [36]. It is generally used for classifier evaluation as a reference, thus making the Gaussian probability density function model an optimal classifier [37]. To demarcate areas of contiguous urban development, the built-up pixels were categorized as urban by applying an iterative

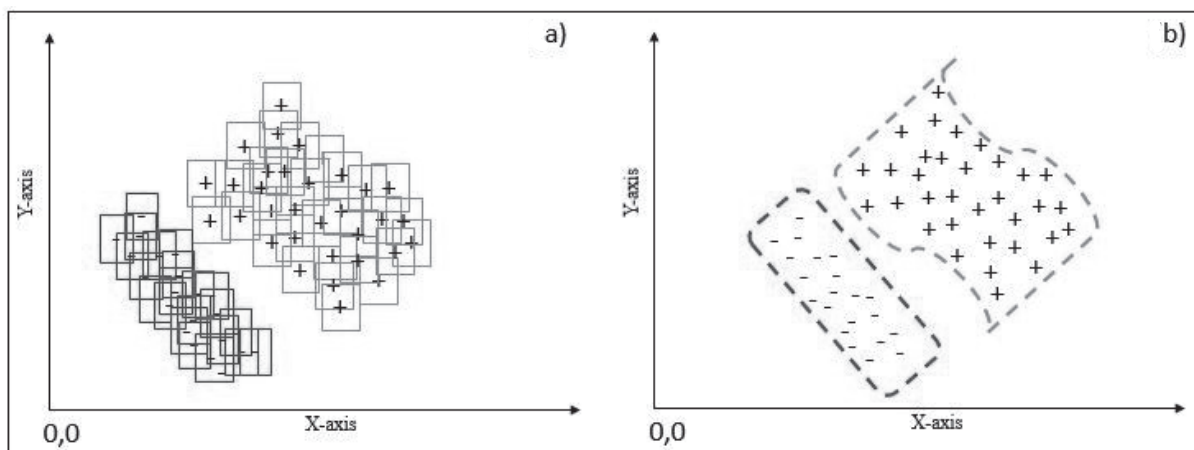


Fig. 2. Maximum Likelihood Clustering.



Fig. 3. Raster workflow – Cellular Automata Approach.

python-based algorithm. The developed algorithm was influenced by the methodology defined by Lincoln Institute of Land Policy, United Nations Habitat, and the New York University (NYU) urbanization project [38]. The algorithm incorporated built-up pixels within the ten min walking distance circle of 1 km² area and 584m radius. Urban pixels with the majority of continuous built-up pixels within the walking distance circle were marked as the functional boundary of the city. The built-up pixels having 10-50% of the built-up within their walking distance were categorized as suburban. The respective urban extents defined functional city boundaries. The workflow of urban extents that were manually refined to address anomalies in the local context shown in Fig. 3. The figure elaborate raster flow of cellular automation of extraction of the built up area of Area of Interest. Urban saturation was calculated based on built-up area pixels and urban extent, where the urban extent was used as the denominator [39].

The final built-up area extracted from the Landsat satellite images after using cellular automata method was converted into binary language and assigned the value of “1” while all other classes were assigned “0” as well it also define as the builtup and non builtup area. The majority of the continuous built-up pixels were classified as the main city. Focal analysis was performed for the neighborhood value assignment of each pixel [35]. Euclidean distance analysis was performed to fill the open spaces and the raster data were reclassified into two types: Urban and Suburban.

Python-based script for cellular automation derived the urban footprint by incorporating urban mask, water cell, and rural area mask was used.

Population Density

The dasymetric concept was used for the division of administrative area into multiple spatial units such as population data sets clusters similarly the dasymetric concept also established to assess the fine resolution population distribution in an area where census data was coarsely available [40]. Thus, the LandScan global model (developed based on ancillary datasets, i.e., land cover, settlement location, slope, and proximity to roads) was used to measure the population distribution as discussed in formula 1. Fig. 4 shows population distribution of the study area; the population unit and raster cell area are overlapped with spatial weight for block-wise population distribution. Small area estimation (SAE) with respect to landscan used to produce estimates of population counts for small areas, and accuracy assessment of estimations [41]. Considering data gaps of population census in Pakistan, the urban population of ten cities was measured by using projected Landscan data, which is the community standard for global and regional population distribution [42]. The database uses sub-national level census counts for each country; integrate it with spatial and imagery analysis (land cover, roads, slope, urban areas, and village locations) using a multi-variable modelling approach to disaggregate census

counts. LandScan characterizes an ambient population of the cells in integer population counts, representing an average within an administrative boundary. Once the pixel grid was converted to the area grid, the number of persons in each cell was divided by the surface area of the cell, which provided the population density as shown in Fig. 4.

The pixel size of the LandScan™ data is 1 km (30" x 30") and it provides sufficient information while estimating data of large cities. Following formula [41] is used to estimate the density of study area.

$$P_{op} \text{ Density} = (l * a_s)^2 * \cos_L / P_{op} \text{ cell} \quad (1)$$

...where as:

$P_{op} \text{ Density}$ = Population density of particular cell,

l = Length of one arc degree at the equation,

a_s = 30 arc-sec in decimal degree and \cos_L = Cosine of latitude.

The demographical data were redistributed across each grid cell for taking the population densities as weights across the entire region [43]. This includes projection and manual verification to improve the precision of population distribution across the ten large cities of Punjab. The multi-source geographical factors such as, population distribution, topography, settlements, traffic network and road network were the core factors used in LandScan [43] and represent a fusion model to stimulate the distribution of population. Urban extent change affects the functions, structures, and surface land use, which in turn influences the variability of eco-system and improvement of human being [44-46].

Cellular Automata

Satellite data of 10 years of equal intervals along with population density, topography and slope, road network distances are used in this study to analyse the cities growth [47,48]. The satellite based urban extent during 2008-2017 was cloned by the stimulated approach of principal component analysis and cellular

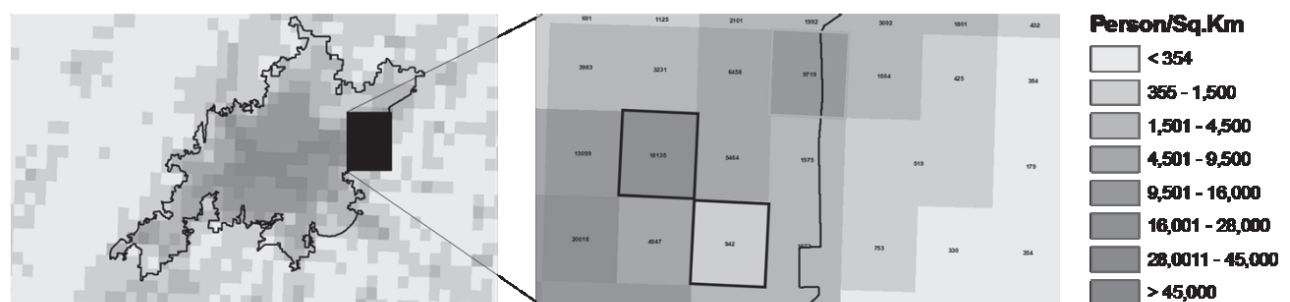
automata to identify the similarity during classification [49, 50].

Results and Discussion

Urban Expansion

The study revealed the temporal growth rate of contiguous urban extents from 2008 and 2018 as 6% per year. In Fig. 5 urban extent of large cities were presented. The urban areas of these ten cities increased from 914 km² in 2008 to 1649 km² in 2018. Angel et al, [51] analyzed the urban sprawl and its patterns as well as changes over the time. They take sprawl to be relative than an urban landscape absolute characterization. Moreover, Galster et al, [52] define and measure the urban landuse and spatial configuration pattern of cities area. They observed the spatial change of cities over the observed time period. Fig. 6 shows the increase in urban spwral of the ten cities with the annual growth rates.

Fig. 6 shows the annual growth rates of the ten large cities in Punjab; Rawalpindi is physically growing at a rate of 8.2% and is expected to be the second-largest city by 2040 following Lahore, which is the biggest city in the province. Lahore's growth has developed mostly in south and southeast directions and the area towards west and north has constituted a physical barrier in those directions. Minallah et al, [53] observed that the population of Gujranwala increased in the observed time period due to migration trend toward Gujranwala. The urban built-up areas of Lahore has been reached its double from 1999 to 2011 as well its increasing pressure on the administration of city [54]. Although, the physical growth of Lahore is expected to be along the major roads including, Multan Road, G.T road, Ferozpur road, and Raiwind road. The next largest city will be Gujranwala with 8.1% annual area growth rate in terms of morphology. With the current growth patterns, Gujranwala intends to become larger than Faisalabad, even to grow as big as today's Faisalabad.



$$Pop_{cell} = A_{cell} * Pop_{block}$$

**Ratio of the population count falling within the boundary has been included*

Fig. 4. Population calculation against each raster grid cell.

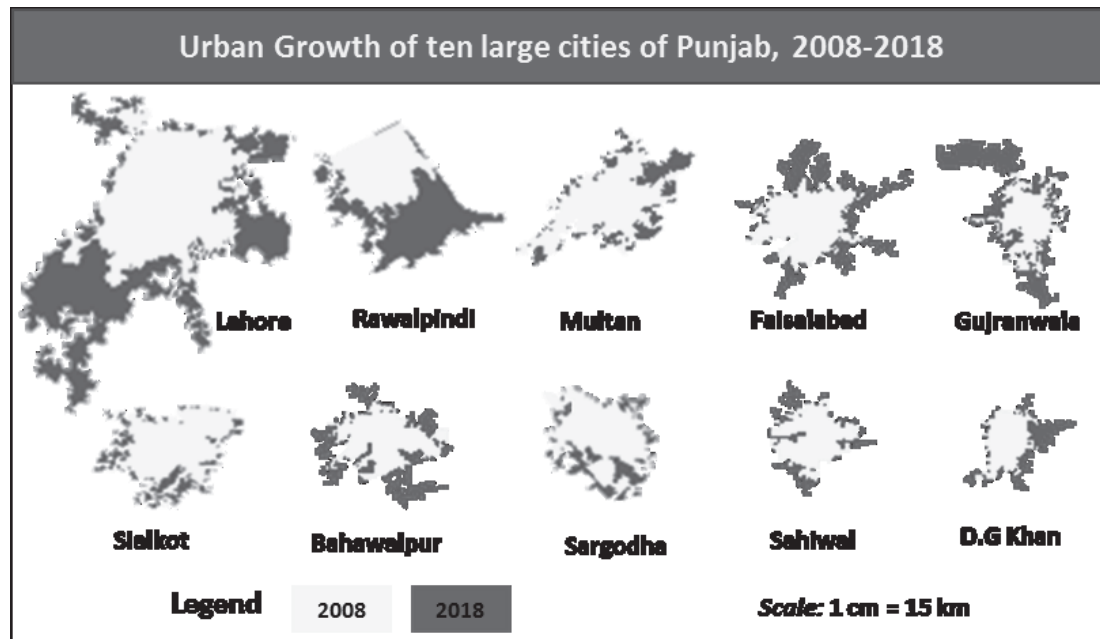


Fig. 5. The urban extent of the ten large cities in Punjab.

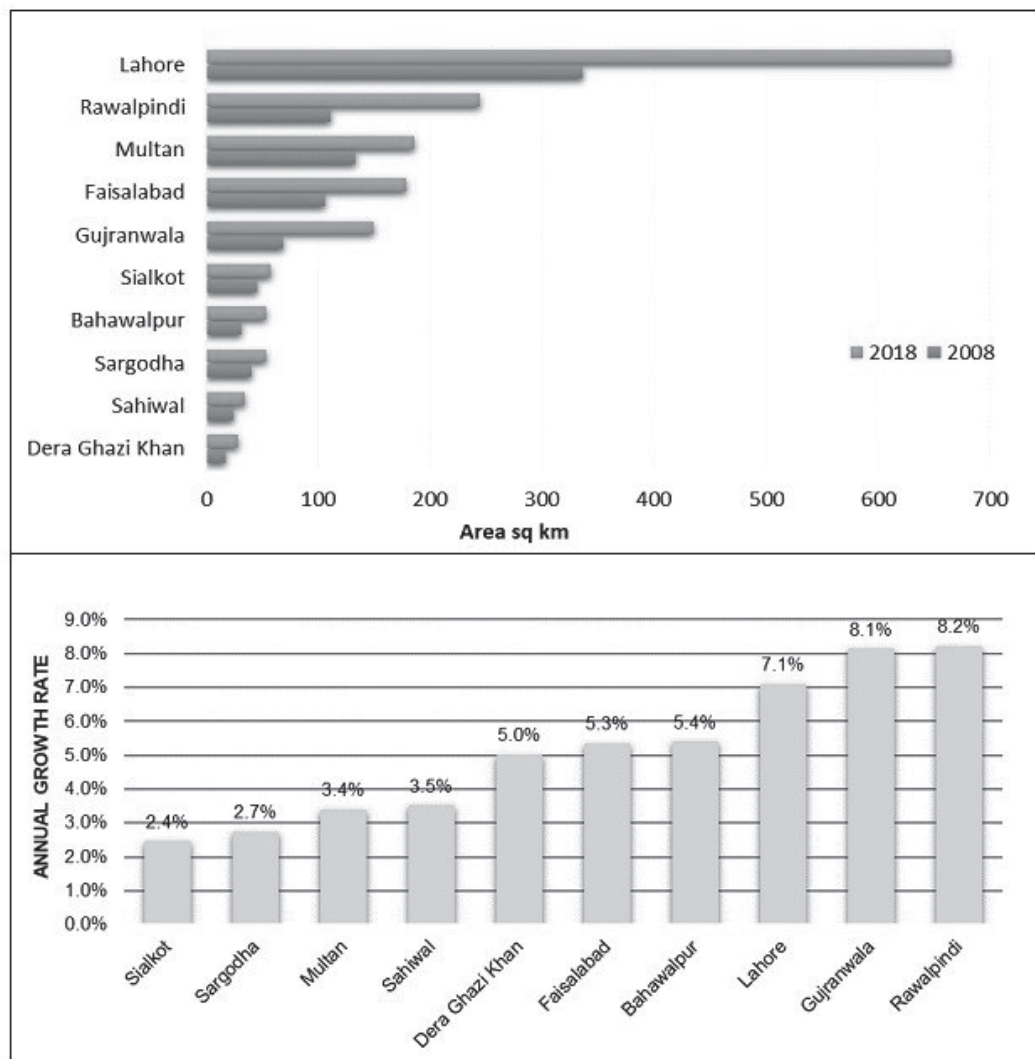


Fig. 6. Urban sprawl in km² and growth rate of the ten large cities in Punjab.

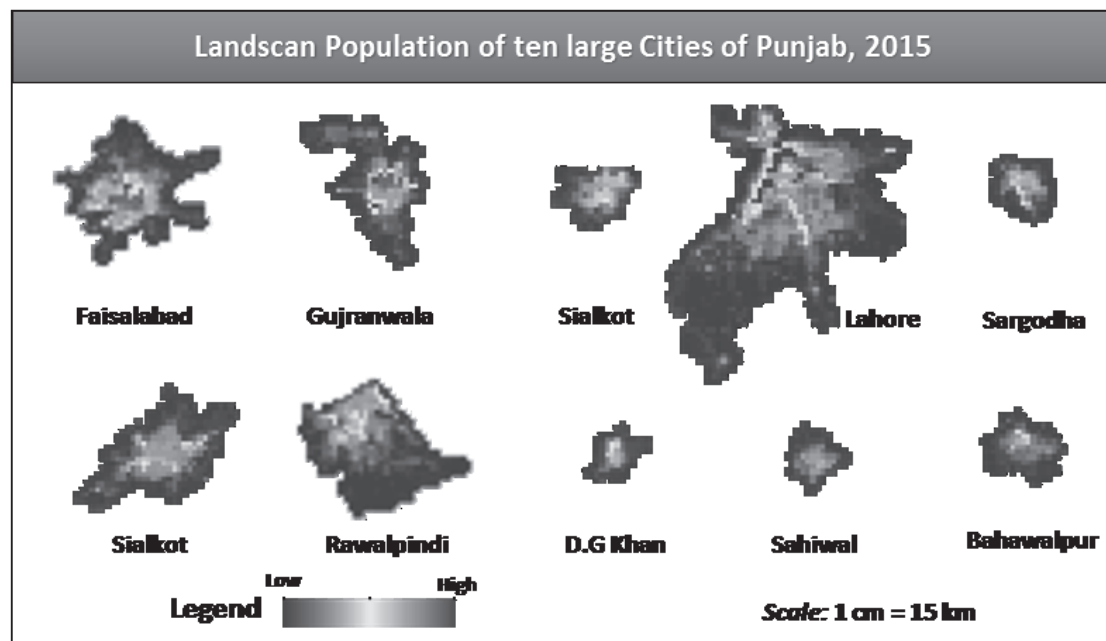


Fig. 7. LandScan population of the ten large cities in Punjab for the year 2018.

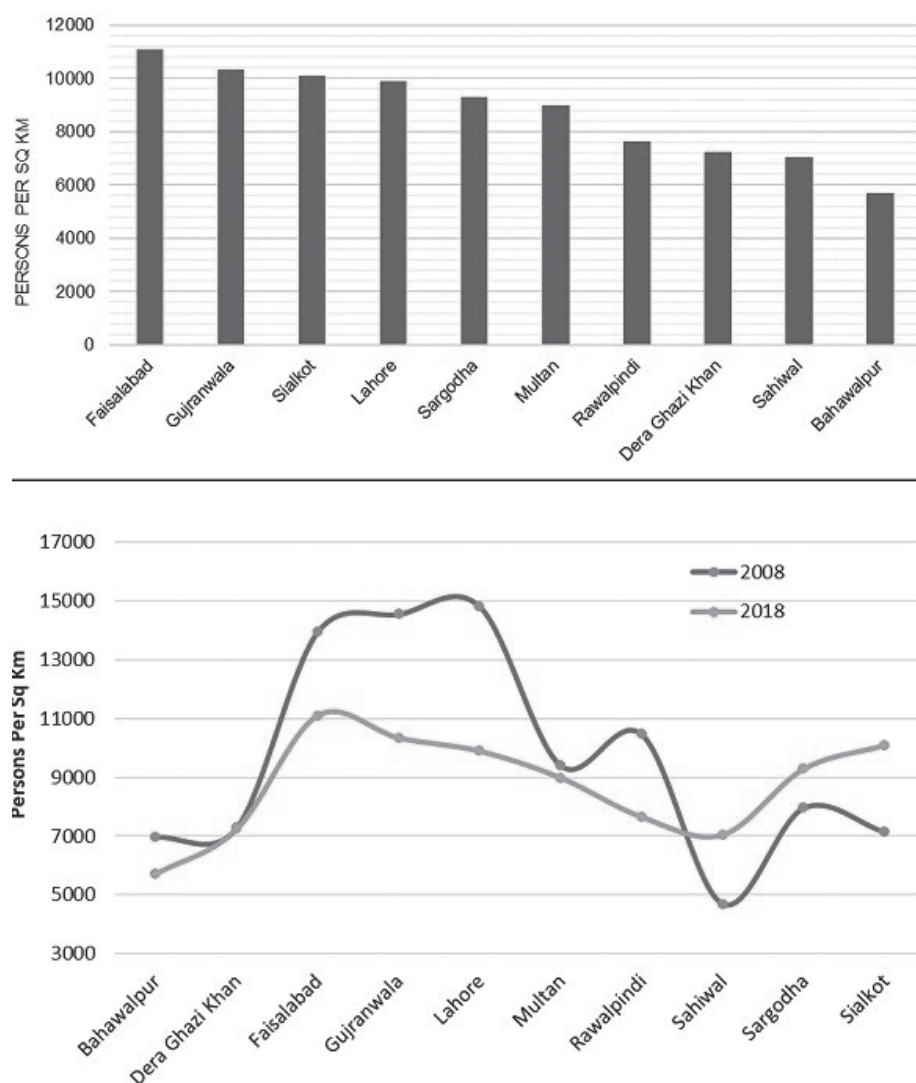


Fig. 8. Population density with ranking of the ten cities.

The satellite images and data analytics showed minimal spatial growth in the past decade i.e. Sialkot (2.4%) and Sargodha (2.7%).

Population Densities

Population density is an interesting criterion to measure city crowdedness (Fig. 7). Most urban settlements in Punjab expanded because of the transformation from agricultural land to urban/peri-urban areas [55]. The increase in urban densities directly affect the transport system and other need as Cervero and Guerra [56] investigate the relationship between transit and urban density in United States and conclude that the increase in urban density would cause increase in ridership on rail system. Akbar et al, [57] analyzed the spatial and temporal trends of LULC from 1988 to 2016 and observed the population growth had been increased also the population of Lahore was 168 km² and it will be reached up to 625.16 km² by 2040. Fig. 8 shows the population density of the ten cities selected in this study and provides an additional perspective on population density change over time. The analysis revealed Faisalabad as the most crowded city (179 km²) with a population of 3,164,704 people, and has an average density of almost 11,092 people per km². Meanwhile, Bahawalpur is the least densely populated city, with 5,715 people per km². Sahiwal and Dera Ghazi Khan come close to the position of the second least populated city, with almost 7000 people per km². Lahore, Gujranwala, and Faisalabad had high densities in 2008 but showed a decrease in the densities in 2018, mainly due to the unregulated growth and fragmented development of new housing schemes in the peripheries of these cities. This research results showing that if the density-wise composition of the city projects that if the current pattern of decreasing densities and unplanned sprawl continues, the city area will have low population densities by 2050.

Urban Saturation

We found that the saturation levels of Lahore, Multan, Rawalpindi, Bahawalpur, and Sargodha have decreased over the last decade. The urban saturation level with infill development showed in Fig. 9. In Gujranwala, infill and sprawl found to be equally increasing as per the data analysis. Faisalabad, Dera Ghazi Khan, Sahiwal, and Sialkot indicated high saturation levels of the built-up spread. For sustainable growth of the cities, the saturation level of the city must be increased by developing vacant areas within the administrative extent of the city before sprawling further outwards. Moreover, vertical growth shall also be promoted. The spatial portrait of the urban saturation level is shown in Fig. 10.

Accuracy Assessment

The overall accuracy was found to be 92.45% for the 2008 urban sprawl and it was 97.21% for 2018 respectively. The six classes obtained includes water bodies, built up, barren land, bare soil, agriculture and other vegetation for 2008 and 2018. User accuracy and the producer accuracy were calculated based on actual map locations and obtain (map locations). For 2008, user accuracy for each class i.e. water bodies 99.55%, built up 86.24%, 81.25% for barren land, 76.01% for bare soil, 81.34% for agriculture and 88.23% for other vegetation. The producer accuracy calculated as 99.67%, 84.18%, 82.67%, 78.54%, 84.32%, and 81.01% for water bodies, built-up, barren land, bare soil, agriculture land and vegetation for the year 2008. For 2018, the user accuracy identified the percentages as 99.82% for water bodies, built-up as 88.24%, barren land as 84.51%, bare soil as 86.44%, 88.21% as agriculture land, and vegetation as 92.54%. The producer accuracy was detected as good as expected and observed that produced map were relatively matched with the ground-truthing location which is found to be exactly as of ground reality.

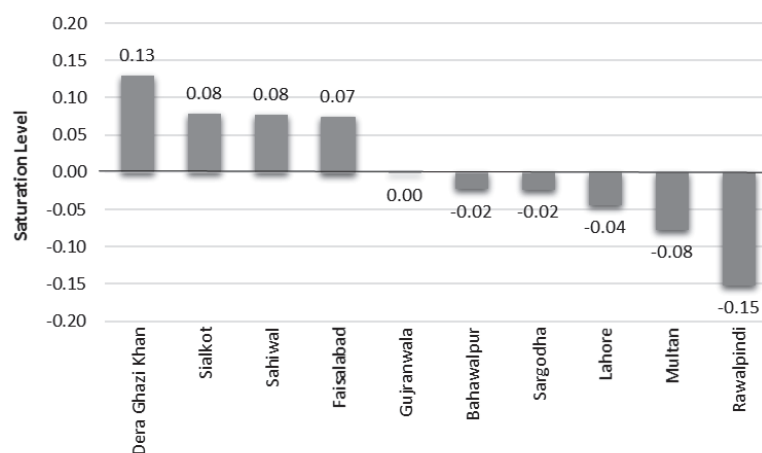


Fig. 9. Urban Saturation - Infill development.

The producer accuracy for the water bodies were 99.82%, 89.36%, 85.43%, 86.84%, 87.92%, 84.65% for built-up, barren land, bare soil, agricultural land and vegetation. The Kappa statistics were 0.90% and

0.95% for 2008 and 2018 which is good as per kappa standardized values. The obtained accuracy was better as compared to the other accuracies used in other studies related to cellular automata model [58].

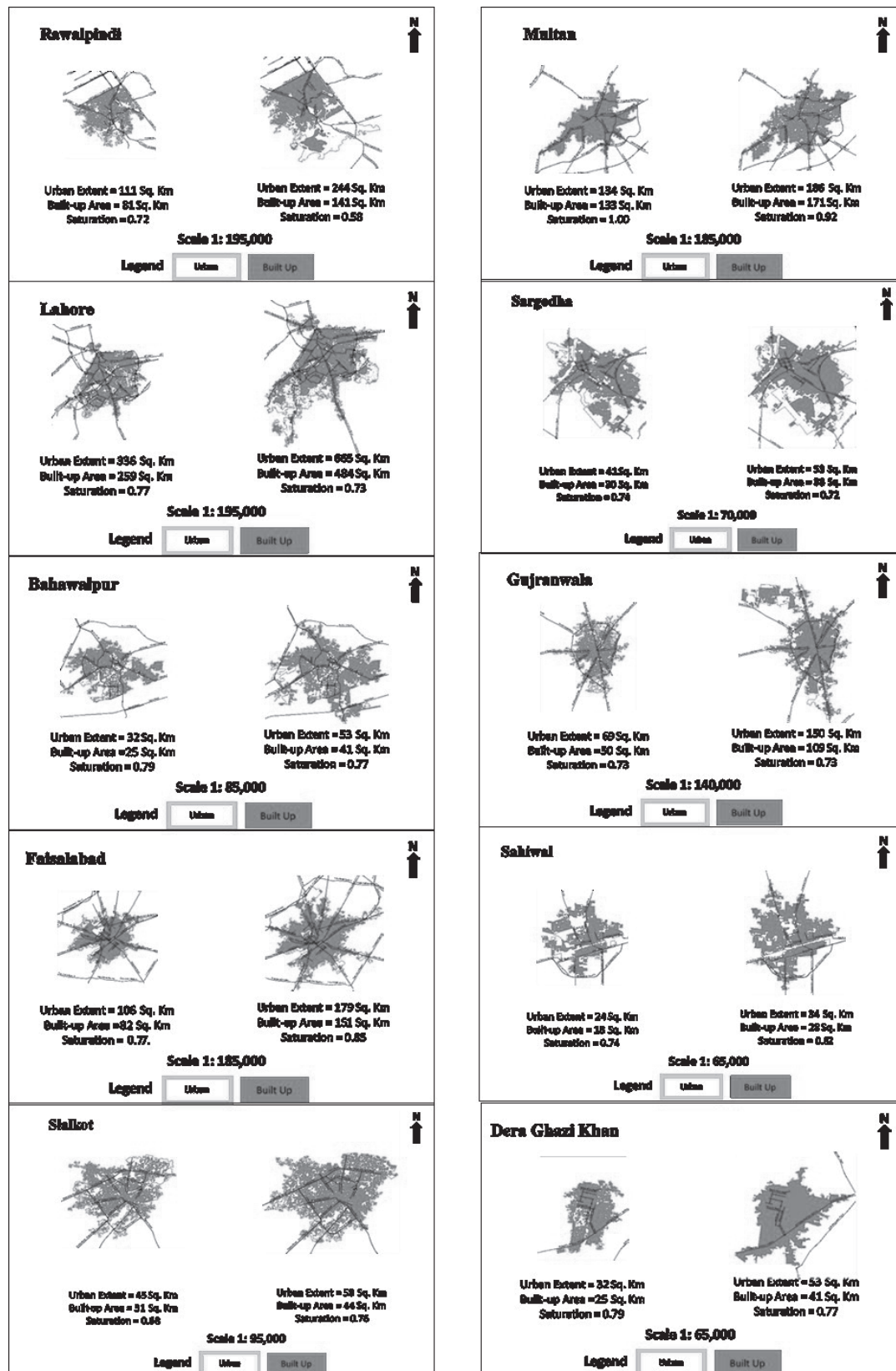


Fig. 10. Urban saturation spatial representation.

Conclusions

This study provided an insight into two important factors of urban dynamics i.e., land use and population. From 2008-2018 the total urban land area increased from 943 km² to 1649 km² with an annual growth rate of 6% and the population of the cities increased from 15.5 to 20.1 M with an annual growth rate of 3%. If the urban land area continues to grow at a similar rate, an expansion of 100% is estimated by 2050. The data and maps witnessed new development in the outer peripheries of the cities resulting in horizontal expansion instead of compact development. The continuity and infill patterns mark the sustainable development of cities and hold potential for land use planning and urban management strategies across different scales. It is important to focus on ways to increase the population density through vertical as opposed to horizontal development, by developing vacant areas within the administrative extents of the cities before sprawling further outwards. The government should focus on developing rules and defining policies to ensure the transformation of these urban areas into compact cities. The vertical growth can also reduce the outer development and operational cost while minimizing the unplanned urbanization pressure on the peripheral land.

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Conflict of Interest

The authors declare no conflict of interest.

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Supplementary Material

Iterative Python Based Script

```

#To import the ArcMap library
import arcpy
#To grant the overwrite permission
arcpy.env.overwriteOutput = 1
#To check the extension required for further processes
arcpy.CheckOutExtension("Spatial")
#Input file will be given here
input = arcpy.GetParameterAsText(0)
#To get the raster properties, i.e. cell size
cellsize = float(arcpy.GetRasterProperties_management(input, "CELLSIZEX").getOutput(0))
#To create a file from the input. In output, 1 represents the buildup and the rest is non-buildup
buildup = arcpy.sa.EqualTo(input, 3)
#To create a neighbourhood circle in map units
NbrCircle = arcpy.sa.NbrCircle(564, "MAP")
#The neighbourhood circle was applied on the buildup created in previous
#step to perform focal analysis. The output represents the urbanness ranging
#from 0 to 1, 1 for urban area and 0 for the other
urbanness = arcpy.sa.FocalStatistics(buildup, NbrCircle, "MEAN", "DATA")
#To determine the buildup classes, reclassify the urbanness map and then multiplied with buildup
buildup_classes = arcpy.sa.Reclassify(urbanness, "Value", remap, "NODATA") * buildup
#To get the required values, the above output is filtered. Urban suburban areas have been
#determined based on the values of previous output. 1 represents urban and 0 non urban.
urb_suburb = arcpy.sa.Test(buildup_classes, "Value = 1 or Value = 2")
#We require just buildup cells, so non-buildup cell were given null value
urb_suburb_1_null = arcpy.sa.SetNull(urb_suburb, 1, "Value = 0")
#To calculate the Euclidean Distance in a distance of 100m from each cell
buildup_dist = arcpy.sa.EucDistance(urb_suburb_1_null, 100)

```