Monitoring and modelling of urban sprawl using remote sensing and GIS techniques

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Abstract

The concentration of people in densely populated urban areas, especially in developing countries, calls for the use of monitoring systems like remote sensing. Such systems along with spatial analysis techniques like digital image processing and geographical information system (GIS) can be used for the monitoring and planning purposes as these enable the reporting of overall sprawl at a detailed level.

In the present work, urban sprawl of the Ajmer city (situated in Rajasthan State of India) has been studied at a mid scale level, over a period of 25 years (1977–2002), to extract the information related to sprawl, area of impervious surfaces and their spatial and temporal variability. Statistical classification approaches have been used for the classification of the remotely sensed images obtained from various sensors viz. Landsat MSS, TM, ETM+ and IRS LISS-III. Urban sprawl and its spatial and temporal characteristics have been derived from the classified satellite images. The Shannon’s entropy and landscape metrics (patchiness and map density) have been computed in terms of spatial phenomenon, in order to quantify the urban form (impervious area). Further, multivariate statistical techniques have been used to establish the relationship between the urban sprawl and its causative factors. Results reveal that land development (160.8%) in Ajmer is more than three times the population growth (50.1%). Shannon’s entropy and landscape metrics has revealed the spatial distribution of the urban sprawl over a period of last 25 years.

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Keywords: Remote sensing; GIS; Urbanisation; Land use; Modelling; Urban sprawl

1. Introduction

Accelerated urban growth is usually associated with and driven by the population concentration in an area. The extent of urbanisation or its growth drives the change in land use/cover pattern. Land use and landcover changes may have adverse impacts on ecology of the area, especially hydro-geomorphology and vegetation. The process of urbanization has a considerable hydrological impact in terms of influencing the nature of runoff and other hydrological characteristics, delivering pollutants to rivers and causing erosion (Gordon et al., 1992; Paul and Meyer, 2001; Weng, 2001). Accurate information on the extent of urban growth is of great interest for the municipalities of growing urban and suburban areas for diverse purposes such as urban planning, water and land resource management, marketing analysis, service allocation, etc. Urban authorities and municipal corporations are required to devote more time, attention and effort to manage the use of land and other resources in order to accommodating the expanding population or other urban land uses. Urban sprawl monitoring and
prediction are the basic information they need for long-
term planning. For balanced development, municipal authorities need tools to monitor how the land is
currently used, assess future demand, and take steps to
assure adequacy of future supply. For a better planning
of future urban development and infrastructure plan-
ning, municipal authorities need to know urban sprawl
phenomenon and in what way it is likely to move in the
years to come.

Unfortunately, the conventional surveying and
mapping techniques are expensive and time consuming
for the estimation of urban sprawl and such information
is not available for most of the urban centres, especially
in developing countries. As a result, increased research
interest is being directed to the mapping and monitoring
of urban sprawl/growth using GIS and remote sensing
techniques (Epstein et al., 2002).

Remote sensing is cost effective and technologically
sound, so is increasingly used for the analysis of urban
sprawl (Sudhira et al., 2004; Yang and Liu, 2005; Haack
and Rafter, 2006). For nearly three decades, extensive
research efforts have been made for urban change
detection using remotely sensed images (Gomarasca
et al., 1993; Green et al., 1994; Yeh and Li, 2001; Yang
and Lo, 2003; Haack and Rafter, 2006). These studies
have been supported through either an image-to-image
comparison or a post-classification comparison.

The impervious (built-up) area is generally con-
sidered as a parameter for quantifying the urban sprawl
(Torrens and Alberti, 2000; Barnes et al., 2001; Epstein
et al., 2002). Here, impervious area refers to the area
consisting of residential, commercial, industrial com-
plexes including paved ways, roads, markets, etc. Urban
sprawl has been quantified by considering the impervi-
ous area as the key feature of urban sprawl, which can
be obtained either from physical survey or through
remotely acquired data.

There are a variety of techniques used to measure/estimate
the area of impervious surfaces. The most time
consuming and costly, yet the most accurate is manual
extraction of impervious surface features from remote
sensing images through heads up digitizing. Point
calling can be used as an alternative to digitizing,
despite this being time consuming and less accurate.
Remote sensing pattern recognition approaches, such as
supervised, unsupervised and knowledge-based expert
system approaches (Greenberg and Bradley, 1997;
Vogelmann et al., 1998; Stuckens et al., 2000; Stefanov
et al., 2001; Sugumaran et al., 2003; Lu and Weng,
2005; Mundia and Aniya, 2005) have been used in
recent past to measure impervious area and urban
sprawl. These require both moderate to high resolution
remote sensing data as well as expertise to process and
analyze. These data and analytical capabilities are often
beyond the reach of many planners and decision makers
at local level, especially in developing countries.

Statistical techniques along with remote sensing and
GIS have been used in many urban sprawl studies (Lo,
2001; Lo and Yang, 2002; Weng, 2001; Cheng
and Masser, 2003; Sudhira et al., 2004; Chabaeva
et al., 2004; Jat et al., 2006). Urban growth studies have
been attempted in several developed countries (Batty
et al., 1999; Torrens and Alberti, 2000; Barnes et al.,
2001; Hurd et al., 2001; Epstein et al., 2002; Li and
Weng, 2005; Jantz et al., 2005; Yang and Liu, 2005).
These are some examples and similar applications also exist
for other countries like China (Yeh and Li, 2001; Weng,
2001; Cheng and Masser, 2003) and India (Lata et al.,
2001; Sudhira et al., 2004; Jat et al., 2006). Statistical
techniques like multivariate regression has been used to
determine the relationship between the percent imper-
vious area and various urban development parameters
such as road density, population density, land use type
and size of development units (Lo, 2001; Lo and Yang,
2002; Weng, 2001; Cheng and Masser, 2003; Chabaeva
et al., 2004, Sudhira et al., 2004). The convergence of
GIS and database management systems has helped in
quantifying, monitoring, modelling, and subsequently
predicting the urban sprawl phenomenon. Characteris-
ing urban sprawl pattern involves detection and
quantification with appropriate scales and statistical
summarization. Appropriate scale of urban sprawl
characterization is the suitable spatial unit used in such
analysis. Statistical summarization of urban growth
pattern refers to representation of this phenomenon in
terms of statistical parameters and indices like Shannon
entropy, Patchiness, etc. Now, there are some metrics
available to describe landscape pattern, quantify urban
growth and its spatial distribution. The landscape
pattern metrics are used for studying the forest patches
(Trani and Giles, 1999; Civco et al., 2002) and detecting
the urban sprawl pattern in village clusters (Sudhira
et al., 2004). Most of the indices are correlated among
themselves, because there are only a few primary
measurements that can be made from patches (patch
type, area, edge and neighbor type). All metrics are then
derived from these primary measures. At the landscape
level, GIS aids in calculating the landscape metrics, like
patchiness and density in order to characterise land-
scape properties in terms of spatial distribution and
change (Trani and Giles, 1999; Yeh and Li, 2001; Civco
et al., 2002, Sudhira et al., 2004). Such metrics have not
been determined so far for most of the urban centres of
India (Sudhira et al., 2004).
Shannon’s entropy has been used in some of the studies to quantify the urban forms, such as impervious area in terms of spatial phenomenon (Yeh and Li, 2001; Sudhira et al., 2004; Joshi et al., 2006). Shannon’s entropy is based on the concept of information theory. It is a measure of uncertainty about the realisation of a random variable, like urban sprawl taking place in the form of impervious patches in newly developed areas. A quantitative measure is required to monitor and identify this fragmented urban sprawl. Developing this analogy, the mathematical representation of urban sprawl as a fragmented phenomenon and the concept of entropy are close (entropy is often used as a measure of dispersion of a random variable) (Joshi et al., 2006). Shannon’s entropy ($H_n$) is used to measure the degree of spatial concentration or dispersion of geophysical variable ($X_i$) among $n$ spatial units/zones (wards). Entropy can be used to indicate the degree of urban sprawl/sprawl by examining whether land development in a city is dispersed or compact (Lata et al., 2001; Sudhira et al., 2004; Joshi et al., 2006). Large value of Shannon’s entropy indicates dispersion of considered random variable (urban sprawl) which indicates occurrence of urban sprawl.

Despite these efforts, further research is needed in order to reinforce absolute and comparative relationship between the magnitude of change in landscape imperviousness, type and intensity of urban land use/cover change and their causative factors.

In India, currently 25.73% of the population (Census of India, 2001) is living in urban centers, while in the next 15 years it is projected to be around 33%. This indicates an alarming rate of urbanisation and possible urban growth that could take place. Measurement and modelling of urban sprawl using satellite images have not been well studied till date, especially in India (Sudhira et al., 2004).

In this research, an attempt has been made to investigate the usefulness of the spatial techniques, like remote sensing and GIS for urban sprawl detection and handling of spatial and temporal variability of the same. Urban sprawl of Ajmer city (situated in Rajasthan State of India) in the last 25 years has been estimated using remote sensing images of eight different years ranging from 1977 to 2002. Remote sensing and GIS techniques have been used to extract the information related to urban sprawl. Spatial and temporal variation of urban sprawl is studied to establish a relationship between urban sprawl and some its causative factors, like population, population density, density of built-up. However, other relevant factors (e.g. socio-economic) are not considered in the present study due to non-availability of data. Statistical image classification approach, like maximum likelihood classifier (MLC) has been used for the analysis of satellite images obtained from various sensor systems. Classified images have been used to understand the dynamics of urban sprawl and to extract the area of impervious surfaces. In order to quantify the urban forms, such as impervious area in terms of spatial phenomenon, the Shannon’s entropy (Yeh and Li, 2001) and the landscape metrics (patchiness, map density, etc.) are computed. The landscape metrics, normally used in ecological investigations, are being extended to enhance understanding of the urban forms. Computation of these indices helped in understanding the process of urbanisation at a landscape level. Further, urban sprawl has been correlated with its causative factors, like population, population density, etc. using multivariate regression analysis to arrive at a functional relationship. In addition to that, these relationships are used to predict the future urban sprawl.

2. Study area

The study area is located between 26°20'N to 26°35'N latitudes and 74°33'E to 74°45'E longitudes (Fig. 1). Ajmer is situated 132 km from Jaipur, the capital of Rajasthan, India and flanked by Aravalli hills on two sides. Ajmer enjoys the status of being one of the major centres of higher learning and specialized education in Rajasthan, apart from having historic importance. Administrative area of Ajmer spreads over an area of 250 km$^2$. Population of Ajmer was 0.49 million in the year 2001, and it is expected to be 0.84 million in 2034, as per the present growth rate. For a better planning of future urban development and infrastructure planning, municipal authorities need to know urban sprawl phenomenon of Ajmer, its distribution and in what way it is likely to move in the years to come.

3. Data used

The data has been collected from primary and secondary data sources (Table 1). The data collected from the primary sources include Survey of India (SOI) topo-sheets (scale, 1:25,000) (No. 45J/10/5, 6 and 45J/11/1, 2, 3, 4) and multi-spectral Landsat MSS, TM, ETM+ and Indian Remote Sensing (IRS) LISS-III images for the years 1977, 1989, 2000 and 2002. The data collected from secondary sources include the demographic data (primary census abstracts for the years 1961, 1971, 1981, 1991 and 2001) from the
Directorate of Census Operations, Census of India (Census of India, 1991; Census of India, 2001). Wardwise population (year 2001) and urban settlement map of the Ajmer city (scale, 1:2500; year 2000) have been obtained from the Rajasthan Urban Infrastructure Development Projects (RUIDP) Ajmer. Other maps of Ajmer city, like ward map, municipal boundary map, drainage and master plan have been obtained from the Town Planning Department, Ajmer.

4. Methodology

Understanding the dynamic phenomenon, such as urban sprawl/growth, requires land use change analyses, urban sprawl pattern identification and computation of landscape metrics. ERDAS (Leica) and ArcGIS software (ESRI) have been used to generate various thematic layers, like ward map, Ajmer municipal boundary map, roads, railway network and administrative boundary map using the topo-sheets and other available maps. Complete methodology has been presented in Fig. 2.

The standard image processing techniques, such as image extraction, rectification, restoration, and classification have been used for the analysis of four satellite images (1977, 1989, 2000 and 2002). ERDAS imagine software has been used for image analysis. First of all, atmospheric correction has been applied using improved dark object subtraction method to bring all the images at common reference spectral characteristics. Water bodies available in the areas have been used as the dark object. Further, these subtracted images have been stretched to 8 bit digital number range. Images are further geo-referenced and geometrically corrected corresponding to the Polyconic projection system using the SOI topo-sheets.

Table 1
Different type of data used

<table>
<thead>
<tr>
<th>S. no.</th>
<th>Type of data used</th>
<th>Scale/resolution</th>
<th>Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Survey of India topo-sheets</td>
<td>1:25,000</td>
<td>1976 and 1977</td>
</tr>
<tr>
<td>2</td>
<td>Landsat MSS image</td>
<td>57 m</td>
<td>1977</td>
</tr>
<tr>
<td>3</td>
<td>Landsat TM image</td>
<td>28.5 m</td>
<td>1989</td>
</tr>
<tr>
<td>4</td>
<td>Landsat ETM+ image</td>
<td>28.5 and 14.25 m</td>
<td>2000</td>
</tr>
<tr>
<td>5</td>
<td>IRS 1D LISS-III image</td>
<td>23 m</td>
<td>2002</td>
</tr>
<tr>
<td>6</td>
<td>Urban settlement map</td>
<td>1:2,500</td>
<td>2000</td>
</tr>
<tr>
<td>7</td>
<td>Municipal boundary map</td>
<td>1:25,000</td>
<td>2000</td>
</tr>
<tr>
<td>8</td>
<td>Drainage map</td>
<td>1:2,500</td>
<td>2000</td>
</tr>
</tbody>
</table>

Fig. 1. Location of study area.
Satellite images have been studied thoroughly to ascertain the probable land use classes and their respective range of reflectance values (DN values). Spectral profiles have been drawn to ascertain the separability and relative difference in pixel values of different land use classes in different spectral bands. Ten separable land use classes have been identified, such as urban settlement, barren land, water, sandy soil, rocky terrain, exposed rocks, shrubs, mix vegetation, fallow land, etc. Initially, supervised classification using MLC algorithm has been performed for the classification of various images (Table 2). To enhance the classification accuracy, knowledge-based expert system was used for post-classification refinement of initially classified outputs.

Initially, the algorithm was trained by supervised training process, after collection of parametric and non-parametric signatures (training samples). Each training sample consisted of at least 90 image pixels to satisfy the $10 \times n$ criterion, where $n$ is the number of bands used for classification (Congalton, 1991). Signatures are further evaluated using three criterion to test whether they truly represent pixels to be classified for each class: (i) histogram plots to examine various statistical parameters, like standard deviation and uni-modality of the histogram, (ii) signatures separability using
transformed divergence (TD), and (iii) contingency matrix, which contains the number and percentage of pixels which are classified as expected. Signatures are refined, deleted, renamed and merged after evaluation to ensure the uni-modality of their histograms, statistical parameters, contingency matrix and TD values. After evaluating the seperability, spectral band combination with good seperability (with highest TD value) have been selected for the final classification.

Initially, hill shadow is classified as a separate class, however after field verification it has been merged with the shrub. Various manipulation techniques, like ratio, subtraction, etc., were tried initially to remove the hill shadow, but no significant improvement was observed. Classification results obtained from supervised classification are not found satisfactory as misclassification has been observed for urban settlement (81.7–89.9%), exposed rocks (88.2–92%), and rocky terrain (75–96.8%), which is substantiated from their lower overall accuracy (81.7–84.7%).

In second stage, knowledge-based expert system has been used for the post-classification refinement, i.e. rule-based system is applied on output from MLC in an attempt to modify and improve the classification. Ancilliary information from various sources (DEM, municipal boundary map, location map of water bodies, soil map) has been integrated with outputs from MLC for the preparation of knowledge base (rule base). Rule base has further been refined from the ground truth data collection. Finally, classification has been done using the Knowledge Classifier Module of ERDAS. Classified results of various images have been found satisfactory with higher overall accuracy of more than 94%, and data collected from other maps (municipal boundary map, soil map, location map of water bodies, SOI topo-sheets and forest cover maps). The original satellite data has also been used for accuracy assessment to avoid errors in the reference dataset for temporally sensitive classes (such as vegetation). Urban settlement map of the city and geographical locations of some of important features, like type of vegetation at a particular location, important buildings, play grounds, water bodies and drains, collected during the field visits have also been used as ground truth data. Classification results of the older images (1977, 1989) have been done using the geographical locations of some of important features, like built-up area, type of vegetation at a particular location, important buildings, play grounds, water bodies and location of reserved forest patches etc available on SOI topo-sheets (printed in 1977) and town planning maps available. Further, accuracy report and Kappa Coefficient have been generated using the ERDAS Imagine’s accuracy assessment utility.

Urban sprawl/growth over a period of 25 years (1977–2002) is obtained from the classified images and results are compared with settlement maps prepared by Ajmer Town Planning Department. To understand the urban sprawl pattern, different landscape metrics (Shannon’s entropy, Patchiness, and Map density) are calculated using the demographical and built-up area statistics.

Population growth of the Ajmer city has been evaluated using the demographic data of four decades, i.e. 1961–2001 (Census of India). Decadal population growth trends are obtained by plotting the data and fitting the different type of distributions, like linear, logarithmic, exponential, power and polynomials. These distributions have been explored for the best form of relationship. Such a relationship could be used for population prediction. The distribution with highest correlation coefficient has been chosen for further use. Urban sprawl dynamics has been analysed considering some of the basic causative factors, like population ($P$), population density (PD), population density for the built-up ($\alpha$ density, $\alpha$D) and population growth rate ($P_{AGR}$). The rationale behind this is to identify such

<table>
<thead>
<tr>
<th>Year</th>
<th>Sensor</th>
<th>Spatial resolution (m)</th>
<th>No. of spectral bands</th>
<th>Spectral bands considered</th>
<th>Transformed divergence (TD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1977</td>
<td>Landsat MSS</td>
<td>57</td>
<td>4</td>
<td>2, 3, 4</td>
<td>1802</td>
</tr>
<tr>
<td>1989</td>
<td>Landsat TM</td>
<td>28.5</td>
<td>7</td>
<td>1, 3, 4, 5</td>
<td>1748</td>
</tr>
<tr>
<td>2000</td>
<td>Landsat ETM+</td>
<td>28.5 and 14.5</td>
<td>6</td>
<td>1, 2, 4, 6</td>
<td>1997</td>
</tr>
<tr>
<td>2002</td>
<td>IRS 1D LISS-III</td>
<td>23</td>
<td>4</td>
<td>1, 3, 4</td>
<td>1993</td>
</tr>
</tbody>
</table>

Table 2
Transformed divergence (TD) for supervised classification of various images
factors that play a significant role in the process of urbanization. Multivariate regression analysis has been performed considering the urban sprawl in terms of percentage of impervious area (PB) as a dependent variable. Regression analysis has been performed for two cases considering the urban area (i) as a whole and (ii) at the ward level (for year 2000 only). Here ward refers to the spatial size of a developmental unit or zone, i.e. geographical area of a planning unit considered by the local development authorities for the landscape planning and administrative purposes. Percentage impervious area of a ward is the ratio of impervious to total area of ward (individual zone). The population density for a ward is the ratio of population in each ward to the impervious area of that ward. The population has been accepted as a key factor of urban sprawl. In the present study, PB, αD and PD are computed and analysed for the whole urban area (Case I) as well as ward-wise (categorised as a sub-zone) (Case II). The annual population growth rate (P_{AGR}) parameter has been used only for Case I. Ward-wise analysis has been carried out for the year 2000 only, as ward-wise population data are not available for other years. Ward-wise impervious area has been obtained from the classified satellite image. The P_{AGR} for the whole urban area is computed from the available population data (1961–2001). Population of in-between years has been obtained by piecewise linear interpolation and fitted regression equation.

In order to identify the probable relationship of PB (dependent variable) and individual causative factors, different distributions (linear, quadratic, exponential and logarithmic) have been explored for Case I. The regression analyses reveal the individual contribution of causative factors on urban sprawl.

To assess the cumulative effect of causative factors, stepwise multivariate regression analysis has been performed. In the multivariate regression, it is assumed that the relationship between variables is linear, which is supported by higher correlation coefficient for all individual causative factors. The multivariate regression gives the cumulative relationship between the variables.

5. Results and discussion

5.1. Image analysis

Signature seperability results are presented (Table 2) in the form of TD values. Values of TD for different land use pair’s lies within the satisfactory limits. Average
value of TD for different images varies between 1941 and 2000, which indicates good separation (TD > 1900). Minimum values of TD for different images lie between 1748 and 1993 (Table 1). Lower values of TD for some land use classes (1748) indicate that separation is fairly good. Best band combinations, corresponding to the highest values of TD have been selected for the supervised classification. From the two separability evaluation criteria, it can be concluded that signatures are good enough for separability. However, these signatures may represent a narrow range of reflectance values for each land use class, as these have been refined to satisfy various evaluation criterion. Separability is slightly poor for the urban settlement as it is mixed with rocky terrain, exposed rocks and wet alluvium soil land use classes. This mixing of urban settlement and rocky land use classes is due to heterogeneous character (different type of construction material and different type of impervious surfaces) of urban area and surrounding hilly topography (exposed rocks and hills, where reflectance is similar to the built-up areas).

For all images, results of accuracy assessment have been presented in Table 3. Results of the rule-based post-classification refinement have been found to be satisfactory with good overall accuracy. Both user and producer accuracies are almost same (Table 3) which further indicate consistent classification accuracy. Overall classification accuracy has been found to be more than 90% for all the images (Table 3). Highest accuracy of 94.9% has been obtained for LISS-III image of the year 2002, while 94.0% accuracy has been obtained for the Landsat TM image of the year 1989.

5.2. Population growth and built-up area

Quadratic model has been found to be best fitted for the population growth of Ajmer city as compared to linear, exponential, logarithmic and power distributions. Following quadratic relationship of population growth has been adopted for projection of population, as it has highest correlation coefficient (0.97) (Fig. 4).

\[
P = 1.7556X^2 + 55.087X + 168.220 \tag{1}
\]

where \(P\) is the population in thousand and \(X\) is years in decade (1961 onwards). Lowest correlation has been found for the logarithmic distribution. Eq. (1) has been used for future population prediction. Values of the correlation coefficient for linear (0.96) and exponential (0.96) relationship are also not significantly different, which may be due to small number of data sets used to form the relationship.

Urban sprawl for the years 1977, 1989, 2000 and 2002 has been estimated in the form of impervious areas, which is obtained from the classified satellite images. Built-up area obtained from the classification may have some error due to mixed land use class pixels. Whether a particular pixel belongs to built-up or not, would depend upon the reflectance value from that pixel. MLC classification algorithm designates a particular pixel to a particular land use class, depending upon its reflectance characteristics (standard deviation and co-variance). In the present study, supervised classification has been used, which does not deal with sub pixel classification. However, results are further refined using knowledge-based approach by reducing the problem of mixed pixels. Urban area statistics for Ajmer city is presented in Table 4 and Fig. 5.

Table 3
Overall accuracy of the image classification

<table>
<thead>
<tr>
<th>Year</th>
<th>Classification accuracy</th>
<th>Overall classification accuracy</th>
<th>Overall kappa statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Producers accuracy (%)</td>
<td>Users accuracy (%)</td>
<td></td>
</tr>
<tr>
<td>1977</td>
<td>96.3</td>
<td>94.8</td>
<td>0.94</td>
</tr>
<tr>
<td>1989</td>
<td>93.7</td>
<td>94.0</td>
<td>0.93</td>
</tr>
<tr>
<td>2000</td>
<td>93.9</td>
<td>94.1</td>
<td>0.94</td>
</tr>
<tr>
<td>2002</td>
<td>94.8</td>
<td>94.9</td>
<td>0.94</td>
</tr>
</tbody>
</table>

Table 4
Urban growth statistics for the Ajmer city

<table>
<thead>
<tr>
<th>Year</th>
<th>Built-up area (ha)</th>
<th>Percentage increase in built-up area (%)</th>
<th>Projected population</th>
<th>Percentage growth in population (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1977</td>
<td>488</td>
<td>–</td>
<td>331,073</td>
<td>–</td>
</tr>
<tr>
<td>1989</td>
<td>838</td>
<td>71.7</td>
<td>397,279</td>
<td>19.9</td>
</tr>
<tr>
<td>2000</td>
<td>1,139</td>
<td>35.8</td>
<td>481,395</td>
<td>21.1</td>
</tr>
<tr>
<td>2002</td>
<td>1,259</td>
<td>10.5</td>
<td>497,160</td>
<td>3.27</td>
</tr>
</tbody>
</table>

Fig. 4. Population growth of Ajmer and best fit distributions.
Impervious area (built-up) has increased from 488 ha in year 1977 to 1259 ha in year 2002. Results in Table 4 reveal that the rate of land development in Ajmer has outstripped the rate of population growth. From the year 1977 to 2002, population in the region grew by about 50.2% while the amount of developed land grew by about 160.8%, i.e. more than three times the rate of population growth (Fig. 5 and Table 4). This implies that the land is being used for urbanization at a faster rate, which indicates that per capita consumption of land has increased exceptionally over last three decades. The per capita land consumption refers to utilisation of all lands for development initiatives, like commercial, industrial, educational, recreational and residential establishments per person.

Spatial distribution of ward-wise urban sprawl in last 25 years has been shown in Fig. 6. Urban sprawl is faster in outer area (ward number 1–6 and ward number 31–55) along the major roads as compared to central portion of the city, which is also substantiated by Fig. 6 and landscape metrics. Here again, the hypothesis is correct that increase in economic conditions and development relates to urban sprawl (Census of India, 2001).

5.3. Metrics of urban sprawl

5.3.1. Shannon’s entropy ($H_n$)

In the present investigation, Shannon’s entropy ($H_n$) is used to measure the degree of spatial concentration or dispersion (homogeneity) of a geophysical variable (impervious area) among n spatial units/zones (wards). Shannon’s entropy (Yeh and Li, 2001) has been computed considering the urban sprawl in different wards to detect the form of urban sprawl phenomenon. Ward boundary map, obtained from the Municipal Corporation of Ajmer is taken as the base for the evaluation of the urban sprawl pattern from year 1977 to 2002. Shannon’s entropy ($H_n$) is given by

$$H_n = - \sum P_i \log_e (P_i)$$

where $P_i$ is the proportion of the variable in the $i$th zone (ward), $n$ is the total number of zones. $P_i$ refers to the impervious areas in $i$th wards, $n$ represents total number of wards (55) and $\log n$ refers to the upper limit of entropy (1.7403). Shannon’s entropy has been calculated across all the wards considering each ward as an individual spatial unit.

In the present study, impervious area (ward wise) has been considered as the geophysical variable, which enables determination of urban sprawl. Entropy may range from 0 to $\log n$, indicating a compact distribution...
of impervious areas in outer wards. Distribution is predominantly dispersed in outer areas, whereas it is compact in areas surrounding central Ajmer. Hence, it can be concluded that Shannon’s entropy is useful and effective in identifying the urban sprawl phenomenon in terms of dispersion of the impervious area.

5.3.2. Patchiness

Patchiness or landscape diversity is the number of different land use classes within the \( n \times n \) window. It is a measure of diversity of all land use class patches. In other words, it is a measure of number of heterogeneous land use/cover polygons over a particular area. Greater the patchiness, more is the heterogeneous landscape. In this study, number of patches of different land use categories has been computed by moving a \( 5 \times 5 \) size kernel on the classified image using model maker utility of the ERDAS Imagine software. Size of kernel has been chosen as per the number of land use categories available in a particular image. There are 10 land use categories available in most of the classified images, which is more than the number of pixels in a \( 3 \times 3 \) size kernel. Therefore, kernel of \( 5 \times 5 \) size has been used in the present study. Land use diversity in terms of patchiness has been determined using the respective classified images for year 1977, 1989, 2000 and 2002.

Ward-wise landscape diversity and its percentage distribution for the different years have been presented in Fig. 7 and Table 6. Results reveal that diversity ranges from 1 to 7 land use class categories. One land use class category represents that only one land use class is available within the kernel, two land use class category represent that any two land use classes are available within the kernel, corresponding to central pixel of the kernel. For all the years, one and two heterogeneous land use classes categories are highest, whereas five to seven heterogeneous class categories have been found to be minimum (Table 6). However, one land use class category has gradually increased from 36.6% in year 1977 to 62.4% in year 2002 and two land use class category has reduced from 50.8% in year 1977 to 32.3% in year 2002. Category fourth has increased from 0.76% in year 1977 to 8.3% in year 2000, which indicates continuous process of urbanisation in new areas. Landscape diversity is more in the year 2000 as compared to 2002. This reveals that the percentage of homogeneous area has increased gradually since 1977, while the remaining area which is heterogeneous with patch class ranging from two to six has reduced. Change in the values of patchiness with time represents the change in land use heterogeneity, like diversity of one land use category has increased from, 36.6% to 62.4%.

Table 5
Shannon’s entropy for the study area

<table>
<thead>
<tr>
<th>Year</th>
<th>Shannon’s entropy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1977</td>
<td>1.54</td>
</tr>
<tr>
<td>1989</td>
<td>1.60</td>
</tr>
<tr>
<td>2000</td>
<td>1.62</td>
</tr>
<tr>
<td>2002</td>
<td>1.61</td>
</tr>
</tbody>
</table>


This indicates that diversity of one type of land use category has increased, which means other land use categories have been changed into this category. Results of the diversity analysis are well in agreement with the Shannon’s entropy results.

5.3.3. Map density

Map density is another index which can be used to examine the homogeneity/dispersion of any spatial phenomenon, like urbanisation. Distribution of impervious areas, which indicates urban sprawl, has been studied using density metrics. Map density values are computed by determining the number of impervious area pixels out of the total number of pixels in a $5 \times 5$ kernel. Here again size of kernel has been chosen as per the maximum number of land use categories available in a particular image. There are 10 land use categories available in most of the classified images, which is more
than the number of pixels in a $3 \times 3$ size kernel. Therefore, kernel of $5 \times 5$ size has been used in the present study. When this is applied to a classified satellite image, it converts land use classes into 25 density classes. For example, density value of 5 for a pixel represents 5 impervious area pixels in a $5 \times 5$ kernel. Depending on the density levels, it is further classified into five categories using the equal interval method as very low, low, medium, high and very high-density classes, corresponding to the density value (number of built-up pixels out of 25 pixels) of 5, 10, 15, 20 and more than 20. Density landscape metrics have been computed for all the 4 years (1977, 1989, 2000 and 2002). Further relative percentage of each density category (percentage of total impervious area in a particular category) has been computed for each year, which enabled identification of different urban sprawl centers. Subsequently results have been correlated with the Shannon’s entropy.

Results of the built-up/impervious area density metrics have been presented in Table 7. Re-classified categories of the densities (in terms of percentage of the total impervious area) have been presented in Table 7. Very high and high density of built-up area would refer to cluster or more compact nature of the built-up theme. While medium density would refer to relatively lesser compact built-up and low and very low density refer to loosely or sparsely spread built-up areas. The percentage of high-density (built-up area) has gradually increased from 19.5% in 1977 to 23.1% in 2002. The percentage of very high-density built-up area is more than 43.7% till the year 1989, however it has reduced afterward (Table 7). This revealed that percentage of compact or highly dense built-up area has reduced on account of development of new areas, which indicates dispersion. This reduction does not mean that impervious areas have decreased since 1989. Relative share of very high compact built-up area has been reduced, though total area under this category has not reduced. In the year 1989, area under very high density was 366 ha, which has increased to 372 ha in year 2002. However, its percentage with respect to the total area under all categories has been reduced. Increase in the value of very low, low, medium and high-density categories reveal urban sprawl and new developmental activities. Fig. 8 reveals that more land development have taken place in outer areas (ward number 1, 2, 3, 4, 5, 35, 39, 40, 53, 54 and 55), along the major roads and railway line. An important inference could be drawn here that high and medium density is found all along the main roads (National Highway), railway station and the city center (near railway station and Anasagar lake area). Most of the high density is found within the central portion of the city. Medium density is found along the city periphery and on the highways. Increase in impervious surfaces (from 1977 to 2002) in outer areas (ward number 1–5, 35, 39, 40, 53, 54 and 55) substantiate the results of density metrics. Further, density results substantiate the results of Shannon’s entropy, which reveal an urban sprawl in outer areas. Hence, these metrics are effective in determination of urban sprawl and its spatial distribution.

### 5.4. Dynamics of urban sprawl

Defining the dynamic urban sprawl phenomenon and its future prediction is a greater challenge than its quantification. Although different sprawl types are identified and defined, there has been an inadequacy with respect to developing mathematical relationships to define them. This necessitates the characterization and modelling of urban sprawl, which may aid in regional planning, planning and development of water resources and designing of urban drainage infrastructure. In the present investigation, population and related densities are used as independent variables for modelling the urban sprawl.
5.5. Modelling of urban sprawl

Initially, analysis has been performed considering the individual causative factor (independent variables) to ascertain their significance (form of equation) on the urban sprawl. The regression analyses reveal the individual contribution of causative factors on urban sprawl. Various relationships and their statistical parameters have been presented in Table 8.

Relationships between PB and \( P \) have been found to be quadratic with lowest standard error of estimate (S.E. = 0.06) and higher correlation coefficient (0.988). Relationships between PB and PD have been found to be linear. Linear regression results shows highest correlation coefficient (0.995) and lowest standard error of estimate (S.E. = 0.507) for PD. Relationships between PB and have been also found to be quadratic with highest correlation coefficient (0.99) and lowest
standard error of estimate (S.E. = 0.48). Relationships between PB and $P_{AGR}$ have been found to be quadratic with highest correlation coefficient (0.85) and lowest standard error of estimate (S.E. = 2.12). The linear and quadratic regression analyses reveal that the population and population density have significant influence on PB. Quadratic relationship is prominent for the $P$, $\alpha D$ and $P_{AGR}$, however linear relationship can be adopted for multivariate analysis as the coefficient of quadratic terms are very small. The quadratic regression analyses

Table 7
Different densities of built-up and their percentage area

<table>
<thead>
<tr>
<th>Category</th>
<th>Percentage of total impervious area (%)</th>
<th>Area (ha)</th>
<th>Percentage of total impervious area (%)</th>
<th>Area (ha)</th>
<th>Percentage of total impervious area (%)</th>
<th>Area (ha)</th>
<th>Percentage of total impervious area (%)</th>
<th>Area (ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very low density</td>
<td>0.4</td>
<td>2</td>
<td>1.03</td>
<td>8.6</td>
<td>7.78</td>
<td>88</td>
<td>7.95</td>
<td>104</td>
</tr>
<tr>
<td>Low density</td>
<td>5</td>
<td>26</td>
<td>15.08</td>
<td>126</td>
<td>17.16</td>
<td>195</td>
<td>17.18</td>
<td>221</td>
</tr>
<tr>
<td>Medium density</td>
<td>17</td>
<td>84</td>
<td>20.3</td>
<td>170</td>
<td>19.81</td>
<td>225</td>
<td>22.72</td>
<td>292</td>
</tr>
<tr>
<td>High density</td>
<td>19</td>
<td>95</td>
<td>19.89</td>
<td>166</td>
<td>22.89</td>
<td>260</td>
<td>23.11</td>
<td>297</td>
</tr>
<tr>
<td>Very high density</td>
<td>57</td>
<td>280</td>
<td>43.7</td>
<td>366</td>
<td>32.36</td>
<td>368</td>
<td>29.55</td>
<td>372</td>
</tr>
</tbody>
</table>

Very low density (1–5 pixels of built-up), low density (6–10 pixels of built-up), medium density (11–15 pixels of built-up), high density (16–20 pixels of built-up), very high density (21–25 pixels of built-up) (out of 25 pixels). Built-up densities have been obtained using a $5 \times 5$ size of kernel. 25 density classes have been obtained. Further density output classified into five classes as mentioned above.

Table 8
Coefficients of casual factors and percentage built-up using regression analysis

<table>
<thead>
<tr>
<th>Dependent variable (y)</th>
<th>Independent variable (x)</th>
<th>Equation ($y = mxx + c$)</th>
<th>S.E. of y estimate</th>
<th>Correlation coefficient, R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear regression</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PB</td>
<td>$P$</td>
<td>$PB = 5.412P - 11.84$</td>
<td>0.507</td>
<td>0.99</td>
</tr>
<tr>
<td>PB</td>
<td>$PD$</td>
<td>$PB = 0.4607PD - 11.84$</td>
<td>0.507</td>
<td>0.99</td>
</tr>
<tr>
<td>PB</td>
<td>$\alpha D$</td>
<td>$PB = -0.0327\alpha D + 26.846$</td>
<td>1.393</td>
<td>0.96</td>
</tr>
<tr>
<td>PB</td>
<td>$P_{AGR}$</td>
<td>$PB = 5.412P_{AGR} - 11.84$</td>
<td>3.679</td>
<td>0.68</td>
</tr>
<tr>
<td>Logarithmic</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PB</td>
<td>$P$</td>
<td>$PB = 22.8 \ln(P) - 284.95$</td>
<td>0.59</td>
<td>0.98</td>
</tr>
<tr>
<td>PB</td>
<td>$PD$</td>
<td>$PB = 22.86 \ln(PD) - 78.027$</td>
<td>0.59</td>
<td>0.98</td>
</tr>
<tr>
<td>PB</td>
<td>$\alpha D$</td>
<td>$PB = -17.436 \ln(\alpha D) + 118.359$</td>
<td>1.13</td>
<td>0.95</td>
</tr>
<tr>
<td>PB</td>
<td>$P_{AGR}$</td>
<td>$PB = -1.61 \ln(P_{AGR}) + 24.33$</td>
<td>3.43</td>
<td>0.38</td>
</tr>
<tr>
<td>Polynomial 2nd order</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PB</td>
<td>$P$</td>
<td>$PB = -6.3E-12P^2 + 5.96E-05P - 12.98$</td>
<td>0.06</td>
<td>0.98</td>
</tr>
<tr>
<td>PB</td>
<td>$PD$</td>
<td>$PB = -4.5E-4PD^2 + 0.506P - 12.98$</td>
<td>0.6</td>
<td>0.98</td>
</tr>
<tr>
<td>PB</td>
<td>$\alpha D$</td>
<td>$PB = 1.48E-04\alpha D^2 - 190.5\alpha D + 66.585$</td>
<td>0.48</td>
<td>0.99</td>
</tr>
<tr>
<td>PB</td>
<td>$P_{AGR}$</td>
<td>$PB = -6.3E-07P^{2.192}<em>{AGR} + 3.35E-03P</em>{AGR} + 9.705$</td>
<td>2.1</td>
<td>0.85</td>
</tr>
<tr>
<td>Power</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PB</td>
<td>$P$</td>
<td>$PB = 5.12E-12P^{2.192}$</td>
<td>0.029</td>
<td>0.98</td>
</tr>
<tr>
<td>PB</td>
<td>$PD$</td>
<td>$PB = 2.05E-3PD^{2.192}$</td>
<td>0.029</td>
<td>0.98</td>
</tr>
<tr>
<td>PB</td>
<td>$\alpha D$</td>
<td>$PB = 4.78E+05\alpha D^{-1.744}$</td>
<td>0.02</td>
<td>0.988</td>
</tr>
<tr>
<td>PB</td>
<td>$P_{AGR}$</td>
<td>$PB = 46.64P^{0.192}_{AGR}$</td>
<td>0.13</td>
<td>0.45</td>
</tr>
</tbody>
</table>
revealed that $\alpha D$ and $P_{AGR}$ have a considerable role in the urban sprawl phenomenon. The power law regression analyses reveal that the population density has influenced the urban sprawl phenomenon, which is evident from the value of exponent. Annual population growth shows positive correlation with percentage built-up, which is again a population-derived parameter.

In multivariate regression, it is assumed that the relationship between variables is linear as the coefficient of quadratic terms is very small and same is supported by the higher correlation coefficient for linear and quadratic relations (Table 9). The multivariate regression gives the cumulative relationship among the independent and dependent variables. Details of the multivariate regression analysis have been presented in Table 9. Following relationship have been found to be most suitable for both the Cases (I and II).

- **Case I**: whole urban area

  $\text{PB} = 0.3564 \text{PD} - 0.00688\alpha D - 3.504$
  $(R = 0.998, F = 2.62E-5, \text{S.E.} = 0.49)$  \hspace{1cm} (3)

  $\text{PB} = -3.1E-05P + 0.6854\text{PD}$
  $- 8.4E-05\text{PGR} - 9.610$  \hspace{1cm} $(R = 0.99)$  \hspace{1cm} (4)

- **Case II**: at ward level

  $\text{PB} = -0.00395P + 0.09524\text{PD}$
  $ - 0.01144\alpha D + 59.058$
  $(R = 0.87, F = 2.25E-15, \text{S.E.} = 16.6)$  \hspace{1cm} (5)

Considering all the causative factors in the stepwise regression, Eq. (3) for Case I and Eq. (5) for Case II have been found to be best fit with highest correlation coefficient, lowest standard error of estimate and lowest significance $F$. In Case I, it is to be noted that correlation coefficient is same for relationships (Eq. (4)) with other parameters, however relationship of PB with PD and $\alpha D$ is found most suitable as its significance $F$ is smallest. Significance $F$ is a statistical criterion which indicates degree of relationship. Smaller value of significance $F$ indicates good relationship. Eqs. (3)–(5) confirm that the causative factors collectively have a significant role in the urban sprawl phenomenon, which can be understood from the satisfactory positive correlation coefficients.

![Fig. 9. Prediction of urban growth for Ajmer.](image-url)
5.6. Predicting scenarios of urban sprawl

Urban sprawl of Ajmer has been predicted using Case I relationship, as ward-wise population is available only for year 2000. Likely increase in the impervious area (built-up) is predicted using Eq. (4) as population, population density and annual population growth rate are available from the historical data. To project the impervious area (built-up) from year 2011 to 2041 (decadal growth) within the notified municipal area, corresponding population has been computed using Eq. (1). It is estimated that the percentage built-up for 2011 and 2051 would be 17.9% and 33.9%, respectively (Fig. 9). This implies that by year 2051, the built-up area in the municipal limits would rise to 2889 ha, which may be nearly 129.3% more than the built-up (1259 ha) in year 2002. Thus, the pressure on land would further grow and the vegetal areas, open grounds and region around the highways are likely to become prime targets for urban sprawl.

Remote sensing technology is indispensable for dealing with dynamic phenomenon, like urban sprawl. Without remote sensing data, one may not be able to monitor and estimate the urban sprawl effectively over a time period, especially for elapsed time period. This technology is cost effective in dealing with phenomenon like urban sprawl, as other conventional data collection and surveying techniques are found to be time consuming and expensive. Spatial and temporal variability of land use/cover change can be monitored using remote sensing data. In the present study, ward wise built-up areas have been determined over a period of 25 years, which would not have been possible without the use of remote sensing data. Landscape metrics have been computed using satellite images to understand the form and spatial distribution of urban sprawl. Such metrics cannot be obtained from the maps prepared using other techniques.

In the present investigation, population and related densities are used as independent variables for modelling the urban sprawl as data were available only for these parameters. Many other parameters, like socio-economic conditions, governmental investments for public sector works, scope of industrialization, tourist activities and distance from important places like railway station can also be considered in urban sprawl modelling. Many other physical barriers are not considered in the present investigation which may influence the urban sprawl phenomenon, like hilly range available in west and north side of the study area. However, availability of such detailed data is a difficult task in developing countries like India.

Other physical and topographical features, like hilly barriers, rocky areas, etc. along with other causative factors (as mentioned above) can be considered in the future urban sprawl modelling studies.

Ward level scale is more suitable for urban sprawl studies as it represents the actual spatial diversity of built-up phenomena within the city. In the present study urban sprawl phenomenon has been studied at ward level to show the dynamic pattern of urban sprawl and its spatial distribution or the changes in urbanization. Use of landscape metrics has been extended to study the urban sprawl, as a spatial phenomenon within the different spatial units or administrative zones of an urban centre. Ward level analysis has been performed for 1 year as data were not available for other years. However, developed relationships can be refined using the data of more number of years in future research work.

6. Conclusion

The urban sprawl is seen as one of the potential challenge to sustainable development where urban planning with effective resource utilization, allocation of natural resources and infrastructure initiatives are key concerns. The study has attempted to understand the urban sprawl of Ajmer city, quantified by defining important metrics (Shannon entropy, Patchiness and Density) and modelling the same for future prediction. Remote sensing and GIS techniques have been used to demonstrate their application for the monitoring and modelling of dynamic phenomena, like urbanisation. The spatial and attribute data of the region have been aided in statistical analysis and defining few of the landscape metrics.

Shannon’s entropy, Patchiness and built-up density landscape metrics have been computed which helped in understanding the form of urban sprawl and its spatial pattern. Larger value of entropy (near to upper limit) reveals the occurrence and spatial distribution of the urban sprawl. Results of the diversity analysis are well in agreement with the Shannon’s entropy. Urban sprawl is taking place continuously at a faster rate in outer areas, bringing more area under built-up category as revealed by metrics (dispersed growth). Built-up density results substantiate the results of Shannon’s entropy, which reveal an urban sprawl in outer areas. Landscape metrics have been found to be effective in determination of urban sprawl and its spatial distribution. Multivariate regression analysis has been performed to develop a relationship between urban sprawl and some of its causative factors. It has been found that
the change in built-up over the period of nearly 25 years is 160.8% and by year 2051, the built-up area in the region would rise to 2889 ha, which would be nearly 129.3% more than the sprawl of 1259 ha in year 2002. Rate of urban sprawl would be about two times the population growth, if projected using the present trend. Further, other causative factors, like socio-economic conditions, governmental investments for public sector works, scope of industrialization, tourist activities, physical barriers and distances from important locations can also be considered for urban growth modelling in future research work.

These metrics and relationship between urban sprawl and some of its causative factors are useful for the local development authorities and municipalities to determine spatial distribution of sprawl. Also such relationships can be used to predict and quantify urban sprawl, which can be used for optimal planning of land and natural resources, zonal and regional planning and designing of urban drainage infrastructure. Remote sensing technology is indispensable for dealing dynamic phenomenon, like urban sprawl. Without remote sensing data, one may not be able to monitor and estimate the urban sprawl effectively over a time period, especially for elapsed time period.

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