Spatial investigation of the temporal urban form to assess impact on transit services and public transportation access

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The rapid urban growth in developing city increases the requirement of the efficient and sustainable public transportation system. The urban growth affects the urban form, which indicates the change in human and urban development activity. Urban form affects directly and indirectly access to the public transportation system as an assessment of potential riders and proximity to stops increase transit services users. Therefore, access is one of the important aspects for the assessment of transit service efficiency. Public transportation access can be represented by a coverage area and useful to estimate potential riders of public transportation. In this study, a Geographical Information System (GIS)-based spatial statistical analysis method is used to examine the spatial relationship of different urban form indicators with population or riders of transit service in a coverage area and to ascertain how urban form influences public transportation trips in this coverage area. The coverage area is delineated using a GIS-based road/street network distance approach. The spatial analysis results suggested that urban forms have certain impact on trips in coverage area at both ward level and zone level. The statistical analysis implies that significant and positive values of spatial lag coefficient indicate a positive spatial interaction between wards and variable like total coverage area; worker density have shown positive and significant effects on trips of public transportation.

Keywords: GIS; spatial analysis; urban form; public transportation

1. Introduction

Rapidly developing cities are characterized by immense urbanization, population dispersion, employment decentralization, and land use fragmentation. Suburban development and population growth exert considerable pressure on infrastructure in urban regions. Jaipur, a rapidly growing city is also facing same problems with an enormous increase in population and prominent decentralization of employment. Jaipur city is one of the fastest growing megacities of India with an annual average growth rate of 5.3% twice that of the nation’s urban growth. With this current growth trend, it is likely to supersede many other cities. Over the last decade, the city has experienced a growth in the range of 5–8% per annum (1). High population density, a high rate of population growth, and urbanization are leading to unplanned development; strains on infrastructure facilities and deteriorating living environment are the biggest threats to development in Jaipur city. According to the City Development Plan for Jaipur (2006), it is lacking a good and reliable public transportation system (2). A survey was conducted for Jaipur city by a local authority under Comprehensive Mobility Plan for Jaipur (CMPJ) (1). This survey report indicated that 45% of trips are on two wheelers, 8% by bus, and 5% by car, indicating the maximum share of private vehicle trips (1).

Urban growth can be explained by urban form patterns, which also influence access to transit services (3). Urban form facilitates analysis of the intensity of human activities and urban development. The Centre for Sustainable Transportation (CST) created indicators using aspects of urban form and termed them as Sustainable Transportation Performance Indicators (STPIs), used to find the transport related sustainable development. Public transportation is recognized as a key component in the management and planning of urban regions (4). Public transportation represents a means by which people can efficiently move throughout a region with the least amount of impact on the environment. Public transportation services are accessed at stations, so it is very important to estimate coverage area of stop (5). The significance of coverage is that the more people work and reside in the proximity of transit, the greater likelihood that the service will be used. If the distance or barriers to access transit are too great at either trip origin or destination, then it is unlikely to be used as a mode of travel (6, 7), but at the same time reliability and efficiency also enhance the opportunity to use services (5, 6). Adequate and efficient transit services are also relevant from an environmental perspective and sustainable development of the city. In Jaipur city, public transportation services are mostly accessed on foot.
(60%) and the percentage of people who travel a distance less than 500 m to arrive at the stop is 45% (1).

To investigate the pattern of urban form, a Geographical Information System (GIS) can be used to analyze and provide valuable insights into the effectiveness of a transportation plan for a public transportation system. GIS technology offers extremely significant power in transportation modeling. The spread of GIS use facilitates the spatial data storage, updating, and processing efficiently. This article will discuss the characteristics of urban form pattern and its correlation with public transportation travel demand. The main objective is to explore the spatio-temporal impact of urban form pattern on transit service travel demand and the coverage area of public transportation plan. To achieve the objective, this study analyzes how a urban form pattern in the coverage and noncoverage areas of a ward and neighboring wards affects the trips/users of public transportation in that ward. A GIS-based spatial statistical analysis method is used for establishing a relationship between urban form and trip of public transportation. Coverage area is delineated using a road/street network-based distance method for current and proposed plan of public transportation for this study. To attain this, GIS and remote sensing tools are used to prepare urban form indicators at zone and ward scale of the city. The analysis performed using current or base 2009 data and projected data for 2031 based on the future planned projects for bus transit service. At present, Jaipur city has only buses as the public transportation mode. In this study, currently operating bus routes and as well proposed bus routes are used for analysis.

2. Materials and methods

The method flow used for analysis is showed in below Figure 1. The spatial data used for this analysis are, city ward boundary, urban, and coverage areas for public transportation. Nonspatial data such as population and worker data were derived from census data of Jaipur city. The data used for analysis area were based on year 2009 and 2031. The travel demand data for Jaipur city were collected from local authorities of Jaipur, which they estimated for 2009 and predicted for 2031. The local bus transit services are used for this study as only buses are available for public transportation of Jaipur city at present. The selection of 2031 year for future analysis is due to two main reasons; first, because of proposed plans of Jaipur metro and the second related reason, the availability of future travel demand data.

2.1. Urban form indicator formulation

Urban form not only reflects the intensity of suburban sprawl but also urban density. Urban form is a useful way to identify, quantitatively evaluate, and explain urban development and changes. The urban form changes have direct and indirect effect on the urban transportation system. It may lead to increase in two wheeler users and decrease in public transportation users.

Many urban form characteristics such as population, employment distribution, land-use density, land-use diversity, and areal compactness affect directly and indirectly to urban transportation activity. An urban form indicator is a statistical measure, a state of a complex system. For example, worker density, through its impact on travel patterns, can influence the activities of a public transportation system. An indicator which represents the growth trend and urban pattern may then be a feasible surrogate measure of that city’s “public transportation system efficiency.” Many indicators encapsulate aspects of land use and urban form such as compactness, land use mix, and worker density. Satellite remote sensing combined with GIS tools can be used to generate these geospatial information layers at a synoptic level. Different indicators are created for the urban form using GIS, remote sensing, and a spatial data in this research. Urban form-based indicators are defined in following subsections.

Figure 1. Flow chart of method.
2.1.1. Compactness

Urban land use per capita is a primary indicator of urban form, distinguished between low compactness and high compactness (4). Consumption of land describes how a city spatially spreads. It is well understood that riders from low density settlements or suburban areas need to travel great distances to arrive at their destinations. This factor subsequently makes public transportation less feasible and stimulates private vehicle use (4, 9). Compactness measures incorporate urban form and define the intensity of urban concentration density of the city. Compactness indicates the complexity of urban structure and design. If compactness is high, it indicates a regular shape (such as rectangle and square) to the urban patch, which creates better street and neighborhood designs. This shape enhances access to transit services. Low compactness indicates a zigzag pattern to the urban patch and increases the transit services access distance. Therefore, a compactness indicator is used to estimate the impact of urban form on public transportation accessibility. Compactness estimated using Equation (1), is a comparison between the perimeters of each developed urban and area of same patch (10).

\[ S = 2\sqrt{\pi A / P} \]  

where \( S \) is the compactness index, \( A \) is the area of urban land patch, and \( P \) is perimeter of the same patch.

2.1.2. Land use mix

A land use mix index is used to ascertain the level of commercial activity in each ward of Jaipur city. Typically, a land use mix shows that people living in suburban and rural–residential areas (e.g. villages near to suburban/outskirt of the city) travel greater distances to jobs. A ratio of 1:1 of land use mix indicates the equality of nonresidential/commercial and residential activity. Low land use mix levels, i.e. residential areas that are segregated from potential work while high level land use mix indicates higher level of nonresidential/commercial activities. This indicator provides information about commercial and residential activities as these activities affect the travel demand. For example, if a ward/zone has more nonresidential activities then more people will travel to that zone for jobs, service, and commercial activities. In the absence of an adequate public transportation system, more private vehicle use is likely. At present, there is no available data source that provides the degree of residential and commercial activities at the ward level of Jaipur city. In this study, a land use mix index is created by using worker population, nonworker population, and number of persons traveling for job/employment data at ward level. The survey analysis report of CMPJ (2008) was used to obtain the percentage of employment travel (services and employment trips) for Jaipur city. Worker and nonworker population is projected using census data of 2001. The land use mix index was calculated using the formula in Equation (2), below.

\[ \text{Land use mix} = \frac{(W_{\text{pop}} + J_{\text{pi}} - J_{\text{po}})}{(W_{\text{pop}} + R_{\text{pop}} + J_{\text{pi}} - J_{\text{po}})} \]  

where \( J_{\text{pi}} \) is the submission of total persons traveling to that ward for job/employment from the rest of the wards, \( W_{\text{pop}} \) is the total worker population of that ward, \( J_{\text{po}} \) is the total persons traveling from that ward to rest of ward for job/employment, and \( R_{\text{pop}} \) is total residential population of that ward. In this calculation, the land use mix index ranges from 0 to 1.

2.1.3. Worker density

Worker density is an indicator of the potential users of public transportation in a ward, as workers need to travel for their job/employment. Worker density is used for spatial and statistical analysis in this study. Worker population data for 2001 is used to project worker population for 2009 and 2031.

2.1.4. Urban area growth estimation

Urban area is a measure of anthropogenic development of a city. Urban area defines residential and commercial activities, influencing the transportation system of a city. Urban area growth includes increases in density as well as sprawl of city. The urban area indicator is used to understand the impact of increasing density and sprawl on public transportation efficiency. The urban area was estimated using Landsat satellite data from 2002 to 2006. The multilayer perceptron and Markov method are used for the simulation/prediction of the urban area for 2009 and 2031 with prepared urban land use data for 2002 and 2006 using IDRISI software.

2.1.5. Estimation of total trips of ward based on trip distance

This indicator was created to estimate the impact of trip distance on public transportation trips. Total trips for each ward are calculated on a basis of travel distance. Two criteria are defined based on a travel distance method such as less than 5 km and more than 5 km. The threshold for less than and more than 5 km was created using a survey analysis report in CMPJ (2008). This report demonstrated that travel distances less than 5 km were the maximum (55%) followed by distances more than 5 km. For the estimation of travel distance from each stop, a bus route network-based distance was used and then, trip distribution data were used to calculate the number of trips within specific distances from each ward. GIS tools were integrated with spatial data to calculate data for this indicator.
2.2. Delineation of coverage area of public transportation stops

The road network-based distance approach is used to estimate coverage area. Network-based distance measurement avoids the overestimation of coverage area, and can be created using GIS capabilities (7, 11, 12). The distance from stops used to create coverage area of 400 m, a comfortable walk under normal situations for all people (6, 7). Therefore, the transit coverage area is delineated by estimation of the 400 m walkable area on a street network for every stop of the public transportation system. Irregular polygons were created to demarcate the coverage area. These polygons are created for all current route stops and also for future planned route stops on this bus transit service (Figure 2).

The methodology used with the GIS for delineation of coverage area.

Delineation steps are as follows:

- A 400 m distance is used for coverage area delineation, representing the maximum distance that most people are willing to walk to use bus services.
- Calculation of the distance over the street network, in accordance with 400 m distances specified from each stop.
- Creation of polygons using the distance over the road network to calculate the coverage area of each PT stop.
- Overlapping this polygon layer with the built area layer in order to calculate the built area within each polygon.

Population, workers, and trips are used in this study for analysis so far. All these data were collected on ward level. At the same time, these information were also used to create data of public transportation coverage area. The area ratio method was used to estimate workers population and trips of public transportation for the coverage area (7, 11, 13). The formula is shown in Equation (3) as follows.

\[ P = P_w \frac{a_{bi}}{a_{zi}} \]  

where \( P \) is the worker/trip in coverage area, \( P_w \) is the worker/trip of the ward, and \( a_{bi} \) is the urban area of the polygon formed from the intersection of coverage area and \( a_{zi} \) is the urban area of the ward.

2.3. Model for spatial statistical analysis

The spatial statistical analysis was performed using year 2009 and 2031 data at the ward level. The Jaipur city area has 77 wards. These wards can be defined as division of city area into small areas. There are two methods used, the first one is ordinary least squares (OLS) model as described in Equation (4):

\[
\text{TRIPSPTCA} = \beta_0 + \beta_1 (\text{TOTAREAPTCA}) + \beta_2 (\text{WRKRDENSPTCA}) \\
+ \beta_3 (\text{COMPACPTCA}) + \beta_4 (\text{LUMIXPTCA}) \\
+ \beta_5 (\text{TOTAREARTWD}) + \beta_6 (\text{WRKRDENSRTWD}) \\
+ \beta_7 (\text{COMPACRTWD}) + \beta_8 (\text{LUMIXRTWD}) \\
+ \beta_9 (\text{TRIPLT5KMWD}) + \beta_{10} (\text{TRIPMT5KMWD}) + \epsilon_i 
\]  

In the next step, spatial diagnostic tests are used for spatial dependence analysis. Anselin and Rey (1991) showed how the Moran I (MI) and Lagrange multiplier are used for different situations, different sample sizes, alternative spatial structures, and under the nonstandard error distributions (14). They suggest that the Lagrange multiplier tests are most powerful in deciphering between a spatial error model and a spatial lag model. In our research, two diagnostic tests of spatial dependence are used for quantifying spatial patterns of urban form on trips in coverage area. Those are MI and Lagrange multiplier (LM) test.

The MI, measures the spatial autocorrelation in regression. The values of this test vary between −1 and +1, where negative values indicate the dispersed data, and positive values indicate that area is clustered. Getis (2007) described advantages of spatial autocorrelation for the spatial analysis (15).
\[ I = \frac{N \sum_i \sum_j W_{ij} (X_i - \bar{X})(X_j - \bar{X})}{(\sum_i \sum_j W_{ij}) \sum_i (X_i - \bar{X})^2} \]  

(5)

where, \( N \) is the number of cases, \( X_i \) is the variable value at a particular location, \( X_j \) is the variable value at another location which is the mean of the variable, and \( W_{ij} \) is a weight applied to the comparison between location \( i \) and location \( j \). If \( MI \) shows positive spatial autocorrelation, then the level of trips in the coverage area of a ward has a similar trend to the neighboring wards. If \( MI \) value is negative then it indicates that level of trips is unlike the neighboring wards. The LM is used to distinguish and choose between a spatial error and a spatial lag alternative (14) in spatial dependence analysis.

The spatial lag/error model was constructed using Equation (7) and defines spatial lag/error models as autoregressive as shown in Equation (6) below (14).

\[ y = \rho Wy + X\beta + u \]  

(6)

where \( W \) is spatial weight matrix, \( \rho \) is spatial autoregressive coefficient, \( y \) is expressed in deviation from the mean, \( X \) is a matrix of \( J \times K \) exogenous variables, \( \beta \) is a \( K \times 1 \) vector of corresponding coefficients, and \( u \) is an independent identical distributed error term.

A weight matrix depends on geographic arrangements of observations. The weight matrix specifies which units in the system affect the observed value at some particular location. Based on the weight matrix, units are considered as neighbors. It also indicates how important each neighbor is to a particular unit. The definition of neighbors can be based on geographical distances between units. If the units in the data have a physical area, two units that share a border can be defined as neighbors. If one variable has neighbors \( k \), \( l \), and \( m \) then in the \( r \)th row of \( W \) there will be three nonzero elements. The binary format is simplest one for defining a weight matrix. So this type of matrix \( w_{ik}, w_{jl}, \) and \( w_{lm} \) are all set to one if \( k, l, \) and \( m \) are considered neighbors to \( i \). All other elements in the \( r \)th row of \( W \) are zero.

There are several definitions of contiguity. Contiguity can be defined as rook contiguity and queen contiguity based on how units are regularly spaced on a lattice. In our research, a queen contiguity is used to establish neighbor relationships, where \( w_{ik} = 1 \) if unit \( i \) has a common border or common vertex with unit \( k \). This contiguity allows identification of neighbors which are not only connected by border but also connected by vertex.

For the spatial lag model, there is distinction between the residual and prediction error. The latter is the difference between observed value and predicted value and uses only exogenous variables, rather than treating the spatial lag \( Wy \) as observed.

In this model, local spatial multiplier \( WX \) measures the spatial spillovers, when only direct neighbors interact. Here \( \rho \) is the spatial autoregressive coefficient that reflects the reaction of \( Y \) to trips from public transportation coverage area in neighboring regions. Equation (7) below was used in the spatial lag/error analysis.

\[
\text{TRIPSPTCA} = b_0 + p(W_{\text{TRIPSPTCA}}) + \sum_{j=1}^{k} (\text{TOTAREAPTCA} + a_j) + \sum_{j=1}^{m} (\text{COMPACTCA} + b_j) + \sum_{j=1}^{n} (\text{WRKRDENSPTCA} + c_j) + \sum_{j=1}^{o} (\text{LUMIXPTCA} + d_j) + \sum_{j=1}^{p} (\text{TRIPLT5KMWD} + e_j) + \sum_{j=1}^{q} (\text{TRIPMT5KMWD} + f_j)
\]  

(7)

The dependent variable is the total of public transportation trips (TRIPSPTCA) of the coverage area of each ward for 2009 and 2031. The trip data are collected at ward level from the Jaipur development authority. Then, the area ratio method was used to calculated trips in coverage area of each ward. Public transportation trips were used to reflect public transportation infrastructure development because increase in public transportation use growth is a development objective.

Demographic data, such as worker population were obtained from the Indian census. An urban area boundary was created using remotely sensed satellite data and GIS. The coverage area delineated using public transportation route and stop maps in a GIS environment. Compactness was measured using urban area for 2009 and 2031. Table 1 contains explanations of the variables used for this analysis. Total urban area coverage (TOTAREAPTCA) and ward (TOTAREARTWD) are used to explain urban area increase impacts on public transportation trips. The urban area was calculated for each coverage area and ward area based on predicted urban area data for 2009 and 2031 using integrated remotely sensed and GIS data. Worker density in the coverage area (WRKRDENSPTCA) and ward area (WRKRDENSRTWD) are calculated using census data of each ward. The worker growth rate was used to project worker data for 2009 and 2031. These variables were used to measure labor market size in urban coverage and ward areas.

Compactness was calculated for both coverage (COMPACTCA) and ward area (COMPACTWD) using urban area data. Compactness represents the sprawl of urban area. High compactness represents the less dispersed area and conversely, the less compact area represents the highly dispersed urban areas. Compactness captures the street network design and very important for public transportation service use. Jaipur has grid pattern street in the city center, which implies less distance to public transportation stops, while it has an irregular street network in inner and outer suburban areas indicating greater distance to public transportation stops.

Land use mix in coverage (LUMIXPTCA) and ward area (LUMIXRTWD) are used to explain the impact of existing nonresidential activities in coverage and ward area on trips of public transportation. It indicates that high nonresidential activities have more impact on travel demand as compared to less nonresidential activities.
Trip distance variables (TRIPLT5KMWD and TRIPMT5KMWD) explain the impact on trips for coverage area travel distances using public transportation in each ward. It represents the use of public transportation for long or short travel distance. The distance of 5 km is used, as it separates the core urban to suburban areas of Jaipur city.

The expected effect of the variable belongs to coverage area are positive and also all variables belong to ward area also have positive expected effect, instead of these, urban area of ward variable expected effect is negative.

### 3. Results and discussion

#### 3.1. Urban form pattern and trips of public transportation at zone level

As mentioned in the introduction, Section 1, the data are analyzed at two levels – the zone and ward levels. Both the zone and ward level analyses were performed for 2009 and 2031. The relationship between trips and compactness, mix ratio, and worker density was spatially analyzed and zones created for Jaipur city. These zones represent the sprawl intensity of the urban area; divided into the core urban (zone 1), core urban ring (zone 2), inner suburban (zone 3), and outer suburban (zone 4) using ward boundaries. The zones are shown in Figure 3.

Figures 4–6 represent the relationship of trips to compactness, the land use mix index, and worker density, respectively, at the zone level. The PTCA trip term used in all figures is defined as public transportation trips in the coverage area. The relationship between trip and compactness is shown in Figure 4. A graph in Figure 4 shows that compactness is decreasing as we move from zone 1 to zone 4 during both periods. At the same time, trips increase from zone 1 to zone 2, but from zone 2 onwards trips are decreasing. Therefore, we can conclude moving away from the city center (from zone 1 to zone 4) the urban area is dispersing, while use of public transportation in the coverage area also decreases. The outer suburban area (zone 4) has the maximum dispersed urban area, and lowest public transportation use as compared to the other three zones. But, there is a big gap between compactness and trips in zone 4 when compared to other zones. This indicates poor public transportation system coverage in the outer zone.

Figure 5 illustrates the relationship between land use mix and trips for 2009 and 2031. Land use mix for both periods shows the same trend. It decreases from zone 1 to zone 4. This indicates that the urban core has the maximum land use mix values and outer suburban has lowest land use mix. The land use mix increased from 2009 to 2031, especially in 2031 for zone 4. Zone 4 has fewer trips as compared to its land use mix and also has a significant difference in trips from other zones for both 2009 and 2031.

Worker density decreased from zone 1 to zone 3 but there is an increase in worker density in zone 4 for both the years (Figure 6). In 2031, there is an enormous increase in worker density in zone 4 as compared to 2009. Worker density decreased from zone 2 to zone 3 while public transportation trips in the coverage area also decreased. Worker density in 2031 in zone 4 is significantly different from 2009 data but at the same time there is not significant increase in trips of public transportation in 2031 for this zone. Trips for all zones have

| Variable          | Definition                                                                 | Scale                                      | Expected effect | Data source          |
|-------------------|---------------------------------------------------------------------------|--------------------------------------------|----------------|----------------------|
| TOTAREAPTCA       | Total urban area in coverage area of public transportation service         | Public transportation coverage area        | +              | Remote sensing/GIS   |
| WRKRDENSPTCA      | Worker density in public transportation coverage area                      | Public transportation coverage area        | +              | Demographic and GIS  |
| COMPACPTCA        | Compactness in public transportation coverage area                         | Public transportation coverage area        | +              | GIS                  |
| LUMIXPTCA         | Land use mix in public transportation coverage area                         | Public transportation coverage area        | +              | GIS and JDA          |
| TOTAREARTWD       | Total urban area in remaining ward area                                    | Ward area                                  | –              | Remote sensing/GIS   |
| WRKRDENSRTWD      | Worker density in remaining ward area                                      | Ward area                                  | +              | Demographic and GIS  |
| COMPACRTWD        | Compactness in remaining ward area                                         | Ward area                                  | +              | GIS                  |
| LUMIXRTWD         | Land use mix in remaining ward area                                        | Ward area                                  | +              | GIS and JDA          |
| TRIPLT5KMWD       | Total No. of trips with in 5 km trip distance from each ward               | Ward area                                  | +              | GIS and JDA          |
| TRIPMT5KMWD       | Total No. of trips with more than 5 km trip distance from each ward        | Ward area                                  | +              | GIS and JDA          |

Note: JDA = Jaipur development authority.
the same trend as worker density except zone 2, where worker density is decreasing but trips are increasing for both periods (Figure 6).

In general, trips always increase with increases in worker density, compactness, and land use mix. However, our findings from a spatial analysis for two periods suggested that the trip production is not increasing monotonously and shows a distributed pattern consistent with the urban form indicators. Compactness, land use mix, and worker density increased from 2009 to 2031 in all zones indicating the increases in public transportation demand in the future.

3.2. Spatial statistical analysis of urban form change impact on trips of public transportation

Spatial statistical analysis is used to analyze the impact of change in urban form on trips at the ward level of Jaipur city. GIS was used to create all variables including dependent and independent variables for this analysis.
(all variables described in Table 1). GeoDa 0.9.5 software was used for spatial relationship analysis (16). Two models were prepared for this analysis using 2009 (model-A) and 2031 (model-B) data.

### 3.2.1. Spatial statistical analysis using model-A (2009)

The model-A was created using urban form and public transportation trip data for 2009. TRIPSPTCA was used as a dependent variable and the variables from Table 1 are used as the independent variables for analysis. In the first step, an OLS regression is used and then a spatial lag/error model was selected based on spatial diagnostic analysis.

The OLS regression analysis results are shown in Table 2. The correlation coefficient value is 0.62 and log likelihood is −467.29. The Akaike Info Criterion (AIC) and Schwarz Criterion (SC) values are 960.6 and 991.1, respectively. Urban form indicators like total area of the coverage area (TOTAREAPTCA), land use mix (LUMIXPTCA), and worker density (WRKRDENSPTCA) for coverage areas are statistically significant at the 0.05 level with positive coefficient values and implying that an increase would lead to an increase in public transportation trips in the coverage area. These variables show the expected positive effects. Other variables at the rest of the ward level, like worker density (WRKRDENSRTWD) and compactness (COMPACTRTWD) are also positively significant and indicate that change in urban form in the rest of the ward area will be influenced positively by trips in coverage area. They also showed the expected positive effects. Instead of above variables, COMPACPTCA and TRIPLT5KMWD are negatively insignificant while LUMIXRTWD and TRIPMT5KMWD are negatively significant and do not correspond to the expected outcomes. The negative impact of variable compactness of coverage area (COMPACPTCA) indicated that compactness is not effectively represented due to small coverage areas in each ward, while at the ward level, compactness satisfactorily represents urban area compactness.

MI test for the model-A is shown in Table 3, and indicates a positive and significant spatial relationship (z = 3.17 and p < 0.00151), which indicates a similar trend of trips to neighboring wards. MI indicated a clustering of wards. Those have a similar impact from change in urban form on public transportation trips. The LM test is displayed in Table 3. All tests for lag and error show positive and significant values instead of Robust LM (error) tests. The higher and significant values of the lag models suggest that lag tests are more significant than the error tests. In the lag test, LM (lag) test has higher positive values (z = 14.593 and p < 0.000133) and significant compared to Robust LM (lag) values (z = 8.056 and p < 0.000003). These test results suggested that the spatial lag model for correlation is the best (16).

The spatial lag model directly specifies the concept of “neighborhood” for each region with the introduction of the spatial weight matrix, W. This weight matrix reveals the effects of spatial dependence between regions. The spatial lag model used all the explanatory variables and also included exogenous variables. The autoregressive coefficient ρ of the spatially weighted lag trip production in coverage area (W_TRIPSPTCA) is shown in Table 4 and has positive value (0.649) and significant probability (p < 0.0000). The values of a spatial autoregressive coefficient indicated that high trips in coverage area considerably increase the trips in nearby wards and denote the existence of a positive spatial relation to neighboring wards. The correlation coefficient value is 0.67 and log likelihood is −432.7. The AIC and

| Variables       | Coefficient | Std. error | r-Statistic | p-value |
|-----------------|-------------|------------|-------------|---------|
| CONSTANT        | 115.7227    | 56.0269    | 2.0654      | 0.0429  |
| TOTAREAPTCA     | 80.2619     | 20.1612    | 3.9810      | 0.0001  |
| WRKRDNSEPCTCA   | 0.0186      | 0.0078     | 2.3798      | 0.0203  |
| COMPACPTCA      | −90.8889    | 77.3581    | −1.7499     | 0.4433  |
| LUMIXPTCA       | 896.4309    | 325.1130   | 2.7572      | 0.0075  |
| TOTAREARTWD     | −5.4603     | 2.5391     | −2.1505     | 0.0352  |
| WRKRDNERTWD     | 0.0054      | 0.0031     | 1.7912      | 0.0779  |
| COMPACRTWD      | 31.1821     | 11.6944    | 2.6664      | 0.0096  |
| LUMIXRTWD       | −599.6913   | 323.1072   | −1.8536     | 0.0683  |
| TRIPMT5KMWD     | −0.0101     | 0.0467     | −0.2159     | 0.8297  |
| TRIPMT55KMWD    | 0.0110      | 0.0614     | 1.0159      | 0.3096  |
| \( R^2 \)       |             |            | 0.62        |         |
| Log likelihood  |             |            | −467.29     |         |
| AIC             |             |            | 960.6       |         |
| SC              |             |            | 991.1       |         |

| Test             | MI/degree of freedom (DF) | z-value | p-value |
|------------------|----------------------------|---------|---------|
| MI (error)       | 0.1207                     | 3.1712  | 0.0015  |
| LM (lag)         | 1                          | 14.5930 | 0.0002  |
| Robust LM (lag)  | 1                          | 8.05644| 0.0030  |
| LM (error)       | 1                          | 6.4015 | 0.0114  |
| Robust LM (error)| 1                          | 0.6141 | 0.4332  |
SC values are 913.6 and 926.2, respectively. Increase in log likelihood values and decrease in AIC and SC relative to OLS model suggest an improvement of fit for the spatial lag specification. The compactness of the coverage area (COMPACTCA), land use mix index in the rest of the ward (LUMIXRTWD), and trip less than 5 km and more than 5 km in the ward (TRIPLT5KMWD) and (TRIPMT5KMWD) are negatively insignificant in the model and do not correspond to expected effects of variables. Total coverage area (TOTAREAPTCA), worker density in the coverage area (WRKRDENSPTCA), and compactness (COMPACTWTWD) in the rest of ward are positively statistical significant at the 0.05 level and correspond to the expected positive effects (Table 4).

3.2.2. Spatial statistical analysis using model-B (2031)

Model-B created using the predicted and projected 2031 data produced a scenario-based analysis of the future impact of change in urban form on bus travel demand in Jaipur city. The TRIPSPTCA was used as a dependent variable and the variables in Table 1 were used as the independent variables for analysis. An OLS regression and spatial lag/error model were used for spatial dependence analysis.

The results of the OLS regression are presented in Table 5. The correlation coefficient value is 0.63 and log likelihood is −432.7. The AIC value is 1000.1 and SC 926.2.

Table 4. Spatial lag results for model-A.

| Variables            | Coefficient | Std. error | t-Statistic | p-value |
|----------------------|-------------|------------|-------------|---------|
| CONSTANT             | −84.1361    | 58.4417    | −1.4396     | 0.1499  |
| W_TRIPSPTCA          | 0.6490      | 0.1448     | 4.4805      | 0.0000  |
| TOTAREAPTCA          | 93.9887     | 16.5205    | 5.6892      | 0.0000  |
| WRKRDDSPTCA          | 0.0153      | 0.0064     | 2.3861      | 0.0170  |
| COMPACTCA            | −49.8667    | 63.3876    | −0.7866     | 0.4314  |
| LUMIXPTCA            | 736.6037    | 266.4129   | 2.7648      | 0.0056  |
| TOTAREARTWD          | −3.8838     | 2.0807     | −1.8666     | 0.0619  |
| WRKRDDSRTWD          | 0.0051      | 0.0025     | 2.0360      | 0.0417  |
| COMPACTWTWD          | 24.0458     | 9.7234     | 2.4729      | 0.0133  |
| LUMIXRTWD            | −355.2622   | 267.3623   | −1.3287     | 0.1839  |
| TRIPLT5KMWD          | −0.0291     | 0.0387     | −0.7530     | 0.4514  |
| TRIPMT5KMWD          | −0.0112     | 0.0092     | −1.2258     | 0.2202  |
| \( R^2 \)            |             |            | 0.67        |         |
| Log likelihood       | −432.7      |            |             |         |
| AIC                  | 913.6       |            |             |         |
| SC                   | 926.2       |            |             |         |

Table 5. OLS regression results for model-B.

| Variables            | Coefficient | Std. error | t-Statistic | p-value |
|----------------------|-------------|------------|-------------|---------|
| CONSTANT             | 268.4261    | 107.6318   | 2.6251      | 0.0108  |
| TOTAREAPTCA          | 121.9511    | 46.4540    | 2.6479      | 0.0171  |
| WRKRDDSPTCA          | 0.0022      | 0.0008     | 2.3861      | 0.0203  |
| COMPACTCA            | −194.0421   | 81.5665    | −2.3789     | 0.0205  |
| LUMIXPTCA            | 315.1268    | 246.2121   | 1.2799      | 0.0205  |
| TOTAREARTWD          | 10.2483     | 4.7696     | 2.1486      | 0.0354  |
| WRKRDDSRTWD          | 0.0000      | 0.0009     | 0.8066      | 0.4017  |
| COMPACTWTWD          | 487.1323    | 199.0547   | 2.4472      | 0.0171  |
| LUMIXRTWD            | −173.2174   | 253.0253   | −0.6845     | 0.4960  |
| TRIPLT5KMWD          | −0.0361     | 0.0378     | −0.9564     | 0.3424  |
| TRIPMT5KMWD          | 0.00401     | 0.0054     | 0.7365      | 0.2202  |
| \( R^2 \)            |             |            | 0.63        |         |
| Log likelihood       | −487.1      |            |             |         |
| AIC                  | 1000.1      |            |             |         |
| SC                   | 1030.6      |            |             |         |

Table 6. Diagnostics for spatial dependence.

| Test          | M/D/F | z-value | p-value |
|---------------|-------|---------|---------|
| MI (error)    | 0.3109| 0.9379  | 0.0348  |
| LM (lag)      | 1     | 3.3670  | 0.0665  |
| Robust LM (lag)| 1     | 5.4715  | 0.0193  |
| LM (error)    | 1     | 0.1953  | 0.6585  |
| Robust LM (error)| 1     | 2.2998  | 0.1293  |
value is 1030.6. Independent variables for the coverage area such as total area (TOTAREAPTCA), worker density (WRKRDENSPTCA), and land use mix (LUMIXPTCA) are statistically significant at the 0.05 level, which follow the expected positive effects, while the compactness of the coverage area (COMPACPTCA) does not correspond to expected effect. The variables in the rest of ward area such as TOTAREAPTCA, worker density in the rest of ward area (WRKRDENSRTWD) have positively significant (0.03483) for model-B. The positive spatial autoregressive coefficient indicates that a higher level of trips in a ward significantly increases with trips in neighboring wards. Independent variables such as TOTAREAPTCA, WRKRDENSPTCA, and LUMIXPTCA are positively significant and correspond to the expected effects. Total urban area of wards (TOTAREARTWD) and urban compactness (COMPACRTWD) are positively significant, while the total urban area of ward (TOTAREARTWD) does not correspond to expected effect (Table 7). The land use mix of ward area (LUMIXRTWD) is insignificant, an unexpected effect. There are some minor differences found in the significance of the regression coefficient for the spatial lag and the OLS model: TOTAREAPTCA has a more positive and significant value and WRKRDENSPTCA and LUMIXPTCA variables are more significant in the lag model as compared to the OLS model.

4. Concluding remarks

Urban form is an important aspect that influences and controls public transportation trips. Urban form-based indicators play an important role in improving the sustainability of public transportation. Various indicators based on the urban form were created for this study and the results indicated that their values and desired impacts change with spatial scale. Urban form directly as well as indirectly controls public transportation. Various indicators based on the urban form were created for this study and the results indicated that their values and desired impacts change with spatial scale. Urban form directly as well as indirectly controls the coverage of public transportation service.

Public transportation coverage is important and is related to use of services. Detailed information about coverage area is required to understand travel behaviors. In this research, a road network-based distance method is used for coverage area delineation and found most suitable. A delineated coverage area was used to ascertain worker population and other important indicators. Those indicators are found useful when assessing travel demand in a coverage area.

A spatial statistics method was integrated in GIS and used to analyze how the urban form influences the public transportation trips in a coverage area. Zone wise spatial analysis revealed Jaipur as a sprawling city. Urban form and relationship between public transportation trips in a coverage area from 2009 and 2031 are monotonically

Table 7. Spatial lag analysis for model-B.

| Variables              | Coefficient | Std. error | t-Statistic | p-value |
|------------------------|-------------|------------|-------------|---------|
| CONSTANT               | −456.2640   | 124.6643   | −3.6599     | 0.0002  |
| W_TRIPSPTCA            | 0.3962      | 0.1826     | 2.1698      | 0.0301  |
| TOTAREAPTCA            | 132.6463    | 41.3344    | 3.2091      | 0.0013  |
| WRKRDENSPTCA           | 0.0023      | 0.0007     | 3.0495      | 0.0022  |
| COMPACPTCA             | −155.3052   | 74.0297    | −2.0978     | 0.0359  |
| LUMIXPTCA              | 301.1364    | 217.6829   | 1.3833      | 0.166   |
| TOTAREARTWD            | 10.8004     | 4.2172     | 2.5610      | 0.0104  |
| WRKRDENSRTWD           | 4.2172      | 2.0978     | 2.1698      | 0.0301  |
| COMPACRTWD             | −0.0002     | 0.0008     | −0.2559     | 0.7980  |
| LUMIXRTWD              | 523.0505    | 176.4542   | 2.9642      | 0.0033  |
| TRIPLT5KMWD            | −82.6306    | 224.5744   | −0.3679     | 0.7129  |
| TRIPMT5KMWD            | −0.0257     | 0.0335     | −0.7687     | 0.4423  |
| TOTAREARTWD            | 0.0031      | 0.0048     | 0.6308      | 0.5281  |
| TOTAREAPTCA            | 155.3052    | 74.0297    | 2.0978      | 0.0359  |
| WRKRDENSRTWD           | 4.2172      | 2.5610     | 1.3833      | 0.166   |
| COMPACRTWD             | −0.0002     | 0.0008     | −0.2559     | 0.7980  |
| LUMIXRTWD              | 523.0505    | 176.4542   | 2.9642      | 0.0033  |
| TRIPLT5KMWD            | −82.6306    | 224.5744   | −0.3679     | 0.7129  |
| TRIPMT5KMWD            | −0.0257     | 0.0335     | −0.7687     | 0.4423  |
| TOTAREARTWD            | 0.0031      | 0.0048     | 0.6308      | 0.5281  |

The log likelihood value is 961.4. Increases in log likelihood value are significant and correspond to the expected effects. The spatial lag model was selected based on diagnostic tests for spatial dependence indicated positive and higher significant (0.03483) for model-B. The spatial lag model was selected based on diagnostic tests for spatial dependence indicated positive and higher significance, the same as model-A. For model-B only, lag variable (W_TRIPSPTCA) represent the autoregressive correlation coefficient, which has a positive value (0.3963) and significant probability (0.0301). The positive spatial autoregressive coefficient indicates that a higher level of trips in a ward significantly increases with trips in neighboring wards.
changing. Spatial analysis demonstrated that public transportation trip production will increase along with the increase in workers and land use mix, but at the same time, service coverage area is also very important for mobility.

This research investigated the extent to which trips in a coverage area of a ward are influenced by different indicators of urban form using spatial statistical analysis. For this purpose, two models were created, one representing the current condition of the city and another showing the future scenario of the city. This statistical analysis exposed one important thing, that compactness of coverage area may induce and decrease in trip production among the coverage areas of ward. Therefore, it can be generalized that a dense urban coverage area does not lead to an increase to trips. The increase in coverage area indicated increases in public transportation trips in this study. This analysis guided the recognition and measurement of spatial associations between change in urban form and its impact on trips in a coverage area. This study entails that developing a coverage area will lead to sustainable urban transportation development.

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