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Urban growth and transport infrastructure interaction in Jeddah between 1980 and 2007

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ABSTRACT

This paper aims to use spatial statistical tools to explore the reciprocal spatial–temporal effects of transport infrastructure and urban growth of Jeddah city, a fast developing polycentric city in Saudi Arabia. Global spatial autocorrelation (Moran's *I*) and local indicators of spatial association (LISA) are first used to analyze the spatial–temporal clustering of urban growth and transport infrastructure from 1980 to 2007. Then, spatial regression analysis is conducted to investigate the mutual spatial–temporal effects of urban growth and transport infrastructure. Results indicate a significant positive global spatial autocorrelation of all defined variables between 1980 and 2007. LISA results also reveal a constant significant spatial association of transport infrastructure expansion and urban growth variables from 1980 to 2007. The results not only indicate a mutual spatial influence of transport infrastructure and urban growth but also reveal that spatial clustering of transport infrastructure seems to be influenced by other factors. This study shows that transport infrastructure is a constant and strong spatial influencing factor of urban growth in the polycentric urban structure that Jeddah has. Overall, this study demonstrates that exploratory spatial data analysis and spatial regression analysis are able to detect the spatial–temporal mutual effects of transport infrastructure and urban growth. Further studies on the reciprocal relationship between urban growth and transport infrastructure using the study approach for the case of monocentric urban structure cities are necessary and encouraged.

1. Introduction

Rapid urban growth is a key concern for urban planners as it has a considerable urban environmental impact (Müller et al., 2010). In 2009, over 3.4 billion people in the world resided in urban areas, and this figure is estimated to increase to 6.5 billion by 2050 (United Nations, 2009).This increase implies that urban areas will continuously witness rapid urban growth, which will impose further challenges to urban planners. Understanding urban growth and its drivers is vital to deal with such challenges. New approaches to the planning and management of urban areas, such as sustainable development and smart growth, will depend upon improvements in our knowledge of causes and drivers of urban growth (Longley and Mesev, 2000; Herold et al., 2003). Moreover, spatial and temporal analyses of the factors that drive urban growth are critical to predict future changes and their potential environmental effects in order to mitigate the negative aspects of urban growth (Aguayo et al., 2007).

In essence, a variety of social and economic factors trigger urban growth, including transportation and communication (Hall and Pfeiffer, 2000; Hart, 2001), internal and international migration (Thorns, 2002) and public policies (Carruthers, 2002). Transportation as such plays a crucial role in urban development through the accessibility it provides to land and activities (Meyer and Miller, 2001). Several studies have demonstrated that transportation infrastructure is one of the main driving forces of urban growth (e.g., Hall and Pfeiffer, 2000; Hart, 2001; Liu et al., 2002; Handy, 2005; Xie et al., 2005; Jha et al., 2006; Ma and Xu, 2010; Müller et al., 2010). Other studies have pointed out the effect of development of high-speed roads on urban expansion and population growth (Brotchie, 1991; Parker, 1995; Priemus et al., 2001). Moreover, most of the urban models use accessibility to transport infrastructure as a main driver of growth and change (see for example Batty, 2000; Liu and Phinn, 2003; Al-Ahmadi et al., 2009; Feng et al., 2011). Nevertheless, only one previous study (Fan et al., 2009) has analyzed the effects of different transportation infrastructure types on urban growth. This study used a geographical information system (GIS) spatial proximity (buffer) analysis to evaluate the influence of

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different types of roads on spatial expansion of Guangzhou; a developed monocentric city in China between 1979 and 2003. Thus, there is a lack of research on the spatial and temporal effects of different types of transport infrastructure on urban growth and vice versa, particularly in the context of fast developing and polycentric cities.

The study of urban growth factors and its driving forces requires sophisticated methods and tools. Recent advances in remote sensing (RS), GIS, spatial analysis and spatial statistics tools provide a rich opportunity for in-depth study of the complex urban growth process and its interaction with the transportation. RS, GIS and spatial analysis functionalities support the examination of geographic patterns, trends, and relationships in between urban systems (Benenson and Torrens, 2004). Newer methods of spatial analysis, spatial statistics in particular, have proven relevance and usefulness for urban analysis (Paez and Scott, 2004). Exploratory spatial data analysis (ESDA), including global spatial autocorrelation (Moran I index) and local indicators of spatial association (LISA), and the spatial regression analysis have gained attention in urban studies. Bamount (2004) has used ESDA to analyze the intra-urban spatial distributions of population and employment in the agglomeration of Dijon, France. Orford (2004) has identified and compared changes in the spatial concentrations of urban poverty and affluence for the case of inner London using a Moran I index and LISA. Deng et al. (2010) has used LISA and spatial regression models to demonstrate the relationship between economic growth and the expansion of urban land for the case of Beijing in China. Nevertheless, up to now only a few studies have been conducted using ESDA and spatial regression analysis in urban studies. In particular, there is a lack of research using these analyses for exploring and analyzing the complex urban growth phenomenon, and its drivers and their interaction.

This paper attempts to use ESDA and spatial regression analysis to explore the spatial–temporal reciprocal effects of transport infrastructure and urban growth for the case of Jeddah city, a developing, polycentric and fast growing city in Saudi Arabia. First, RS and GIS techniques are used to quantify and prepare the data on spatial–temporal urban growth and transport infrastructure in Jeddah city during the period 1980–2007. Next, global spatial autocorrelation (Moran's I) and LISA are detected to analyze the spatial–temporal clustering of urban growth and transport infrastructure. Finally, spatial regression analysis is conducted to investigate the reciprocal spatial–temporal effects of urban growth and transport infrastructure.

2. Material and methods

2.1. Study area

Jeddah is the second largest city in the Kingdom of Saudi Arabia, with a population exceeding three million. Jeddah is located on the west coast of the Kingdom, at the confluence of latitude 29.21 north and longitude 39.7 east, in the middle of the eastern shore of the Red Sea, and it is surrounded by the plains of the Tahoma in the east (Fig. 1). Saudi Arabia has experienced high urban growth rates over the last four decades, and the major cities in Saudi Arabia have experienced a rapid population increase (Al-Hathloul and Mughal, 2004). Compared to the total Saudi population, the urban population has increased, from 21% in 1950 to 58% in 1975 and 81% in 2005 (Al-Ahmadi et al., 2009). This huge increase has created excessive spatial expansion and demand for transportation infrastructure in the major Saudi cities, including Jeddah (Al-Hathloul and Mughal, 1991, Al-Hathloul and Mughal, 2004), and this demand imposes constant urban planning challenges. Jeddah has experienced rapid urban growth, spatial expansion and transportation infrastructure expansion over the last 40 years, with rates of change ranging from 0% to over 100%, indicating a wide variability across space and a complex urban dynamic (Aljoufie et al., 2011). The highest level of urban growth and transport infrastructure expansion

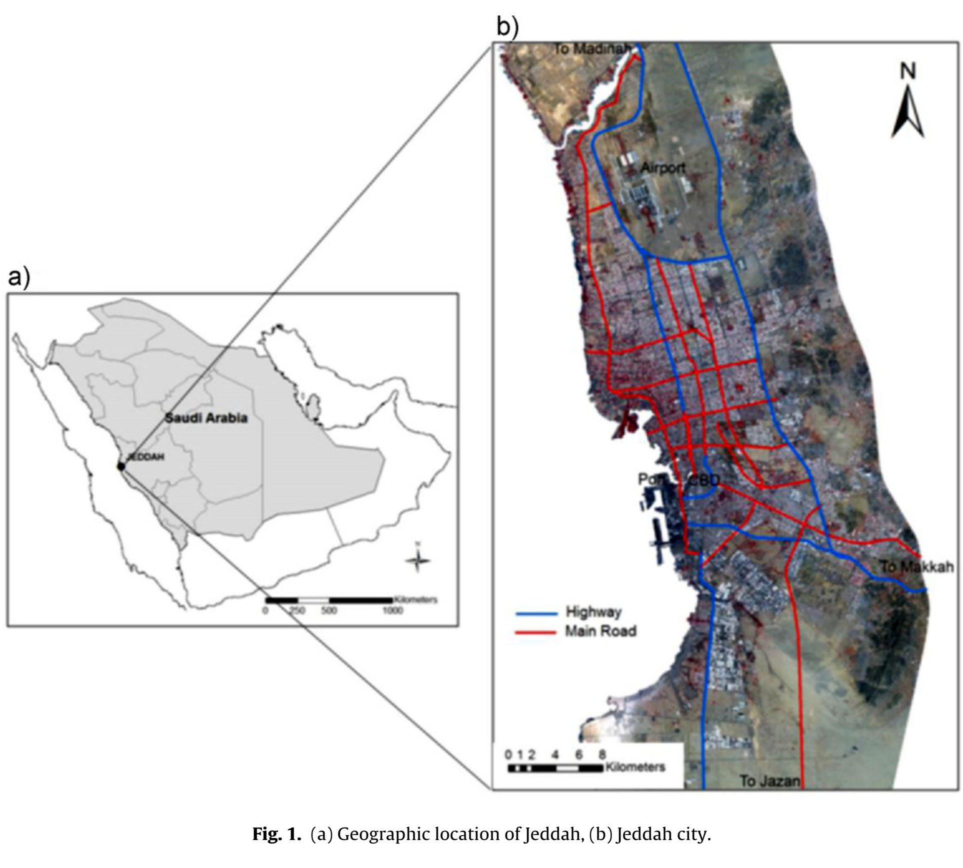

Fig. 1. (a) Geographic location of Jeddah, (b) Jeddah city.

has occurred and escalated significantly during the country's oil boom from 1970 to 1980 (Aljoufie et al., 2012). During this period, different urban growth abrupt changes and patterns have established. For instance, airport and some major public places have been relocated during this period (Aljoufie et al., 2012). After 1980, Jeddah has experienced a tremendous and more homogenous gradual urban growth pattern and transport infrastructure expansion (Aljoufie et al., 2012). Jeddah's population has grown rapidly, from 960,000 in 1980 to 3,247,134 in 2007. Jeddah's urban mass has also expanded dramatically, from 32,500 ha in 1980 to 54,175 ha in 2007 (Aljoufie et al., 2011). The transportation infrastructure at the same time has also expanded significantly, from 435 km in to 826 km in 2007 (Aljoufie et al., 2011). As a result, the local government in Jeddah currently faces unprecedented challenges related to urban growth and transportation. However, no systematic study has been conducted on the spatial–temporal dynamics of urban growth and transportation changes and their reciprocal relationship in Jeddah.

2.2. Data and image processing

2.2.1. Data acquisition, collection and geo-referencing

This study utilizes a time series of aerial photos and satellite images to quantify the spatial–temporal urban growth and transportation infrastructure situation from 1980 to 2007. Aerial photo data from 1980 and spot satellite image data from 1993, 2002 and 2007 were used. Moreover, a variety of secondary data was collected to facilitate the spatial–temporal analysis of urban growth and transportation infrastructure. These data include the following: Jeddah's master plans for 1980, 1987, and 2004; transportation studies of Jeddah for 1980, 1995, 2004 and 2007; census data for 1993 and 2005; an urban growth boundary study for 1986; and topographic maps of Jeddah for 2000.

2.2.2. Image processing

Given the inconsistent spatial and temporal resolution of the available RS data for this study and the different formats, a consistent method of quantifying spatial and temporal urban growth and transportation infrastructure changes was critical. Visual image interpretation continues to be extensively used even with the development of digital image processing techniques (Jensen, 2000). It has been widely used in urban applications with high accuracy (Liu and Chen, 2008). RS data can be interpreted either visually by human experts or automatically by digital image processing and pattern recognition methods (Jensen, 2000). Human experts can comprehensively use shape, size, color, orientation, pattern, texture and context in their interpretations (Zhou et al., 2010). Although these characteristics are crucial for identifying urban landscape patterns, they are difficult to incorporate into conventional digital image processing techniques (Richards and Jia, 2006; Shao and Wu, 2008). Hence, combining of both human knowledge and computer processing will be more conducive in the extraction of information from RS data.

Accordingly, a cooperative visual interpretation method (Fig. 2) was adopted to quantify temporal urban land use and transportation infrastructure as the main aspects of urban growth and transportation in Jeddah. Cooperative interpretation is a method in which people work with computers to interpret RS data (Liu and Chen, 2008). This method cooperatively combines the computer automatic interpretation, reference land use and transport infrastructure data, and human experience.

First, an image-to-image registration strategy was adopted to geo-reference the various images using a second-order polynomial function in ERDAS IMAGINE. Subsequently, a cooperative visual interpretation method was applied. The process started with an unsupervised image classification to differentiate between urban built-up elements and non-built-up elements using the ISODATA clustering algorithm in ERDAS IMAGINE. This process shows the spatial pattern of the urban built-up area in Jeddah, which facilitates better understanding of the elements of built-up areas, such as buildings, road infrastructure and green areas. Next, land use and transportation infrastructure reference data from master plans and transportation study reports were integrated with built-up and non-built-up images, using the overlay function in ArcGIS. Ten urban land use classes were specified for extraction: residential, commercial, industrial, institutional, informal settlements, airport, port, roads, vacant lands and green areas. Then, visual

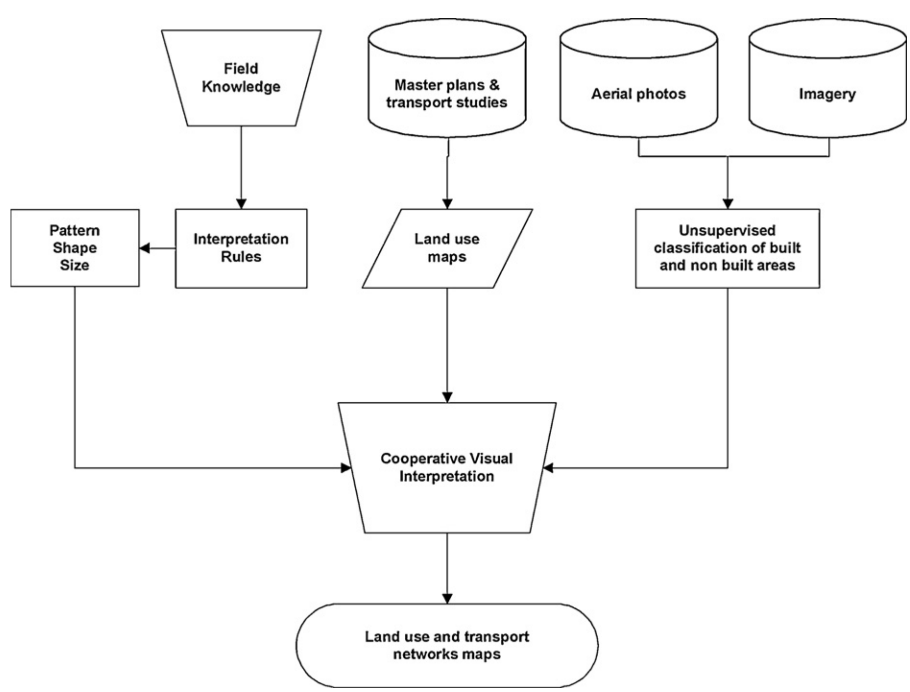

Fig. 2. Visual interpretation method used to process various data sources.

interpretation indicators, such as pattern, shape and size, were extensively used to identify features from aerial photographs and satellite images based on field knowledge of local urban planners. Consequently, a final interpretation was conducted incorporating all the aforementioned processes in ArcGIS v9.3 using on-screen digitizing, overlay tools and area of interest (AOI) functionality. Accordingly, land use and transportation infrastructure maps for 1983, 1993 and 2007 were obtained. Finally, accuracy assessments were performed based on a comparison of the cooperative interpretation outputs with the reference data. The average overall accuracy of land use maps produced by this approach was 90%, which exceeds the minimum 85% accuracy for land use data as required by Anderson et al. (1976) for satisfactory land use maps (Anderson et al., 1976).

2.2.3. Variables, data disaggregation and preparation for analysis

Urban growth is a complex process involving spatial–temporal changes of socio-economic and physical components at different scales (Han et al., 2009). The socio-economic components of urban growth are related to urban population growth and economic growth (Black and Henderson, 1999), while physical components of urban growth are related to spatial expansion, land cover change and land use change (Thapa and Murayama, 2011). In this study, urban growth is defined and expressed using three variables population growth, spatial expansion and residential land use expansion. Transport infrastructure expansion is expressed using three variables: highway expansion, main road expansion and secondary road expansion. Table 1 shows the defined variables with temporal aggregated data and their unit of measurement.

To fulfill the practical requirements of a spatial statistical analysis, the extracted RS data (Fig. 3) was disaggregated to district level, an urban administrative unit in the study area. Because the temporal population data were collected at the district level, other defined variables of urban growth and transportation infrastructure were disaggregated to the same spatial level. The spatial statistical analysis considered 117 districts that constituted Jeddah's entire urban authority. A GIS-based approach was conducted to disaggregate the study's defined variables (*population growth, spatial expansion, residential land use expansion, highway expansion, main road expansion* and *secondary road expansion).*

2.3. Spatial statistical analysis

Choosing an appropriate model and analytical technique depends on the type of variable under investigation and the objective of the analysis. Accordingly, to achieve the objectives of this study, we applied spatial autocorrelation analysis and spatial regression analysis to capture the mutual spatial–temporal effects of the defined urban growth and transport infrastructure variables.

2.3.1. Spatial autocorrelation analysis

To analyze the reciprocal spatial–temporal effects of urban growth and transportation, a spatial cluster analysis was conducted. A spatial autocorrelation indicator, Moran's Index, was performed in GeoDa software to capture the global spatial autocorrelation and local spatial clustering of urban growth and transportation infrastructure variables. Spatial autocorrelation statistics have been widely used to measure the correlation among neighboring observations in a pattern and the levels of spatial clustering among neighboring districts (Boots and Getis, 1998). Moran's Index, in particular, has been used to study urban structure, complex urban growth and the intra-urban spatial distribution of socio-economic factors (Frank, 2003; Baumont et al., 2004; Orford, 2004; Yu and Wei, 2008).

To analyze the spatial distribution and capture the global spatial autocorrelation of urban growth and transportation infrastructure variables (*population growth, spatial expansion, residential land use expansion, highway expansion, main road expansion and secondary road expansion*), the Global Moran's Index IM statistic, which is similar to the Pearson correlation coefficient (Moran, 1950; Cliff and Ord, 1980) and LISA were calculated for the years 1980, 1993, 2002 and 2007. The Moran's Index test statistic is given by:

$$I_M = \left(\frac{n}{\sum_i \sum_j W_{ij}} \right) \frac{\sum_i \sum_j W_{ij} (Y_{(R)i} - \overline{Y}_{(R)})(Y_{(R)j} - \overline{Y}_{(R)})}{\sum_i (Y_{(R)i} - \overline{Y}_{(R)})^2}, \qquad (1)$$

where W_{ij} is the element in the spatial weights matrix corresponding to the district pairs *i, j*, and $Y_{(R)i}$ and $Y_{(R)j}$ are the different urban growth and transportation infrastructure variables (e.g., population growth or residential expansion) for districts *i* and *j* with the mean urban growth and transportation variables expansion rate $\overline{Y}_{(R)}$. Because the weights are not row-standardized, the scaling factor $n/\sum_i \sum_j W_{ij}$ is applied. Moran's Index indicates the strength of the spatial similarity or dissimilarity of neighboring districts. A positive Moran's *I* indicates the presence and degree of spatial autocorrelation.

The first step in the analysis of spatial autocorrelation is to construct a spatial weights matrix that contains information on the neighborhood structure for each location. The (*i, j*) element of the matrix *W*, denoted Dist *ij*, quantifies the spatial dependency between district *i* and *j*. Collectively, the W_{ij} defines the neighboring structure over the entire area. A first-order connectivity weight matrix was constructed. This weight matrix was selected hence the local connectivity of transport infrastructure is defined by a grid pattern, which is more compatible with the rook weight matrix. In addition, the spatial configurations of districts in the study area (Fig. 4) support the rook weight matrix. In this approach, spatial units (districts) are defined as neighbors if they share a common boundary. Accordingly:

$$W_{ij} = \begin{cases} 1 & \text{if districts } i \text{ and } j \text{ share common boundary} \\ 0 & \text{Otherwise} \end{cases}.$$

Finally, a significance test against the null hypothesis of no spatial autocorrelation through a permutation procedure of 999 Monte Carlo replications was used to test for the significance of the statistic.

Table 1
Description of the defined variables' characteristics at the aggregated level.

Variables	Unit	1980	1993	2002	2007
Spatial expansion	Hectare	32,500	40,739	49,700	54,175
Population growth	Person	960,000	2,046,000	2,560,000	3,247,134
Residential land use expansion	Hectare	8724	14,921	19,318	21,365
Highways expansion	Kilometer (length)	112	132	132	132
Main roads expansion	Kilometer (length)	155	163	163	183
Secondary roads expansion	Kilometer (length)	168	217	380	475

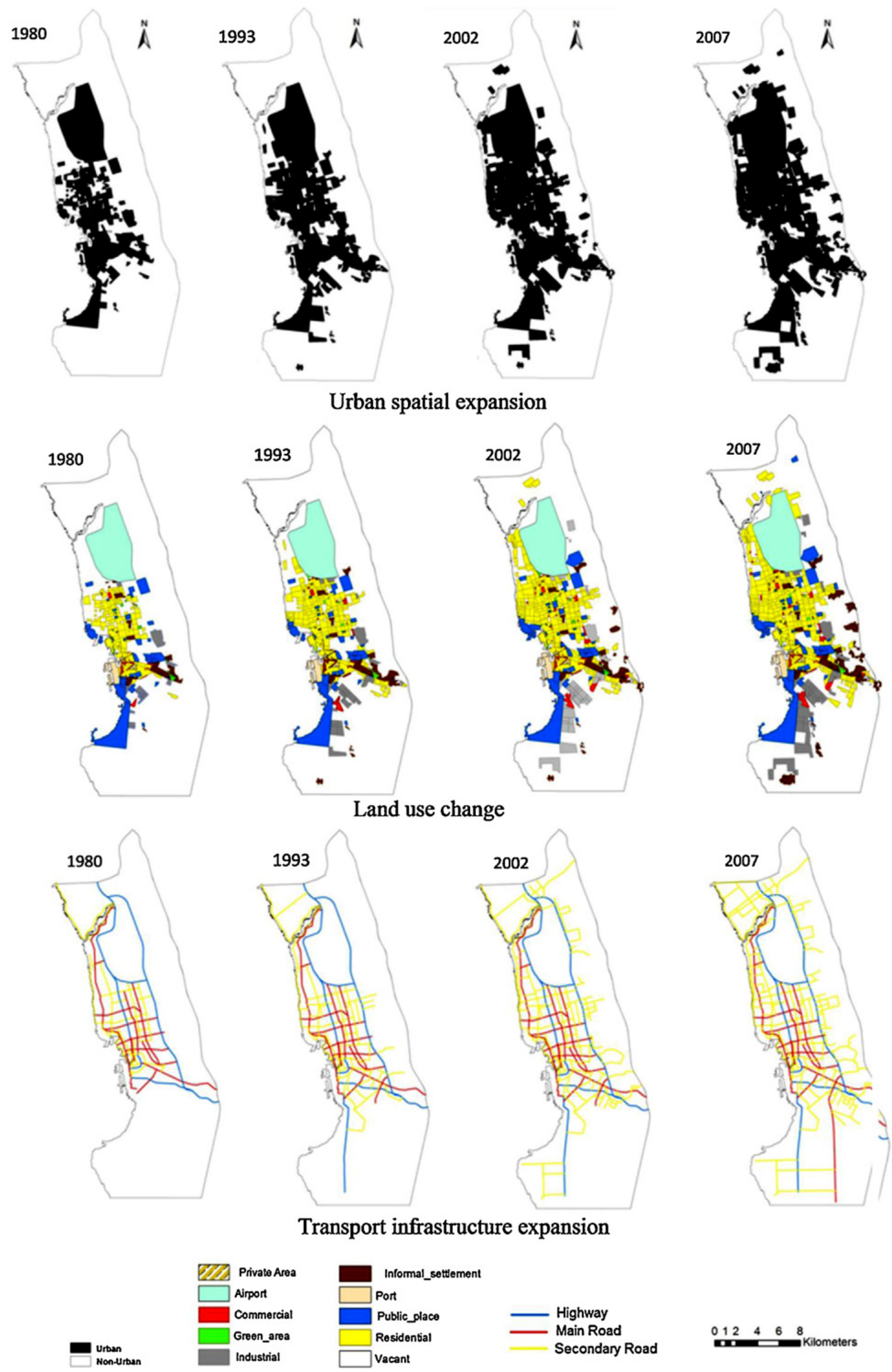

Fig. 3. Jeddah' spatial–temporal changes.

2.3.2. Spatial regression analysis

When standard linear regression (i.e., ordinary least square (OLS)) models are estimated for cross-sectional data on neighboring spatial units, the presence of spatial dependency may cause serious problems with model misspecification. Spatial relationships can be modeled in a variety of ways. One way is to hypothesize that the value of the dependent variable (e.g. spatial expansion) observed at a particular location is partially determined by some function of the value of the dependent variable of its neighbors. The variable measuring these effects is typically formulated as a spatially weighted average of the neighboring values of the dependent variable, where the neighbors are specified through the use of a so-called spatial weights matrix (Anselin, 1988). The methodologies for spatial regression consist of examining and testing for the potential presence of such misspecification and providing more appropriate modeling that incorporates the spatial dependence (Anselin et al., 1997; Varga, 1998). Spatial dependency can be incorporated into the OLS model in two distinct ways: as an additional predictor in the form of a spatially lagged dependent variable (spatial lag model) or in the error structure (spatial error model).

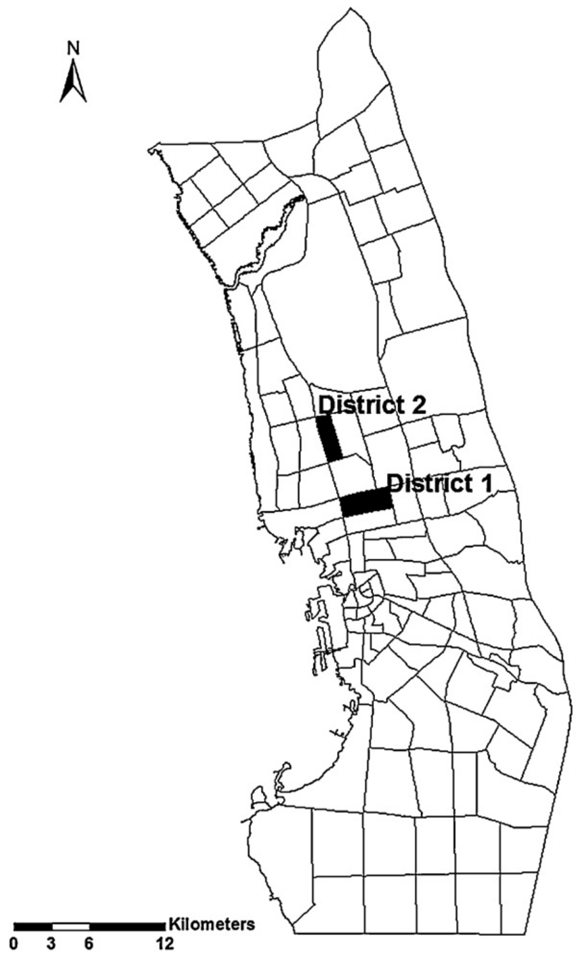

Fig. 4. Spatial configurations of districts in study area; district 1 and 2 used for LISA results analysis.

Specifically, in matrix notation, the general form of the spatial lag model is given by:

$$Y = \rho W_y + X\beta + \varepsilon, \quad (2)$$

where y is the dependent variable; W is a spatial weights matrix, which specifies the neighbors used in the averaging (resulting in the spatially lagged dependent variable W_y); ρ is an autoregressive coefficient of the lag variable; X is the explanatory variables; β is a regression coefficient; and ε is an error term. The model is applied to measure the level of spatial dependency and to determine the effect of different groups of variables.

The other method of incorporating spatial relationships is by modeling the effects through the spatial dependence that enters the relationship through the error term. When accounting for spatial dependence through the error term, the model accounts for a situation in which the errors associated with any one observation are spatially weighted (or neighborhood) averages of the errors plus a random error component. Specifically, the spatial error model in matrix form is given by:

$$y = X\beta + \varepsilon \quad \text{where} \quad \varepsilon = \lambda W + \mu, \quad (3)$$

where ε is a vector of spatially autocorrelated error terms; μ is a vector of errors; and λ is a scalar parameter, known as the spatial autoregressive coefficient.

Spatial dependency was used in this study to investigate the spatial patterns and to determine the factors that contribute to the spatial similarity or dissimilarity for urban growth and transportation variables. The spatial effect of transportation infrastructure on urban growth was investigated using different explanatory variables on the dependent variable, as follows:

$$\begin{aligned}&\text{Population growth}\\&\quad = f(\text{Highway expansion, Main road expansion,}\\&\qquad \text{Secondary road expansion})\end{aligned} \quad (4)$$

$$\begin{aligned}&\text{Spatial expansion}\\&\quad = f(\text{Highway expansion, Main road expansion,}\\&\qquad \text{Secondary road expansion})\end{aligned} \quad (5)$$

$$\begin{aligned}&\text{Residential land use expansion}\\&\quad = f(\text{Highway expansion, Main road expansion,}\\&\qquad \text{Secondary road expansion}).\end{aligned} \quad (6)$$

Conversely, the spatial influence of urban growth variables on the different transport infrastructure types was investigated as follows:

$$\begin{aligned}&\text{Highway expansion}\\&\quad = f(\text{Population growth, Spatial expansion,}\\&\quad \text{Residential land use expansion})\end{aligned} \quad (7)$$

$$\begin{aligned}&\text{Main road expansion}\\&\quad = f(\text{Population growth, Spatial expansion,}\\&\qquad \text{Residential land use expansion})\end{aligned} \quad (8)$$

$$\begin{aligned}&\text{Secondary road expansion}\\&\quad = f(\text{Population growth, Spatial expansion,}\\&\qquad \text{Residential land use expansion}).\end{aligned} \quad (9)$$

Before modeling spatial dependency, the nature of spatial dependency (in terms of spatial lag or spatial error) was first determined in order to choose the most appropriate alternative model (spatial lag model or spatial error model). To determine this, a Lagrange Multiplier (LM) test was conducted (Anselin and Florax, 1995; Anselin et al., 1996).

3. Results

3.1. Spatial autocorrelation analysis

The extent to which neighboring values are correlated was measured using the Global Moran's Index. A Moran's Index analysis is conducted by generating scatter plots with the log of the different urban growth and transportation infrastructure variables. In essence, the scatter plots illustrate the Global Moran's I (e.g., Fig. 5), which is a commonly used test statistic for spatial autocorrelation. A significance assessment through a permutation procedure was implemented to determine the significance of the computed Moran's Index. Table 2 shows the values of the Global Moran's I statistic for all variables. Moran's Index is positive and statistically significant ($p < 0.05$) for all urban growth and transportation infrastructure variables. This result indicates that nearby districts tend

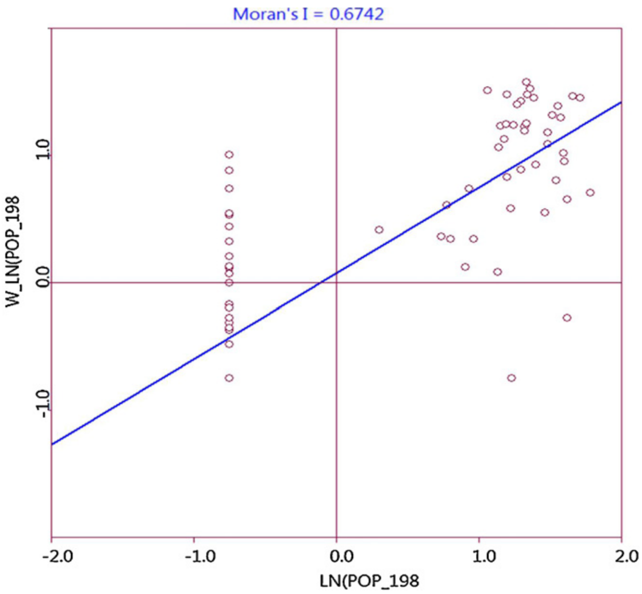

Fig. 5. Spatial autocorrelation Moran scatter plot (Ln population for 1980).

to have similar attributes. It is noted that the values of the Global Moran's I change from 1980 to 2007 for all variables. The highest clustering of nearly all variables occurred in 1980. The decrease in values of population growth and spatial expansion variables from 1980 to 2002 reflects the sprawl pattern of development that occurred in Jeddah wherein developments were not very much concentrated in space, but took place in several parts of the city at the same time. In addition, population growth and spatial expansion during this period were more autocorrelated in the city center area, whereas for the other parts this was less the case. It is also noted that the values of the transportation infrastructure variables are lower than the urban growth variables. This result indicates that the values of transportation infrastructure variables are independently clustered with similar values. Although Moran's I for the transportation infrastructure variables shows low values, the space among other factors catalyzed the expansion of these variables.

The results of the LISA identify the local spatial clustering of urban growth and transportation infrastructure variables at the district level. Fig. 6 and Fig. 7 show the temporal LISA for different urban growth and transportation infrastructure expansion variables. Districts with a significant LISA are classified by the type of spatial correlation: bright red for the high–high association, bright blue for low–low, light blue for low–high, and light red for high–low. The high–high and low–low locations suggest clustering of similar values of one variable, whereas the high–low and low–high locations indicate spatial outliers of the same variable. By comparing these figures, it is possible to identify the significant spatial clustering of urban growth and transportation infrastructure variables from 1980 to 2007.

In general, this study finds that the spatial clustering of urban growth variables coincides with the spatial clustering of transportation infrastructure expansion variables. It is observed that the temporal–spatial clustering of population growth is associated, to some extent, with the temporal–spatial clustering of highway expansion. It is also noted that the temporal–spatial clustering of the spatial expansion variable largely overlaps with the temporal–spatial clustering of the variable of main road expansion. Additionally, the temporal–spatial clustering of the residential land-use expansion variable largely coincides with the temporal–spatial clustering of the secondary road expansion variable.

In addition, Tables 3 and 4 summarize LISA's results of each variable over time for the case of two districts in study area (Fig. 4). These tables depict a constant high–high spatial association of transport infrastructure expansion and urban growth variables over time. This indicates that spatial influence of transportation infrastructure expansion on the clustering of population growth, spatial expansion and residential land-use expansion is significant and constant over time and vice versa.

Table 2
Moran's I statistics.

Variables	1980	1993	2002	2007
Population growth	0.674	0.428	0.571	0.611
Spatial expansion	0.700	0.448	0.759	0.621
Residential land use	0.618	0.619	0.741	0.625
Highway expansion	0.335	0.285	0.249	0.283
Main roads expansion	0.338	0.462	0.683	0.560
Secondary roads expansion	0.730	0.420	0.351	0.203

Table 3
LISA statistics of district 1.

Variables	1980	1993	2002	2007
Population growth	HH**	HH**	HH**	HH**
Spatial expansion	HH**	HH**	HH**	HH**
Residential land use	HH**	HH	HH**	HH**
Highway expansion	HH*	Ns	HH*	HH*
Main roads expansion	HH*	HH**	HH**	HH**
Secondary roads expansion	HH**	HH**	HH**	HH*

Ns: not significant.
* Significant at 5%.
** Significant at 1%.

3.2. Spatial regression analysis

Table 5 depicts the result of the LM test. Results indicate that both LM Lag and LM Error tests are significant for all dependent variables and over time. In contrast, the results also indicate that only the Robust LM Lag statistic is significant for all dependent variables and over time, while the Robust LM Error statistic is not. Following the spatial regression model selection decision rule (Anselin, 2005) we conclude that the spatial lag model is the proper alternative. Accordingly, spatial lag models have been estimated for all specified dependent variables (Eqs. (4)–(9)).

The estimates of the coefficients produced by the spatial regression (econometric) models are presented in Tables 6–11. Table 6 shows the effect of different transport infrastructure types on population growth dependent variable (Eq. (4)). The spatial autoregressive coefficient ρ (the coefficient on the spatial lag of the dependent variable) is positive (0.732) and is highly significant at the 5% level for the observations in 1980. Similarly, the coefficient for the observations in 1993, 2002 and 2007 is positive (ρ 1993 = 0.485, ρ 2002 = 0.554 and ρ 2007 = 0.603) and highly significant. This result indicates the presence of spatial dependence, implying that the interaction between neighbors significantly

Table 4
LISA statistics of district 2.

Variables	1980	1993	2002	2007
Population growth	HH**	HH**	HH**	HH**
Spatial expansion	HH*	HH**	HH**	HH**
Residential land use	HH**	HH**	HH**	HH**
Highway expansion	HH*	HH**	HH*	HH*
Main roads expansion	Ns	HH*	HH*	HH*
Secondary roads expansion	HH**	HH**	HH*	Ns

Ns: not significant.
* Significant at 5%.
** Significant at 1%.

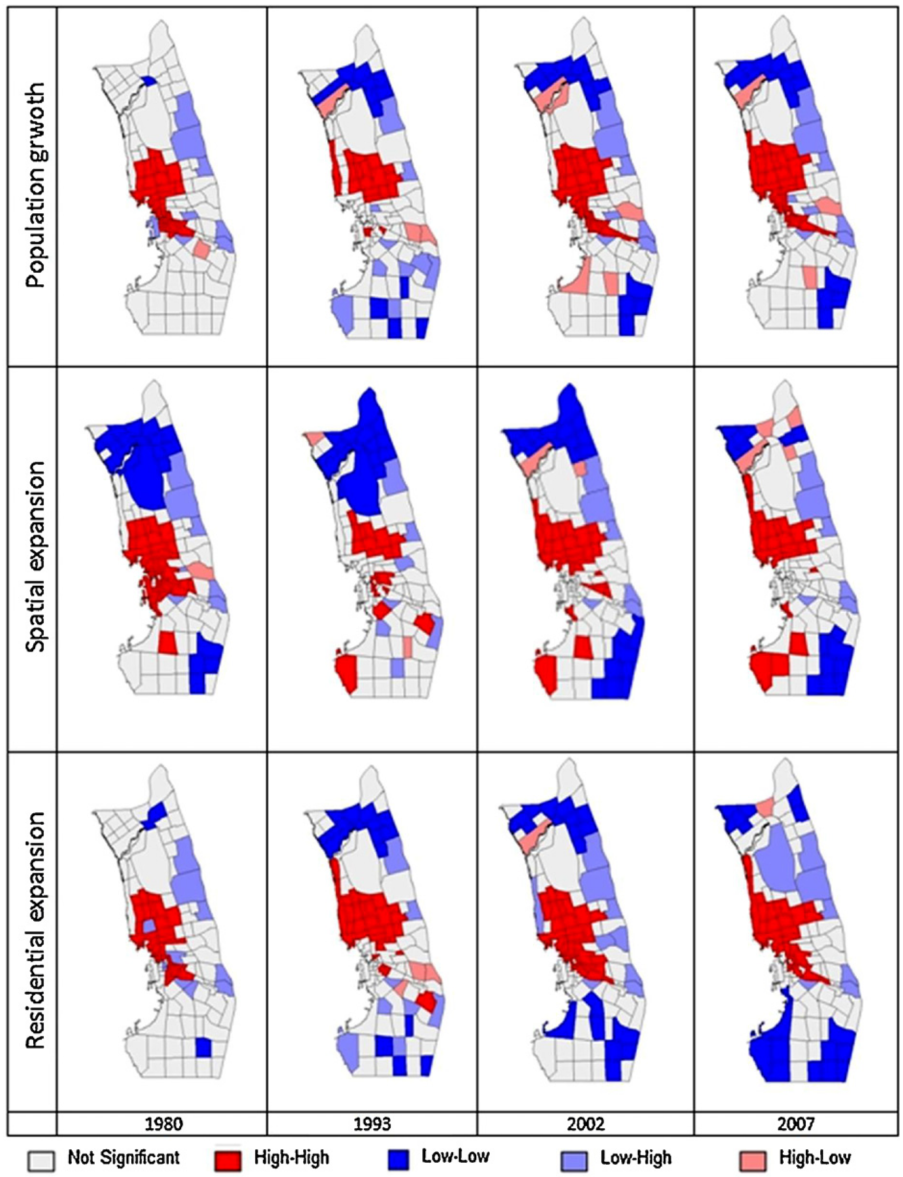

Fig. 6. LISA cluster maps of urban growth variables.

affects the growth of Jeddah's urban population. Furthermore, the coefficients of the highway, main road, and secondary road variables are positive and significant, and the magnitude of the coefficients increases over time. This means that the expansion of the transport infrastructure across space contributes to the increase in the urban population over this period. Thus, the findings reveal that the expansion of highways, main roads and secondary roads is a contributing factor for the spatial clustering of urban population growth.

Table 7 depicts the spatial influence of different transport infrastructure types on the spatial expansion dependent variable (Eq. (5)). The analysis of the spatial relationship among the different urban transport infrastructures reveals that the coefficients of highways and secondary roads are significantly positive for the observations in 1980, 1993, 2002 and 2007, whereas the coefficient for main roads is only positively significant for the observations in 2002 and 2007 (Table 7). This result demonstrates that the spatial expansion of highways, main roads and secondary roads contributes to the increase in urban spatial expansion over the study period, which, in turn, implies that transport infrastructure expansion is a contributing factor to the spatial clustering of urban spatial expansion.

Table 8 presents the spatial influence of different transport infrastructures on residential land use development dependent variable (Eq. (6)). Examining the effect of different urban transport infrastructures, the analysis reveals that the coefficients of highways and main roads for the observations in 1993 are significantly positive, whereas the coefficients for secondary roads in 1980 and 2007 are positive and significant at 5% (Table 8). This finding demonstrates that spatial expansion in transport infrastructure contributes to the increase in urban residential development over the indicated period, which, in turn, implies that transport infrastructure expansion is a contributing factor to the spatial clustering of urban residential development.

Table 9 shows the effect of urban growth variables on highway expansion dependent variable (Eq. (7)). The coefficient of the residential development variable is negative for 1980 and 2002 and significant at 5%, and the magnitude of the coefficient increases

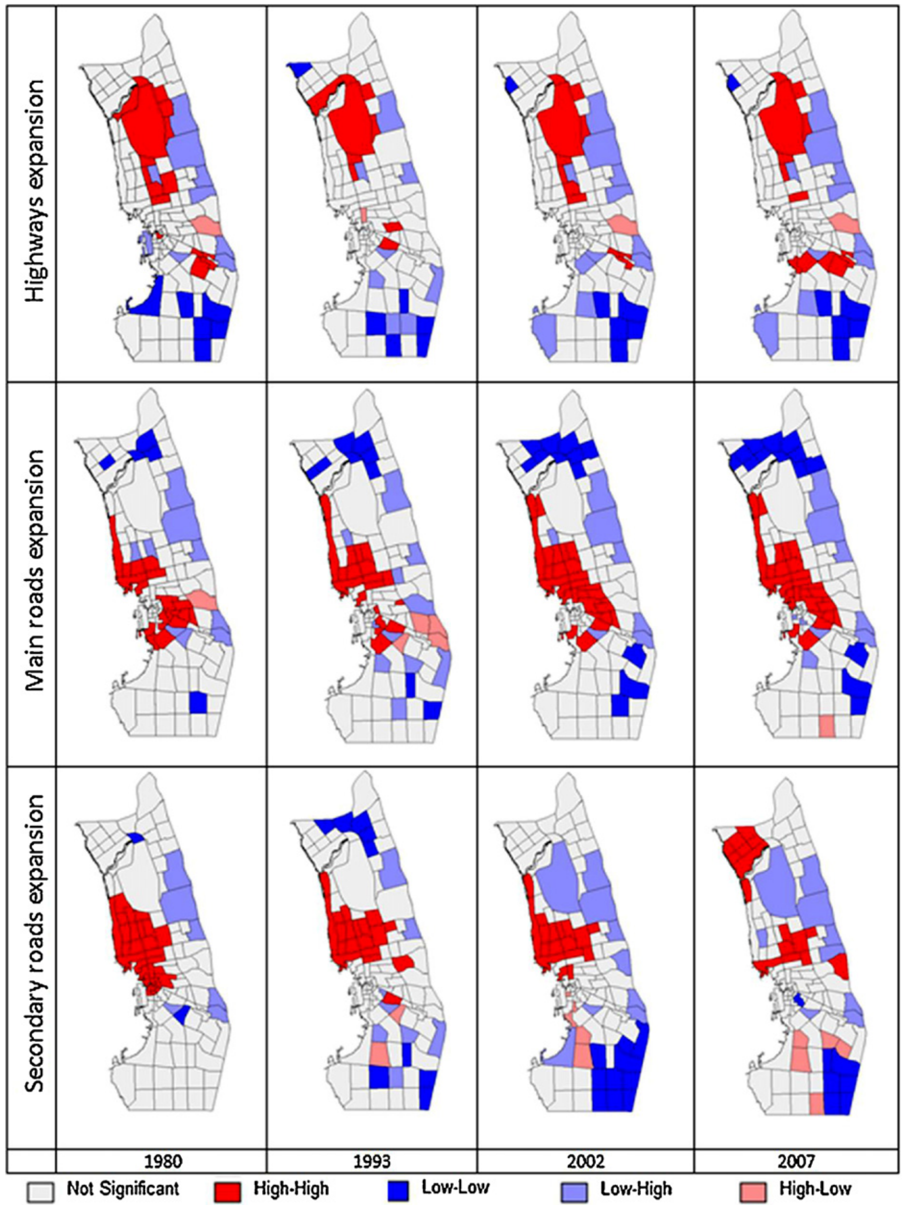

Fig. 7. LISA cluster maps of transport infrastructure variables.

over time, implying that the spatial expansion of residential development negatively contributes to the increase in highways over this period. In contrast, the coefficient for spatial expansion is positive and significant only for the year 2007 (Table 5), indicating that the increase in spatial expansion contributes positively to the increase in highways for 2007. Thus, the result reveals that population growth contributes positively to the spatial clustering of urban highway expansion, whereas residential development expansion negatively contributes to the spatial clustering in urban highway expansion.

The results of the effects of urban growth variables on the main road dependent variable (Eq. (8)) and secondary road expansion dependent variable (Eq. (9)) are given in Tables 10 and 11 below. The spatial autoregressive coefficient ρ for both main and secondary roads is positive and significant at the 5% level for the observations in 1980, 1993, 2002 and 2007. This result demonstrates the existence of spatial dependence, implying a relation between urban growth and transportation infrastructure expansion. Moreover, the coefficient of the residential development variable is significantly positive for the year 1993, showing that the spatial expansion of residential development positively contributes to the increase in the main roads for 1993 (Table 10). In contrast, the coefficients of spatial expansion for the observations in 1993, 2002 and 2007 are positive and significant at 5% and 1% (Table 11), indicating that spatial expansion is a contributing factor to the spatial increase in secondary roads and highways for 2007. The analysis further indicates that the coefficient of the population for the observation in 2007 is significantly negative, implying that population growth contributes negatively to the spatial clustering of urban secondary roads (Table 11).

4. Discussion

Spatial autocorrelation analysis results indicate a significant positive global spatial autocorrelation of all defined variables between 1980 and 2007. The results of the LISA revealed that the spatial clustering of urban growth variables coincided with the spatial clustering of transportation infrastructure expansion variables.

Table 5
LM test results for different dependent variables.

Dependent variable	Test	1980		1993		2002		2007	
		Value	p	Value	p	Value	p	Value	p
Ln (population growth) (4)	LM (lag)	32.55	0.000	12.21	0.000	25.37	0.000	33.85	0.000
	Robust LM (lag)	8.6	0.003	7.77	0.005	7.55	0.005	12.17	0.000
	LM (Error)	24.3	0.000	4.98	0.025	18.1	0.000	21.81	0.000
	Robust LM (Error)	0.41	0.521	0.551	0.457	0.283	0.594	0.135	0.712
Ln (spatial expansion) (5)	LM (lag)	70.2	0.000	12.95	0.000	90.87	0.000	49.44	0.000
	Robust LM (lag)	9.57	0.001	3.54	0.041	28.63	0.000	27.11	0.000
	LM (Error)	62.7	0.000	9.42	0.002	64.44	0.000	22.44	0.000
	Robust LM (Error)	1.9	0.157	0.016	0.899	2.209	0.137	0.126	0.722
Ln (Residential land use expansion) (6)	LM (lag)	24.95	0.000	42.8	0.000	60.06	0.000	50.41	0.000
	Robust LM (lag)	14.28	0.000	22.21	0.000	22.24	0.000	13.18	0.000
	LM (Error)	11.92	0.000	20.96	0.000	37.85	0.000	38.11	0.000
	Robust LM (Error)	1.26	0.261	0.372	0.541	0.038	0.844	0.878	0.348
Ln (Highway expansion) (7)	LM (lag)	27.4	0.000	17.9	0.000	17.11	0.000	15.96	0.000
	Robust LM (lag)	5.27	0.021	1.15	0.028	6.858	0.008	4.93	0.026
	LM (Error)	22.4	0.000	16.9	0.000	11.22	0.000	11.3	0.000
	Robust LM (Error)	0.33	0.561	0.162	0.686	0.962	0.326	0.279	0.596
Ln (Main road expansion) (8)	LM (lag)	10.82	0.001	9.84	0.001	41.6	0.000	24.94	0.000
	Robust LM (lag)	4.21	0.04	5.96	0.014	7.33	0.006	5.81	0.015
	LM (Error)	7.8	0.005	4.61	0.031	35.32	0.304	19.52	0.000
	Robust LM (Error)	1.18	0.275	0.724	0.394	1.05	0.000	0.39	0.530
Ln (Secondary road expansion) (9)	LM (lag)	50	0.000	9.36	0.002	18.63	0.000	8.94	0.001
	Robust LM (lag)	12.95	0.000	3.32	0.041	11.64	0.000	4.66	0.030
	LM (Error)	37.76	0.000	6.08	0.013	8.35	0.000	6.42	0.011
	Robust LM (Error)	0.708	0.399	0.047	0.827	1.37	0.241	0.425	0.514

Table 6
The maximum likelihood estimation result of the spatial lag model: dependent variable—ln of population.

	1980	1993	2002	2007
	Lag	Lag	Lag	Lag
Ln (Highways)	0.089 (1.44)	0.192 (2.13)*	0.248 (2.66)*	0.280 (3.15)*
Ln (Main roads)	0.012 (0.154)	0.210 (1.99)*	0.320 (3.37)*	0.352 (4.07)*
Ln (Secondary roads)	0.329 (4.37)*	0.386 (3.91)*	0.174 (1.77)**	0.035 (0.34)
ρ	0.732 (13.13)*	0.485 (6.04)*	0.554 (7.52)*	0.603 (8.77)*
Adjusted R^2	0.73	0.54	0.65	0.68

Notes: Absolute values of z-statistics in parentheses.
* Significant at 5%.
** Significant at 1%.

Table 7
The maximum likelihood estimation result of the spatial lag model: dependent variable—ln spatial expansion.

	1980	1993	2002	2007
	Lag	Lag	Lag	Lag
Ln (Highways)	0.199 (1.94)**	0.157 (1.92)**	0.185 (1.80)**	0.196 (2.34)*
Ln (Main roads)	−0.007 (0.057)	0.123 (0.760)	0.217 (2.13)*	0.295 (3.72)*
Ln (Secondary roads)	0.211 (1.93)**	0.353 (2.31)*	0.317 (2.89)*	0.283 (2.89)*
ρ	0.858 (23.89)*	0.552 (6.81)*	0.696 (13.05)*	0.503 (5.62)*
Adjusted R^2	0.69	0.38	0.66	0.57

Notes: Absolute values of z-statistics in parentheses.
* Significant at 5%
** Significant at 1%.

Table 8
The maximum likelihood estimation result of the spatial lag model: dependent variable—ln residential development.

	1980	1993	2002	2007
	Lag	Lag	Lag	Lag
Ln (Highways)	−0.091 (0.091)	0.205 (2.01)*	0.0215 (0.213)	0.119 (1.06)
Ln (Main roads)	−0.069 (0.579)	0.376 (3.16)*	0.129 (1.33)	0.146 (1.41)
Ln (Secondary roads)	0.458 (4.15)*	0.104 (0.947)	0.261 (2.43)	0.394 (2.97)*
ρ	0.81 (18.10)*	0.752 (14.72)*	0.839 (22.18)*	0.78 (16.67)*
Adjusted R^2	0.70	0.69	0.71	0.60

Notes: Absolute values of z-statistics in parentheses.
* Significant at 5%.
** Significant at 1%.

Table 9
The maximum likelihood estimation result of the spatial lag model: dependent variable—ln of highways.

	1980 Lag	1993 Lag	2002 Lag	2007 Lag
Ln (Population)	0.214 (1.92)**	0.084 (0.83)	0.291 (2.71)*	0.112 (1.23)
Ln (Residential develop.)	−0.202 (2.63)*	0.01 (0.13)	−0.162 (2.00)*	−0.003 (−0.045)
Ln (Spatial expansion)	0.085 (1.47)	0.002 (0.04)	0.065 (0.99)	0.141 (1.75)**
ρ	0.722 (11.7)*	0.702 (10.6)*	0.489 (6.25)*	0.515 (5.87)*
Adjusted R^2	0.38	0.25	0.42	0.33

Notes: Absolute values of *z*-statistics in parentheses.
* Significant at 5%.
** Significant at 1%.

Table 10
The maximum likelihood estimation result of the spatial lag model: dependent variable—ln of main roads.

	1980 Lag	1993 Lag	2002 Lag	2007 Lag
Ln (Population)	0.016 (0.17)	0.052 (0.60)	0.108 (1.47)	0.219 (2.83)*
Ln (Residential dev.)	0.008 (0.13)	0.183 (2.72)*	−0.072 (−1.30)	−0.062 (1.03)
Ln (Spatial expansion)	−0.001 (0.022)	0.002 (0.05)	0.039 (0.87)	0.097 (1.45)
ρ	0.81 (16.6)*	0.488 (5.61)*	0.938 (49.61)*	0.645 (9.4)*
Adjusted R^2	0.33	0.49	0.67	0.53

Notes: Absolute values of *z*-statistics in parentheses.
* Significant at 5%.
** Significant at 1%.

Table 11
The maximum likelihood estimation result of the spatial lag model: dependent variable—ln of Secondary roads.

	1980 Lag	1993 Lag	2002 Lag	2007 Lag
Ln (Population)	0.129 (2.04)*	0.332 (3.48)	0.099 (0.95)	−0.151 (1.90)**
Ln (Residential dev.	0.055 (1.26)	−0.072 (−1.02)*	0.006 (0.08)	0.157 (2.67)*
Ln (Spatial expansion)	−0.022 (0.687)	0.158 (1.82)**	0.121 (1.97)*	0.220 (3.19)*
ρ	0.845 (22.66)*	0.532 (6.44)*	0.348 (3.66)*	0.152 (1.58)
Adjusted R^2	0.80	0.46	0.26	0.29

Notes: Absolute values of *z*-statistics in parentheses.
* Significant at 5%.
** Significant at 1%.

The results of the spatial statistical analysis reveal reciprocal spatial–temporal effects of urban growth and transport infrastructure for the city of Jeddah. Interestingly, this study indicates that the spatial influence of variables related to transportation infrastructure expansion (highway expansion, main road expansion and secondary road expansion) on the clustering of population growth and spatial expansion is constant over time. This finding reflects the significant role of the expansion of different types of transportation infrastructures on the spatial clustering of population growth and spatial expansion.

In contrast, this study finds that the spatial influence of variables related to transportation infrastructure expansion on residential land use expansion changes over time (Tables 6–8). This finding indicates that different types of transport infrastructures have different spatial–temporal influences on the spatial clustering of residential land use expansion.

It is also observed that the spatial influence of urban growth variables (population growth, spatial expansion, and residential land use expansion) on the clustering of transportation infrastructure expansion variables changes over time (Tables 9–11). This finding indicates that different urban growth variables have different spatial–temporal influences on the spatial clustering of different types of transport infrastructures. This study finds that the spatial clustering of population growth and spatial expansion stimulates the spatial clustering of urban highways expansion. Furthermore, population growth and residential land use expansion contribute to the spatial clustering of main roads, whereas spatial expansion catalyzes the spatial expansion of secondary roads in Jeddah. Although, population growth amongst other urban growth variables seems to play stronger effect on the spatial clustering of transport infrastructure in Jeddah, transportation infrastructure seems to be influenced by other factors. In essence, urban transportation systems are complex networks shaped by various geographical, social, economic, and environmental factors (Wang et al., 2008).

The results of this study reveal that transport infrastructure is a constantly strong spatial influencing factor of urban growth in Jeddah city. The polycentric urban structure of Jeddah city and an arterial grid pattern of transport infrastructure with high connectivity seem to support this finding. In addition, Jeddah car-oriented transport system characteristics also seem to support this finding. Other developed monocentric urban structure cities are expected to show different results. The influence of transport infrastructure on urban growth is expected be lower as compared to a polycentric urban structure like Jeddah city.

This study shows that ESDA and spatial regression analysis are sophisticated tools to study the mutual effects of urban growth and transportation infrastructure expansion for the case of a developing, polycentric and fast growing city. These tools were able to detect the spatial–temporal reciprocal effects of transport infrastructure and urban growth. This in turn enriches insight, strengthens the understanding of the relationship between the complex urban growth phenomenon and transportation, and extends the knowledge of urban analysis using these tools. In essence, spatial and temporal analysis of the factors that drive urban growth is critical to predict future changes and their potential environmental effects in order to mitigate the negative aspects of urban growth (Aguayo et al., 2007).

This study provides urban planners and policy makers with a new methodological approach to understand the complex urban growth phenomenon in rapidly growing cities. This approach facilitates the investigation of the causes and drivers of urban growth; the complex interaction between the physical components of urban growth (spatial expansion and land use changes) and socio-economic components (population growth and economic growth). Enriched understanding of these issues is essential and crucial to mitigate the negative consequences of urban growth and to plan for future appropriate policies (Longley and Mesev, 2000; Herold et al., 2003).

5. Conclusion

This paper has explored the spatial–temporal mutual effects of transport infrastructure and urban growth using ESDA and spatial regression analysis tools for the case of Jeddah city; a developing, polycentric and fast growing city in Saudi Arabia between 1980 and 2007. This paper finds a significant positive global spatial autocorrelation of all defined variables from 1980 to 2007. The LISA results also find a constant significance spatial association of transport infrastructure expansion and urban growth variables from 1980 to 2007.

Spatial statistical analysis results find that the spatial influence of transportation infrastructure expansion variables on the clustering of population growth and spatial expansion is constant over time and different transport infrastructure types have different spatial–temporal influences on the spatial clustering of residential land use expansion. Conversely, results find that the spatial clustering of population growth and spatial expansion influences the spatial clustering of urban highways expansion. In addition, population growth and residential land use expansion find to contribute to the spatial clustering of main roads, whereas spatial expansion finds to catalyze the spatial expansion of secondary roads. Furthermore, spatial clustering of transport infrastructure in Jeddah seems to be influenced by other factors.

This study reveals that transport infrastructure is a constantly strong spatial influencing factor of urban growth. The polycentric urban structure and an arterial grid pattern of transport infrastructure with high connectivity of the study area seem to support this finding. Overall, this study demonstrates that ESDA and spatial regression analysis were able detect the spatial–temporal mutual effects of transport infrastructure and urban growth. This has extended the knowledge of urban analysis using these tools. These tools provide urban planners and policy makers with new methodological approach to understand the complex urban growth phenomenon in rapidly growing cities in order to mitigate the negative consequences of urban growth and to plan the future appropriate policies.

The results of this study provide several directions for further research. First, given the promising results of this study approach, further studies of the mutual relationship between urban growth and transport infrastructure using the presented study approach for the case of other monocentric urban structured cities are necessary. Second, given the complexity of the urban growth phenomenon, further investigation using ESDA and spatial regression analysis of (1) the causes and drivers of urban growth; (2) the complex interaction between the physical components of urban growth (spatial expansion and land use changes) and socio-economic components (population growth and economic growth) is encouraged.

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