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Land Use/Land Cover Planning Nexus: a Space-Time Multi-Scalar Assessment of Urban Growth in the Tulsa Metropolitan Statistical Area

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Abstract This study employs remote sensing, geographic information systems (GIS), and spatial statistical modeling to structurally characterize urban growth and spatially understand its drivers in an effort to assess the outcome of the 1974 Tulsa Metropolitan Statistical Area (TMSA) comprehensive land use plan. Results demonstrate that the TMSA witnessed significant alterations in land use/land cover (LULC) spatial extent and structure over the assessment period and further illustrate that median household income, population density, sales, and construction cost are key drivers that influenced the structural character of LULC between 1990 and 2011. The assessment shows that the spatial and temporal patterns within development districts deviated from that prescribed in the comprehensive plan while spatial development within intensity corridors mirrors the goals and objectives set in the plan. Aberrations between plan objectives and outcomes can be attributed to upward mobility in financial status, growth in markets, and political climate.

Keywords Land use/land cover · Urban growth · Planning · Anthropogenic drivers · Tulsa · USA

Introduction

Determining the scope and trajectory of changes in land use and land cover (LULC) is essential to urban and regional planning, environmental management, and an array of elements that are connected to ecological and man-made systems. Changes in LULC are more pronounced in urban areas as a result of higher human habitation and activities (Miller and Small 2003; Schneider and Woodcock 2008). LULC alterations in urban areas have been characterized into land conversion and modification resulting in land fragmentation (Herold *et al.* 2002; Jenerette and Wu. 2001). Such changes can have detrimental social and ecological implications if not properly monitored and assessed (Seto *et al.* 2011; Veldkamp and Verburg 2004). The activities of administrative jurisdictions at various scales are informed by urban and regional comprehensive plans which are generally implemented over a 20 to 30 year period. Within the United States, these plans are normally configured at city, county, regional and state levels. All comprehensive plans have a land use section that outlines the short-to-medium term prescribed extent, configuration, and trajectory of the landscape, and also the processes of implementation of plan objectives. This is done to insure that subsequent configurations of land use conform to socioeconomic, political, and other developments within the specific jurisdiction (Faludi 1987) and at times serves as a guide for future planning decisions (Baer 1997). While these plans are periodically assessed and revised mainly within the scope of socioeconomic development, few if any *ex-post facto* land-use evaluations are conducted (Laurian *et al.* 2010).

Anthropogenic drivers are mainly responsible for changes in urban LULC (Lambin *et al.* 2001; Wilson and Wilson 2013). These drivers include but are not limited to population dynamics, socioeconomic transformation, industrialization, land market, political climate, and government policies (Long *et al.* 2008; Seto and Kaufmann 2003; Thapa and Murayama 2010). Anthropogenic drivers of urban LULC change can trigger other ecosystem changes that have a relationship with LULC, which can result in negative

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ramifications in uncontrolled urban growth situations (Wilson and Weng 2011). Urban growth can manifest in multiple dimensions with significant implications for urban and regional planning. In a study of urban growth in 25 global cities, Schneider and Woodcock (2008) reported four typological urban growth patterns encompassing low growth, high growth characterized by fragmented development, expansive-growth, and frantic growth cities with remarkable rates of land cover changes at high population densities. In evaluating land-use patterns in the central Arizona-Phoenix region, Jenerette and Wu. (2001) observed an exponential expansion in the extent of urban area that was correlated with a key land change driver – growth in population (see also Seto and Kaufmann 2003; Wilson 2015).

Some studies have utilized urban growth models to understand recent trajectories in metropolitan landscape and predict changes in future LULC (Rounsevell *et al.* 2006; Wilson and Weng 2011). Such studies normally engage policy-based scenarios in modeling (Jantz *et al.* 2003; Verburg *et al.* 2004). For instance, Jantz *et al.* (2003) utilized three distinct policy scenarios to predict the nature of the landscape within the Washington-Baltimore metropolitan region by 2030. In a related study, Wilson and Weng (2011) employed multiple planning scenarios in generating future LULC data for the Chicago Metropolitan area. This approach has great potential to rank the efficacies of proposed land use plans for various socioeconomic and environmental applications, thereby limiting deviations between plan objectives and outcomes.

It is a planning tradition to evaluate the efficiency of various components of comprehensive plans whether for land use, sustainability, water quality, and other attributes of the physical or cultural environment (Kaiser *et al.* 1995; Snyder and Coglianese 2005). Plan evaluation has become increasingly important with a greater number of administrative units at various levels demanding the development and implementation of comprehensive plans (Baer 1997). Comprehensive plans are fundamental to growth and development at various spatiotemporal scales (Dalton 1989). Yet little attention has been devoted to plan evaluation within the planning community (Oliveira and Pinho 2010). This lapse has resulted in plan practitioners utilizing mainly conceptual assumptions rather than empirical assessments in the evaluation of plans (Laurian *et al.* 2004; Oliveira and Pinho 2010). This scenario is further compounded by the dearth of effective spatiotemporal methodology in evaluating land use plans (Laurian *et al.* 2010) and the apparent fuzziness of some their goals (Bengston *et al.* 2004). As a result, additional efforts are needed in developing effective strategies and methods in comprehensive plan evaluation to better inform planning practice (Baer 1997; Oliveira and Pinho 2010).

Plan evaluation can take several forms and approaches (see Baer 1997, and Oliveira and Pinho 2010, for a detailed discussion). One area of plan evaluation that is rarely conducted is post hoc evaluation, undertaken following plan implementation in order to appraise conformity or performance (Faludi 1987; Snyder and Coglianese 2005). This is dichotomized into two theoretical constructs: conformance-based approach and performance-based strategy (Baer 1997). Conformance-based approach examines the interface between planning outcomes and actual development. This evaluation model visualizes a plan as a blueprint and assumes a linear relationship between the objectives and outcomes (Chapin and Deyle 2008). In other words, deviations between the plan outcomes and objectives are envisioned as a relative success/failure in achieving plan objectives. The performance-based approach to plan evaluation envisages planning as a guide for future planning decisions focussing more on processes rather than outcomes (Mastop and Faludi 1997), and is an ongoing evaluation during each phase of plan implementation. In evaluating land use plans, several scholars recommend the conformance-based approach because the outcome of a plan can be used to inform future plans, is more relevant in land use decisions, and can be quantitatively assessed easily compared to performance-based approaches (Laurian *et al.* 2004).

In an evaluation of how well plans promote sustainable development, Berke and Conroy (2000) found that a majority of plans promote the livable built-environment principle of new urbanism at the expense of ecological integrity. Brody and Highfield (2005) and Berke *et al.* (2006) observed weak associations between both plan conformance and performance vis-à-vis planning objectives, suggesting deviations between the two (see also Chapin and Deyle 2008). Pauleit and Duhme (2000) characterized and evaluated land use patterns in the City of Munich for various environmental applications. Though their study made a significant improvement in integrating LULC spatial analysis into urban planning, it presented recommendations to be included in land use plans rather than evaluation of an implemented land use plan for conformity or performance. The empirical studies examined suggest that a spatiotemporal LULC ex post facto evaluation is largely absent, and as such the extent of conformity between changes in LULC and those prescribed in land use comprehensive plans remain elusive. Therefore, a space-time evaluation of LULC changes within the scope of land use planning prescriptions is needed to better inform future land use planning efforts. Such an exercise can applicable to a wider variety of settings if conducted at a multi-scalar dimension. An evaluation of the Tulsa 1974 Comprehensive Plan is prudent not only because no prior assessment has been done but more importantly to use this case study to fill the aforementioned hiatus in the literature. Tulsa is a major city in the U.S. state of Oklahoma that has witnessed significant areal growth over the past three decades and presents an apropos landscape for the plan evaluation exercise presented here.

Our overarching goal is to assess and evaluate the spatial composition, configuration, and process of urban growth in the Tulsa Metropolitan Statistical Area (TMSA) within the context of the 1974 Comprehensive Plan of the region. Specific objectives include i) to quantify the changes in urban LULC between 1990 and 2011; ii) to gauge the role of proximate and underlying drivers in influencing urban LULC change; and iii) to evaluate the conformity between some of the prescriptions of the Tulsa 1974 Comprehensive Plan and actual growth in LULC.

Methods

Study Area

The TMSA located in Northeastern Oklahoma spans an area of 17,831.3 km^2 (Fig. 1). The TMSA lies between 35° 22′ 54″ to 37° 0′ 14″ north latitude and 95° 12′ 28″ to 97° 4′ 7″ west longitude, covers eight counties, and is a substantial part of an area generally called the 'green country' encompassing several cities including the largest, Tulsa (Fig. 2). This region is characterized by two major physiographic conditions, the Sandstone Hills on the west and the Prairie Plains on the east (Tulsa Metropolitan Area [TMA] Planning Commission 1974). Topographic variation is common in the Sandstone Hills where some hills rise between 61 m and 76 m above the Arkansas River, while some peaks reach approximately 107 m. The Prairie Plains have gentler topography with slopes rarely exceeding 10 %. The TMSA has several water sources and distinct natural vegetation. The water resources in the study area comprise surface and underground water characterized by five years average cyclic flood plains (TMA Planning Commission 1974). Natural vegetation is dominated by trees of various types and growth patterns, including oaks, pines, cypress, prairie, and Postoak (Hoagland 2000). The study area is situated in a humid subtropical climatic zone with annual average temperatures ranging between 10 °C and 21.7 °C, with an annual mean temperature of 15.9 °C (National Climate Data Center 2014). Mean annual precipitation is 1078 mm.

The TMSA is an economic engine of the northeastern region. Its gross metropolitan product (GMP) was $43.4 billion in 2009 and rose to $46.4 billion in 2011, about 33 % of Oklahoma's economy (Global Insights 2012). The primary economic activities include energy production, aerospace, telecommunications, and manufacturing. The population was 937,478 in 2010, rising to an estimated 953,000 as of 2014 (Minnesota Population Center 2011). In 2010, the TMSA had 367,091 households and a population density of 386 persons per km^2 (Minnesota Population Center 2011). According to the 2010 U.S. Census, Tulsa was one of the three largest 20 cities in Oklahoma that has witnessed a population decline over the last decade. Nevertheless, its outer-lying cities and suburbs are experiencing significant population growth as more people emigrate from downtown Tulsa.

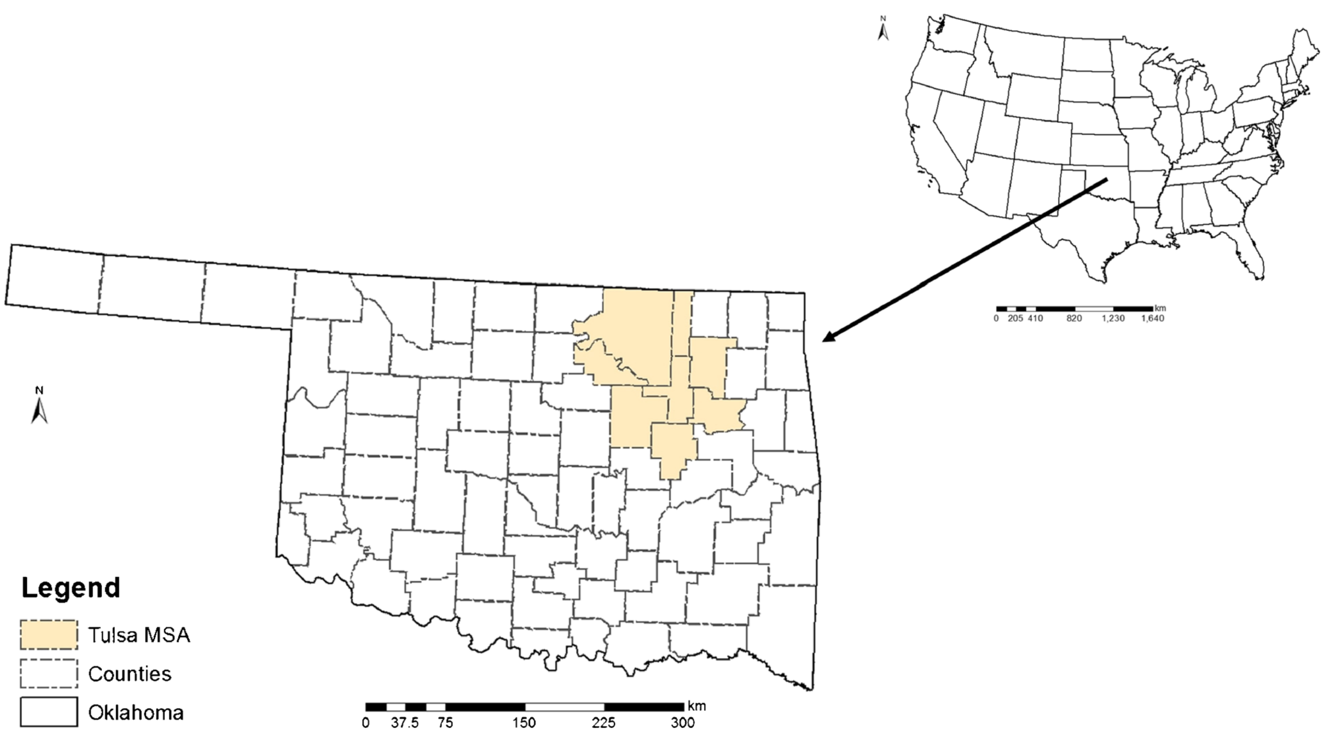

Fig. 1 Map of the U.S. showing Oklahoma and Tulsa Metropolitan Statistical Area

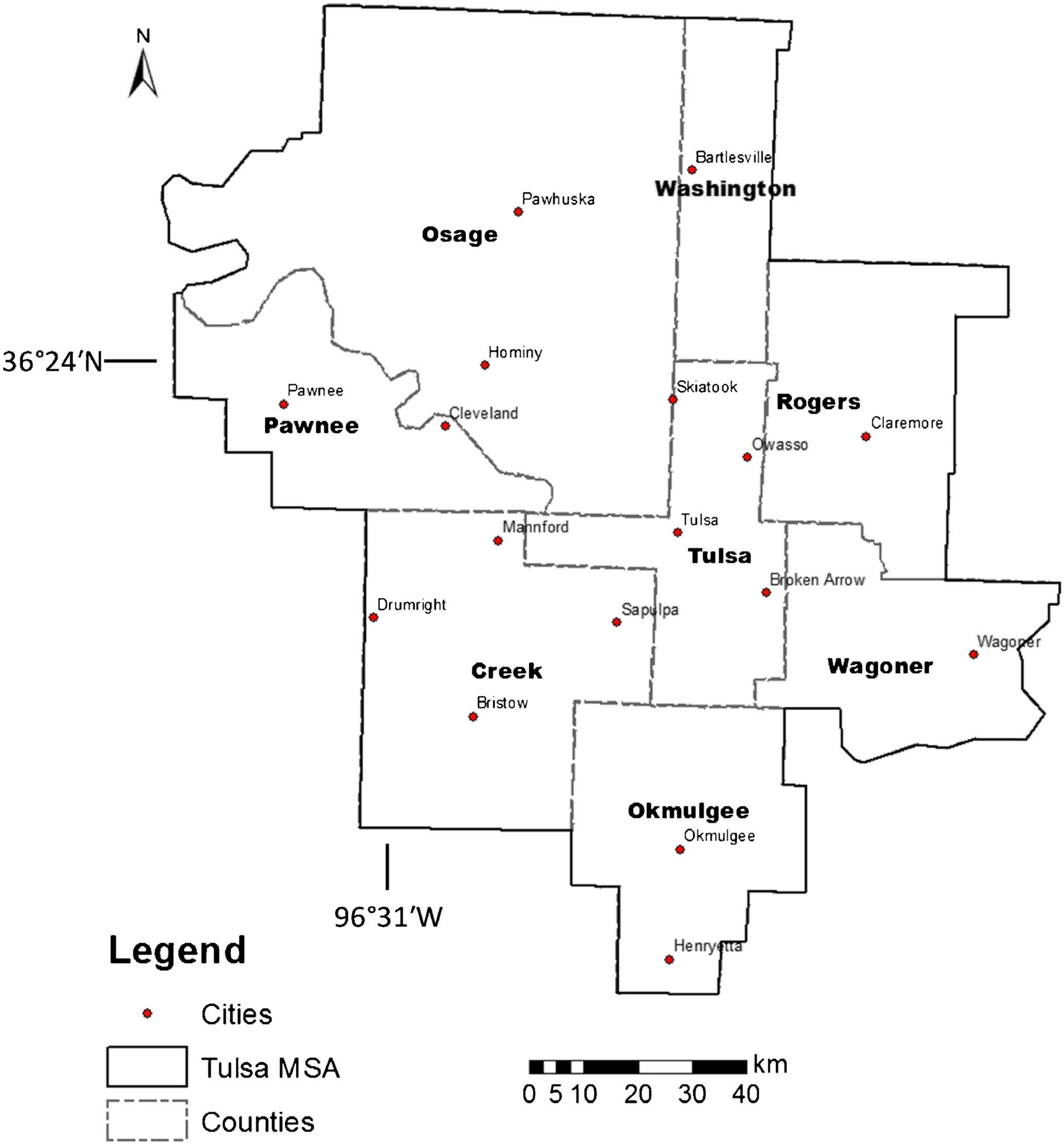

Fig. 2 Map of Tulsa MSA showing counties and cities

Data

We used three sets of Landsat-5 Thematic Mapper (TM) satellite images to provide LULC data for this study. Landsat-5 TM images are available in six reflective bands at a spatial resolution of 30 m (USGS 2014) (Table 1).

The images were carefully chosen to minimize variation in vegetation phenology, soil moisture, and other environmental attributes. However, due to excessive cloud cover in one of the scenes (Path 27 row 35) for 2010, it was not feasible to effectively use 2010 images. Thus we used images captured in 2011 for the 2010 time-step of the study. Other geospatial data employed include Google Earth high-resolution images (Google Earth 2014), National Agriculture Imagery Program high-resolution orthoimagery (USDA 2014), digital raster graphics

Table 1 Landsat-5 images used in study

	TM 1990	TM 2000	TM 2011
Scene	Path 26 row 35	Path 26 row 35	Path 26 row 35
Date	July 8	August 20	August 3
Scene	Path 27 row 34	Path 27 row 34	Path 27 row 34
Date	June 29	August 27	August 26
Scene	Path 27 row 35	Path 27 row 35	Path 27 row 35
Date	June 29	August 27	August 26

TM Thematic Mapper

(USDA 2014), and the enhanced historical land-use and land-cover data sets (GIRAS) of the U.S. Geological Survey (Price *et al.* 2006). Decennial U.S. Census data at the block group level for 1990, 2000, and 2010 was obtained from the National Historical Geographic Information System (Minnesota Population Center 2011). Additional data include real output per county (Center for Economic and Management Research 2002); records of all types of sales, and construction cost (Oklahoma Integrated Information Network 2015).

Satellite Image Processing

Landsat-5 images were geometrically corrected by image-to-map rectification procedure for the 1990 images, followed by image-to-image registration technique for the subsequent images using a third order polynomial equation and nearest neighbor resampling algorithm (Toutin 2004). We used 180 ground control points (GCPs) in the rectification process with a total root mean square (RMS) error of less than 0.1 pixels for all images. The images are delivered by the USGS already corrected for atmospheric interference with the use of the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) algorithm (Schmidt *et al.* 2013).

In extracting LULC information from the Landsat-5 satellite images, we employed a comprehensive (hard) classification in two stages (Fig. 3). Stage one utilized an object-based image analysis (OBIA) ruleset, while stage two utilized an expert system/decision tree classifier (Blaschke 2010; Kahya *et al.* 2010). An OBIA takes into consideration both the spectral and spatial characteristics of features contained in a remotely sensed image in extracting information from images (Blaschke 2010). At the end of OBIA, six LULC informational classes were produced which include Urban/built-up, forest, grass/open space, agriculture, water, and bare land. Results of stage one classification were pushed into an expert system/decision tree classifier to disaggregate the urban/built-up land cover into its respective land uses and also to properly delineate grass/shrub from open space vegetation.

An expert system/decision tree applies a rule-based approach to images with the aid of user-defined ancillary data (Kahya *et al.* 2010). At the end of stage two classification nine LULC classes were produced (Fig. 4). In order to understand the dynamics of LULC transitions that occurred in the TMSA between 1990 and 2011, a detailed from-to post-classification change detection was implemented (Lu *et al.* 2004). This exercise lucidly unearthed the major LULC transitions that occurred in the study area (Fig. 5).

In assessing the accuracy of image classification, 1200 reference points (ground reference information) were obtained for each image through stratified random sampling technique (Congalton 1991). Selection of ground reference information was aided by the National Agriculture Imagery Program high-resolution orthoimagery and Google Earth high-resolution images for the 1990, 2000, and 2011 images respectively. Overall accuracy of image classification ranged between 86.3 % and 89.5 % (see Table 2).

Development of Landscape Metrics and Socio-Geospatial Models

Three landscape indicators were developed to better understand the structural character of LULC in the TMSA. The landscape indicators, henceforth landscape metrics encompass patch density, patch compactness, and the normalized entropy (Eastman 2015). Patch density (PD) measures the number of patches per unit area in a landscape denoted by the following equation:

$$\mathrm{PD} = \frac{n_i}{A} \tag{1}$$

where n_i is the number of patches in a landscape of patch class type i, A is the total landscape area. Patch compactness (PC) amalgamates adjacent pixels of similar LULC category into patches based on a neighborhood and calculates their compactness using the following relation:

$$\mathrm{PC} = \sqrt{\frac{Ap}{Ac}} \quad 0 \le \mathrm{PC} \le 1 \tag{2}$$

where Ap is the area of a patch being calculated, Ac is the area of a circle bearing the same perimeter as that of the patch being calculated. Values closer to one signify more compact patches whereas those close to zero illustrate little compactness. The normalized entropy (NE) is a measure that normalizes Shannon's Entropy by the maximum entropy for the number of LULC classes involved. In other words, it portrays the abundance of a particular

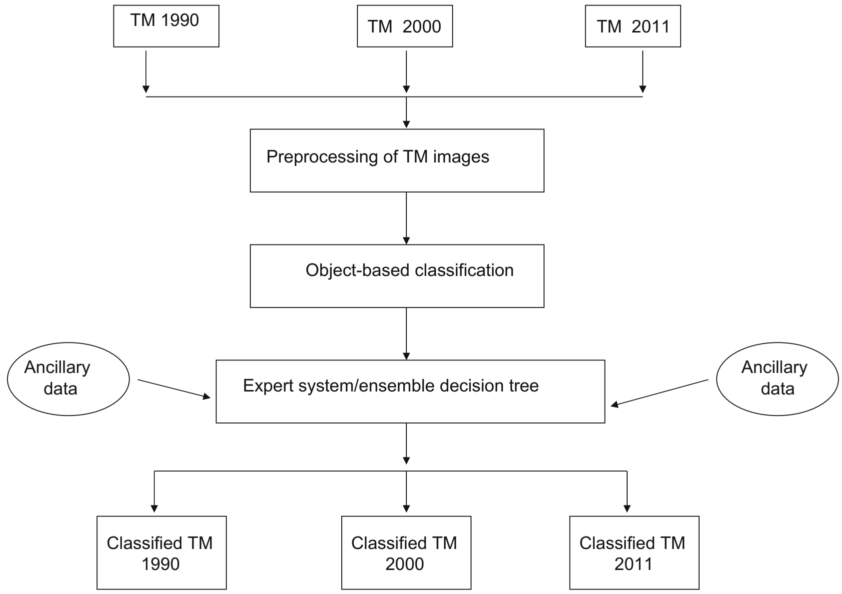

Fig. 3 Image processing flow chart. *TM* Thematic Mapper

LULC class in relation to other LULC classes within a neighborhood. NE is calculated as such:

$$\mathrm{NE} = -\sum \left(\frac{p \times \ln(p)}{\ln(n)} \right), \qquad 0 \leq \mathrm{NE} \leq 1 \tag{3}$$

where *p* is the proportion of each LULC class within the neighborhood, *ln* is the natural logarithm, and *n* is the number of classes. A normalized-entropy close to zero indicates uneven areal distribution and less diversity in LULC, whereas a NE close to one signifies even distribution or maximum diversity of LULC within a neighborhood (see Table 3).

To assess the role of proximate and underlying drivers on the spatial extent and configuration of LULC, three proximate and three underlying drivers of LULC change were engaged (Table 4). Five proximate drivers were initially considered but two were discarded after failing multicollinearity tests. Geographically weighted regression (GWR) models were developed and applied to evaluate the role of proximate drivers on LULC change while a mixed modeling approach was utilized for the underlying drivers. The GWR modeling was executed at the block group level while the mixed modeling was applied at two different scales. In a GWR, the dependent variable *Y* at each location (g,r) is a function of the explanatory variables at each specific location (Fotheringham *et al.* 2002; Nakaya *et al.* 2014). The following equation outlines the configuration of a GWR:

$$Y(\mathrm{g,r}) = \beta_0(\mathrm{g,r}) + \beta_1(\mathrm{g,r})X_1 + \beta_2(\mathrm{g,r})X_2 + \ldots\ldots\beta_\eta(\mathrm{g,r})X_\eta + \varepsilon_{(g,r)} \tag{4}$$

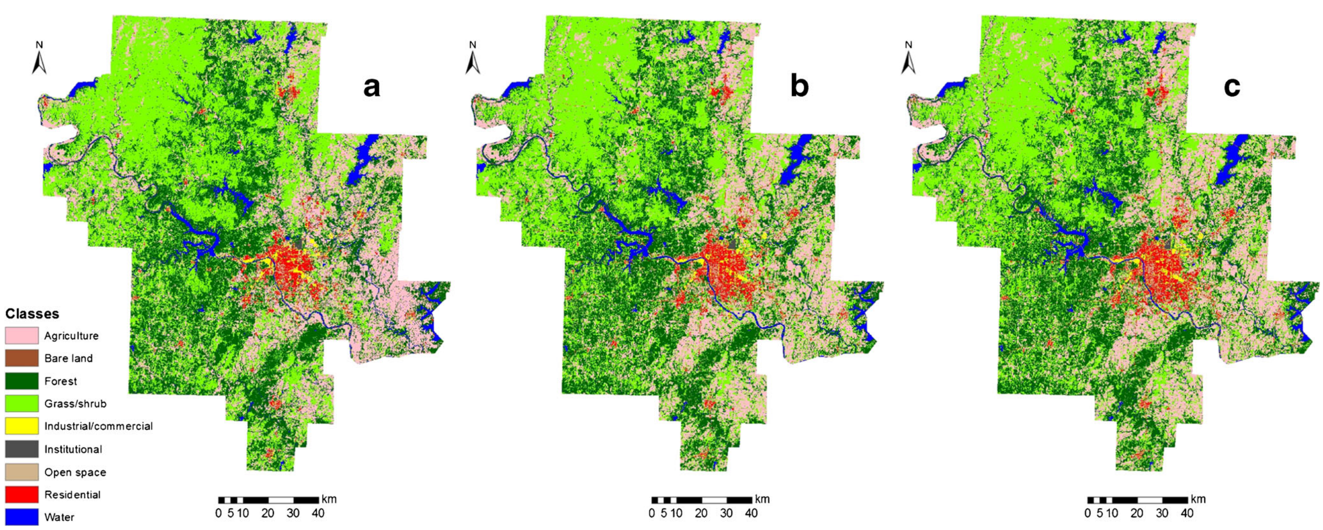

Fig. 4 Land use/land cover maps for 1990 (**a**), 2000 (**b**), and 2011 (**c**)

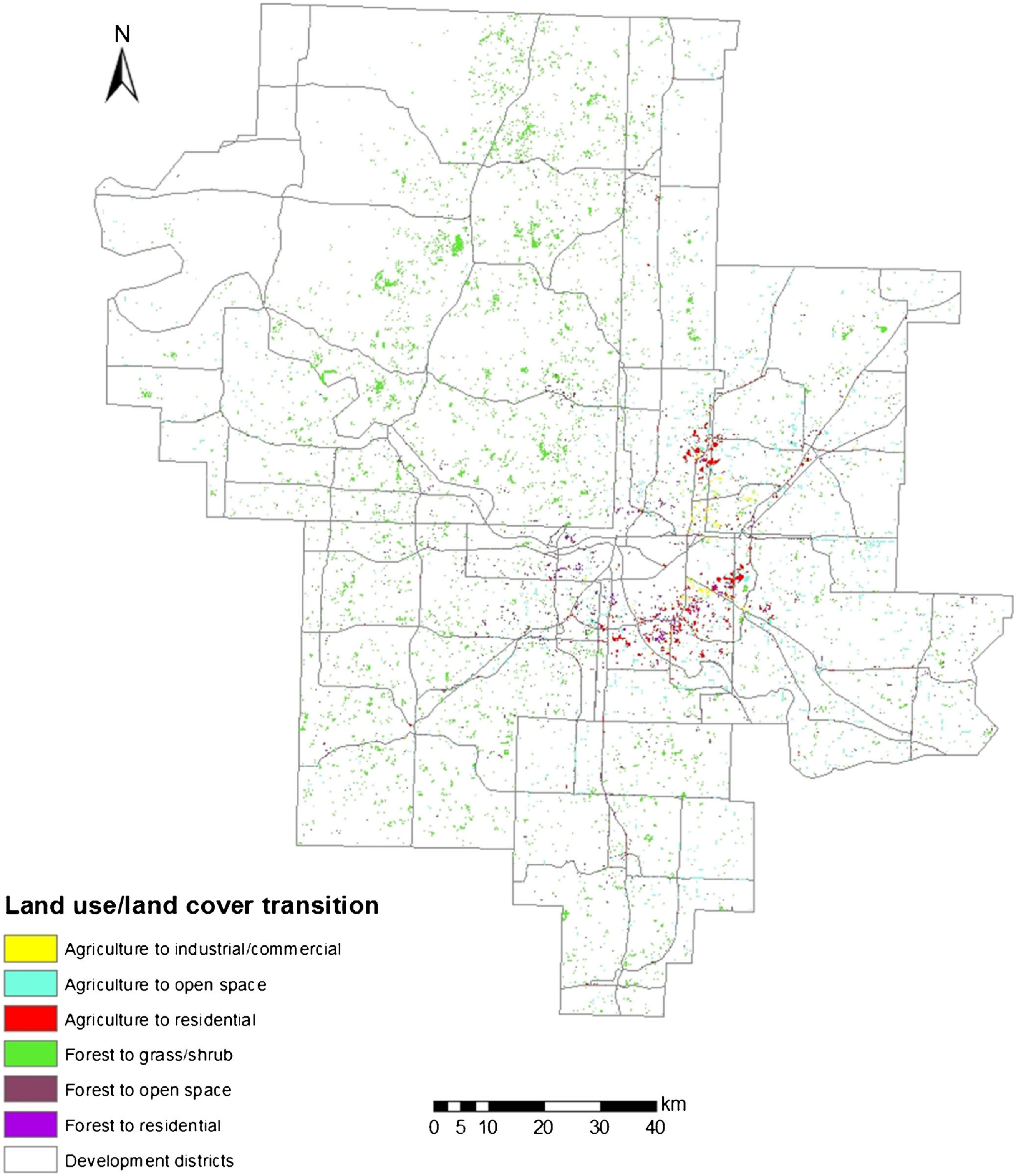

Fig. 5 Major land use/land cover transitions of planning significance between 1990 and 2011

where Y(g,r) is the dependent variable (landscape metric) at location coordinates g and r (centroid of block group); X_1, X_2 and X_η represent the explanatory variables at each location; β_0, β_1, β_2, and β_η are parameters to be estimated for every location whose coordinates are represented by (g,r); and $\varepsilon_{(g,r)}$ is the Gaussian error term or residual at location (g,r). Spatial coordinates of the data points are used in calculating inter-point distances which are subsequently inputted into a kernel function to develop weights. Weights are greater on observations that are

Table 2 Producers, users, and overall accuracy for classified images

		Water	Indst/com	Forest	Grass	Residential	Inst	Agric	Open	BG
1990	PA(%)	96	80	90	72	81	85	86	76	84
	UA(%)	95	93	85	86	87	93	92	44	93
2000	PA(%)	95	86	92	68	83	82	83	78	74
	UA(%)	91	78	84	89	86	92	91	93	92
2011	PA(%)	98	91	96	74	90	81	81	86	81
	UA(%)	97	79	83	85	96	95	89	92	88

OO 1990 = 86.3 %, OO 2000 = 88.6 %, OO 2011 = 89.5 %

Indst/com commercial/industrial, *Inst* institutional, *Agric* agriculture, *Open* open space, *BG* bare ground, *PA* producer's accuracy, *UA* user's accuracy, *OO* overall accuracy

proximate to the calibrated coordinate location (g,r) than those that are farther away.

GWR modeling was implemented using the GWR 4 software package (Nakaya *et al.* 2014). A Gaussian model was utilized to fit each model using an adaptive bi-square kernel. The adaptive bi-square kernel is superior to the Gaussian fixed and bi-square kernels because it provides a more decisive goodness of fit and also better overcomes potential subtle multicollinearity problems between the estimates and produces white noise residuals (Chasco *et al.* 2007). An adaptive bi-square weighting function is demonstrated in the following relation:

$$W_{\mathrm{ij}} = \begin{cases} \left[1-\left(d_{ij}/h_i\right)^2\right]^2, & \text{if } d_{ij} < h_i \\ 0 & , \quad \text{otherwise} \end{cases} \tag{5}$$

where W_{ij} is the weight assigned to data point j to estimate the coefficient for regression point i, d_{ij} is the Euclidean distance between observations i and j, and h_i represents the different bandwidths, that precepts the fraction of observations to take into cognizance in the estimation of regression at location i. An adaptive bi-square kernel is equipped with a bandwidth that varies spatially in relation to the variations in density of observations over space. The optimal bandwidth was achieved by minimizing the corrected Akaike Information Criteria (AICc) (Nakaya *et al.* 2014). Sixteen GWR models were developed for each time step of the study with landscape metrics serving as dependent variables in each model run while the proximate drivers served as explanatory variables (Table 4). Each model was tested for statistical significance using the pseudo t-test at the 95 % confidence interval ($P < 0.05$).

Prior to the execution of the mixed modeling technique, key planning policies from the Tulsa 1974 Comprehensive Plan were examined, quantified and developed into a GIS feature class. The major prescription of the Tulsa 1974 Comprehensive Plan was the implementation of a balanced growth model that constitutes development districts, development sub-districts, intensity corridor, intensity nodes, conservation sectors, and special districts (TMA Planning Commission 1974). In this study, development districts and intensity corridor that were the least fuzzy objectives in the plan were quantified and developed into a GIS to facilitate modeling of the underlying drivers' influence on the spatial configuration of the landscape. According to the Tulsa 1974 Comprehensive plan, development districts are those bounded by freeways and highways (existing or officially planned), the Arkansas River, the edge of a designated conservation sector, and key jurisdictional boundaries. An intensity corridor is a 1.2 km (¾ of a mile) zone proximate to freeways with the intensity of use diminishing the farther away from the freeway (TMA Planning Commission 1974). With the aid of satellite images and U.S. Census Tigerline road file, development

Table 3 Landscape metrics used in study

Landscape metric	Description
DEN_BLT	Patch density of urban/built-up land
PC_ALL	Patch compactness of all LULC
NE_ALL	Normalized entropy of all LULC
RESD_PC	Patch compactness of residential LULC
RESD_NE	Normalized entropy of residential LULC
INC_PC	Patch compactness of industrial/commercial LULC
INC_NE	Normalized entropy of industrial/commercial LULC
FRST_PC	Patch compactness of forest LULC
FRST_NE	Normalized entropy of forest LULC
AGRIC_PC	Patch compactness of agricultural LULC
AGRIC_NE	Normalized entropy of agricultural LULC

Table 4 Explanatory variables used in study

Housing units*
Median household income*
Population density*
Real output+
Total construction cost+
Total value of sales+

U.S. Census Bureau & Oklahoma Integrated Information Network

* proximate, + underlying

districts were generated for the entire study area. Satellite images were used to extract freeways not covered by Tigerline road network and to provide spatial context for the development districts. These districts were intersected with the counties in order to arrive at the geographic unit of a county to be comparable with the underlying driver variables. In generating the intensity corridors, a four zone multiple ring buffer at 0.8 km intervals was generated along the freeways within the TMSA and aggregated at the county level to be consistent with the rest of the data during this stage of modeling.

Due to the unavailability of underlying driver variables at the block group level and to forestall multicollinearity, which is common in GWR as scale becomes coarse, multiple linear regression and descriptive statistics were utilized to assess the role of underlying drivers on the spatial configuration of LULC within counties at the development district and intensity corridor levels. A total of seven models were developed for each time step of the study using the landscape metrics as dependent variables and the underlying driver variables as independents (Table 4). Each model was tested for statistical significance at the 95 % confidence interval ($P < 0.05$). Furthermore, the mean of each landscape metric within development districts and intensity corridors were calculated in order to assess the spatiotemporal patterns.

Results

Land Use/Land Cover Change Trajectory, 1990 to 2011

The analysis of LULC trajectory illustrated an increase in the spatial extent of residential, industrial/commercial, institutional, open space, and grass/shrub over the entire study period (Table 5). Increase in the spatial extent of residential land was more pronounced between 1990 and 2000 (35.3 %) compared with the most recent period (11.6 %), while the increase in industrial/commercial was notable between 2000 and 2011(Table 5). Increase in extent of residential land over the study period resulted from the conversion of forest, agricultural, and grass/shrub LULC (Table 6). The expansion of industrial/commercial LULC mainly resulted from significant loss of bare land and to some extent agricultural areas. TMSA experienced significant growth in open space (26.9 %) between 1990 and 2000, which also coincides with the greater increase in residential land over this same period (Table 6). LULC that demonstrated continuous loss of spatial extent throughout the 21-year period are agriculture, forest, and water (Table 5). These LULC types exhibited greater loss between 1990 and 2000, mostly transitioned to open space, grass/shrub, and residential (Table 6). Significant increase in residential land between 1990 and 2000 can be partly attributed to growth in population (12.3 %), while the relatively slower expansion in residential area between 2000 and 2011 can also be partially ascribed to the smaller increase in population (6.5 %) between 2000 and 2010.

Table 5 Land use/land cover change (% change)

Classes	1990–2000	2000–2011
Water	-6.5	-0.3
Forest	-2.8	-1.9
Agriculture	-11.5	-1.3
Grass/shrub	5.1	0.8
Residential	35.3	11.6
Open space	26.9	2.2
Industrial/commercial	8.8	15.0
Bare land	-67.8	6.0
Institutional	10.1	4.4

Trajectory of residential LULC can be further credited to differential economic growth patterns; for example, average sales for the region surged by 51 % between 1990 and 2000 while the increase for the recent period was 39.5 %. Most of the increase in residential, industrial/commercial, and open space occurred within Tulsa, Rogers and Washington Counties (Figs 4 and 5). Reduction in agricultural and forest LULC can be ascribed to the need for additional space for residential and its attendant land uses in the TMSA. Analysis of Census results over the study period showed that employees in the agriculture sector fell by 53 % between 1990 and 2000 but slightly increased by 6.6 % during the recent time-step of the study. This trend partly reflects the loss of agricultural land.

Role of Anthropogenic Drivers on Land Use/Land Cover Character and Process

GWR models suggested that the proximate drivers (population density, median household income and housing units) explained more than 50 % of the variation in the NE of residential and forested LULC over the entire study period. The proximate drivers further accounted for over 50 % of the variance in the structural characteristics of industrial/commercial, forest, and agricultural lands in 2000 and 2010. When the density of urban/built-up land is taken into consideration, the proximate drivers were only able to explain more than 50 % of model variance in 1990.

GWR model results indicate that the density of urban/built-up land is influenced mostly by population density. Pseudo t-test illustrates that block groups with high population density resulted in greater density in urban/built-up land. Pseudo t-test also shows that approximately 30 % of medium income block groups (Table 7) that are two to three times above the poverty level contributed to higher density in urban/built-up land compared with lower income areas. When the 1970s GIRAS urban/built-up land was compared with the 1990 classified

Table 6 Land use/land cover transition matrix (hectares)

		To 2011								
		Water	Forest	Agriculture	Grass/shrub	Residential	Open space	Industrial/ commercial	Bare land	Institutional
From 1990	Water	NA	2311	80	3054	0	524	0	0	0
	Forest	0	NA	0	25,244	4052	12,146	0	50	61
	Agriculture	0	14,392	NA	30,559	8267	556	891	293	53
	Grass/shrub	0	0	1570	NA	3784	16,857	0	0	0
	Residential	0	0	0	0	NA	0	0	0	0
	Open space	0	0	0	0	0	NA	1142	0	978
	Industrial/ commercial	0	0	0	0	1076	0	NA	0	0
	Bare land	0	0	0	83	113	0	1067	NA	423
	Institutional	0	0	0	0	186	0	496	0	NA

NA Not applicable

LULC map, it showed a notable increase in the spatial extent of urban/built-up area (~38 %). Analysis of U.S. census results between 1970 and 1990 show a 31 % increase in population, necessitating additional housing and related infrastructural facilities.

GWR model results for the landscape metrics of industrial/commercial land show that median household income is the most effective proximate driver determining the spatial configuration of this land over the entire study period. Pseudo t-tests indicate that in block groups with low income in Tulsa, Rogers and Creek Counties, there is a compact but disproportionately lower share of industrial/commercial outlets per unit area, even though the population within some of these block groups is relatively high. However, in the south and portions of northwest Tulsa City and the Owasso-Claremore corridor characterized by medium and high income, fragmented but greater proportions of industrial/commercial lands per unit area are evident. An exploration of the influence of population density suggested that low population centers outside the major cities have more fragmented industrial/commercial centers compared with high population areas within the City of Tulsa. However, few block group clusters with relatively high population in northern Tulsa City showed fragmented development in industrial/commercial landscape.

Table 7 Medium household income brackets (U.S. dollars)

	1990	2000	2010
Low	< 13,254	< 17,463	< 22,113
Medium	13,255–53,016	17,464–69,852	22,114–88,452
High	>53,016	>69,852	>88,452

Family of four. *Low* below poverty line

U.S. Census Bureau

The NE of residential lands illustrated consistent statistically significant relationships with the proximate drivers over the entire study period (Figs 6, 7, and 8), while residential PC displayed invariable relationships with median household income. Median household income was found to be the strongest proximate driver that conditions the NE of residential land in 1990 and 2000, while population density emerged as a decisive driver in 2010. On average, population density was slightly more instrumental in determining PC of residential land compared with median household income over the study period. In 1990 and 2000, block groups characterized by low income in counties adjacent to Tulsa displayed high NE of residential lands (Figs 6d and 7d). Similar spatial pattern was found in a number of block groups located in the northern section of the City of Tulsa signifying smaller share of residential lands per unit area in relatively low-income communities and vice-versa. Notwithstanding, this trend partially veered in 2010 when a smaller share of residential land per unit area was dominant in middle-income block groups (Fig. 8d). Within the City of Tulsa, few block groups to the south and around the Owasso area in east Tulsa County, characterized by high income demonstrated relatively compact residential lands but highly mixed use type of development from 2000 and beyond. Further examination of the LULC maps revealed that these block groups have a high proportion of industrial/commercial, forest, and open space LULC. This finding signifies that high income block groups have more compact residential areas while the opposite is found in the north and northwest of the city, a zone characterized by low and medium income threshold. Analysis of the NE and PC of residential areas suggest that block groups characterized by low population density contributed to greater fragmentation in residential lands with the exception of two cities in Rogers and Okmulgee County where population density contributed

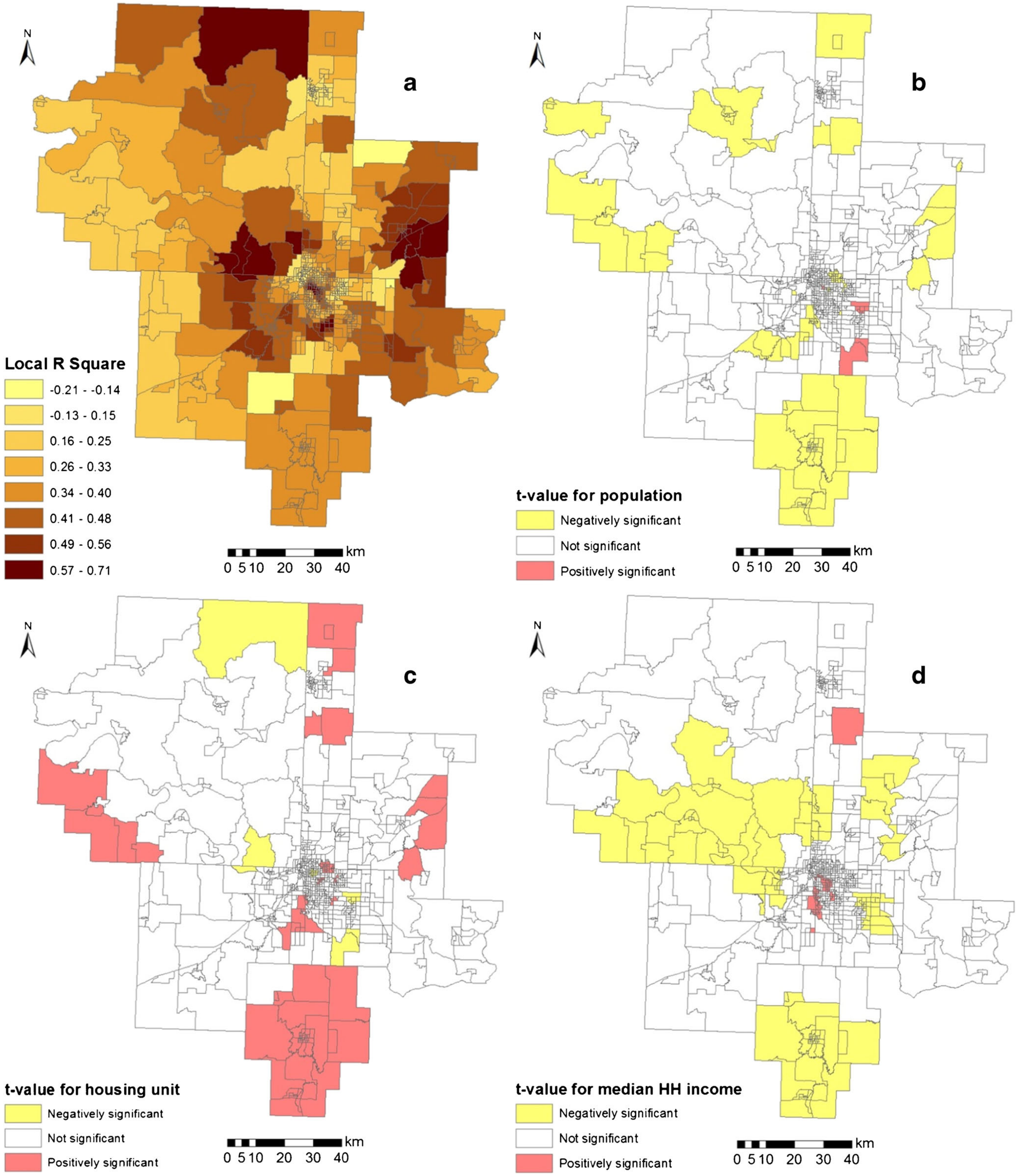

Fig. 6 GWR local R^2 for normalized entropy of residential land and *t* values for statistically significant proximate driver variables in 1990. *t* values significant at $p < 0.05$, *HH* household

to moderate fragmentation (Figs 6b-8b). Pseudo t-tests for the landscape metrics show that housing units contributed to minimum fragmentation in residential landscape (Figs 6c-8c).

The structural character of forest cover was influenced mostly by median household income throughout the study period with the exception of population density, which was instrumental in forest cover compactness in 1990. Pseudo t-

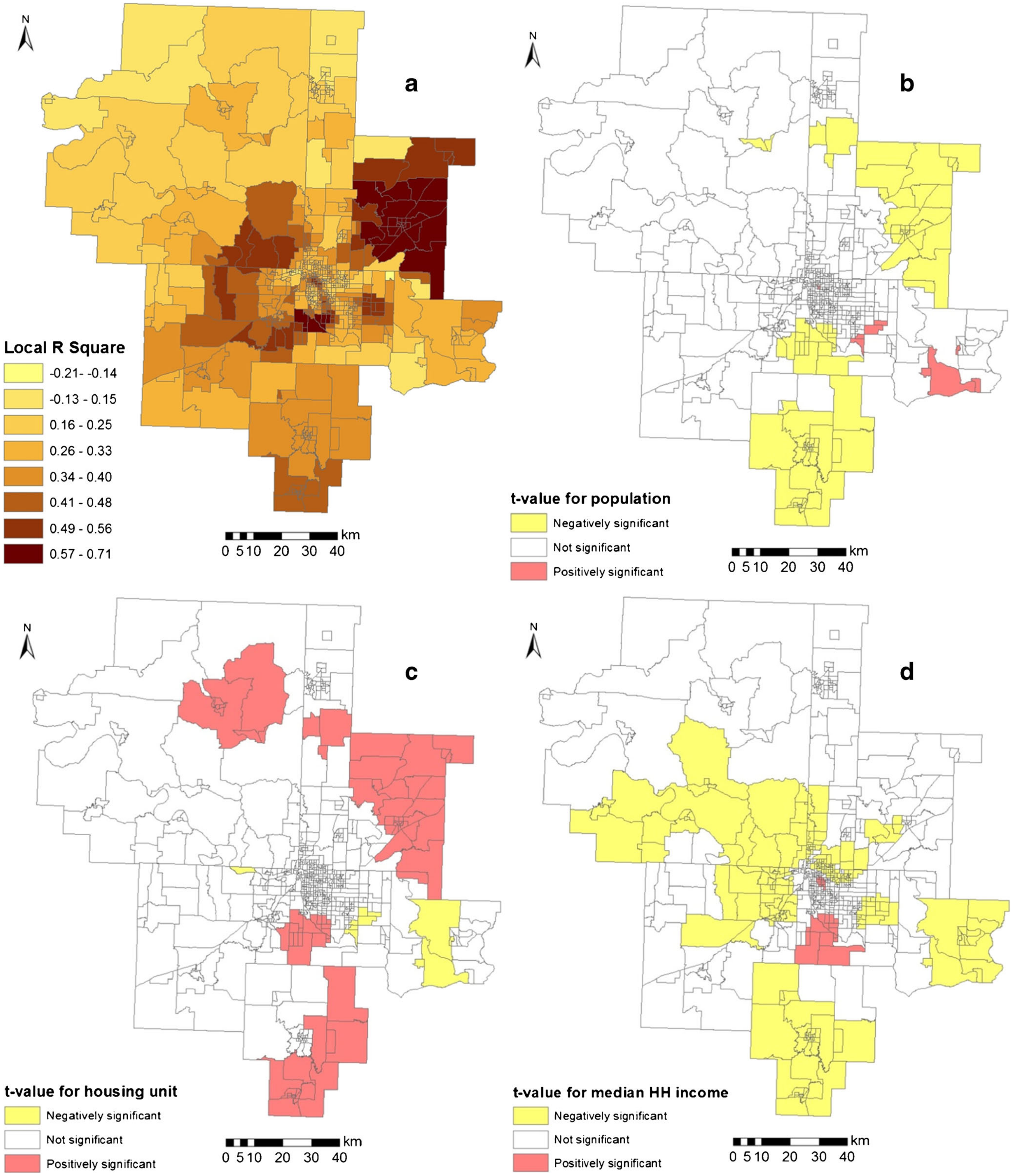

Fig. 7 GWR local R^2 for normalized entropy of residential land and t values for statistically significant proximate driver variables in 2000. t values significant at $p < 0.05$, *HH* household

tests suggested that median household income influenced between moderate and moderately high fragmentation in forested lands proximate to the City of Tulsa. Analysis of the LULC maps and transition matrix within these zones shows that forest was encroached upon for the development of new residential areas beyond 1990. Most of the block groups that demonstrated very low to minimal fragmentation in forested lands are low to moderately low-income areas outside major

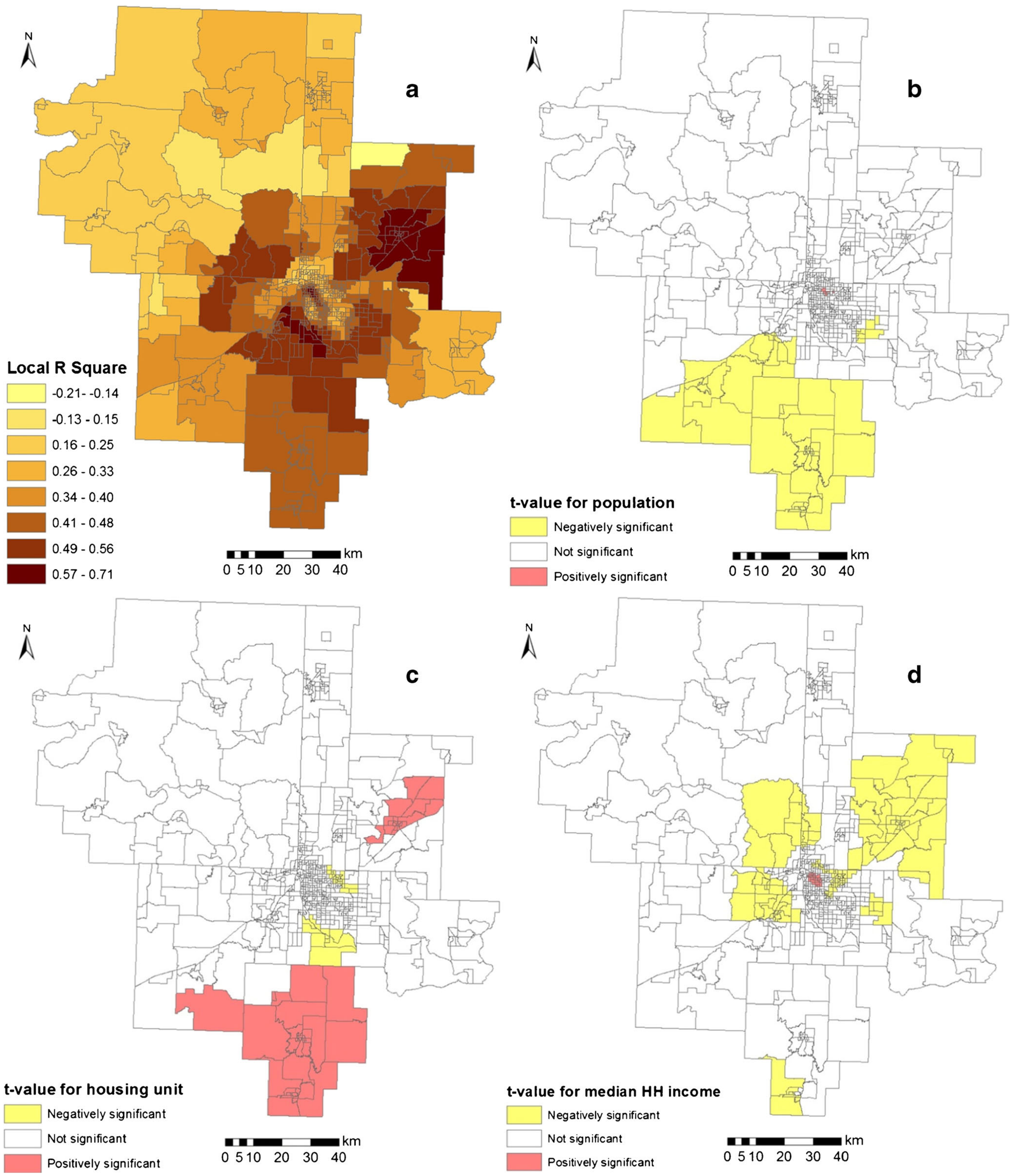

Fig. 8 GWR local R^2 for normalized entropy of residential land and *t* values for statistically significant proximate driver variables in 2010. *t* values significant at $p < 0.05$, *HH* household

cities with the exception of Claremore and Broken Arrow. Areas of low population outside the major cities demonstrated minimal influence on forest fragmentation while two low population clusters of block groups in north Tulsa County and central Wagoner County exerted greater influence on fragmentation of forested land. A closer examination of the LULC maps shows the development of sprawling satellite settlements in these areas. The influence of housing units on the NE of forested land displayed similar spatial patterns with that of population density.

GWR models for the NE and PC of agricultural lands demonstrated shifting dominant roles in the proximate drivers over time. While median household income was instrumental in conditioning the configuration of agricultural lands in 1990 and 2000, population density and housing units emerged stronger in 2010. Spatial analysis of pseudo t-tests indicated that median household income resulted in mainly low compactness but greater share of agricultural lands mostly outside but proximate to the City of Tulsa and in portions of Okmulgee County with low and few medium level income. Few high-income block groups south of the City of Tulsa contributed to very fragmented agricultural lands. Block groups generally of low to medium median income farther away from the City of Tulsa displayed a more compact but relatively lower share of agricultural lands per unit area. The spatial patterns exemplified by housing units on the NE of agricultural lands mirrored that of median household income. Population density contributed to low agricultural PC but a proportionally larger share of agricultural land per unit area farther away from the City of Tulsa, but the reverse was observed within block groups that are proximate to the City of Tulsa.

Spatial Patterns of Growth within Development Districts and Intensity Corridors

A pivotal component of the TMSA 1974 comprehensive plan is the achievement of balanced growth within development districts and intensity corridors. At the development district level of analysis, average PC for all LULC notably increased between 1990 and 2000 in most areas with the exception of those in central Tulsa County, an area occupied by the City of Tulsa, and its proximate cities in Creek and Okmulgee counties (Fig. 9a). At the intensity corridor level of inquiry, the trend in PC for all LULC between 1990 and 2000 showed the lowest increase in Tulsa and Washington Counties compared to the rest of the study area. Within Tulsa County, increase in PC was more striking in zone one which suggested that high-density development occurred closest to major highways. The spatial patterns of PC within intensity corridors of Washington County mirrored that of Tulsa County. The dynamic of PC within intensity corridors for the rest of the counties did not show much variation.

The spatial patterns of PC for all LULC between 2000 and 2010 demonstrated differential and a marked reduction in central Tulsa County. This suggests greater fragmentation partly comparable to the previous time-step of the study (Fig. 9b). When the intensity corridor is examined within this same period, it shows distinct reduction in PC in the first two zones within Tulsa and Washington counties and to a lesser extent in Wagoner County. This shows that development was further intensified within zones one and two resulting in increased fragmented land development.

Increase in NE for all LULC between 1990 and 2000 was palpable in development districts outside major cities while a similar but different level of magnitude was witnessed between 2000 and 2010 (Fig. 10). Analysis of multiple linear regression results at the county level suggested that sales and real output had a statistically significant relationship with PC of the amalgamated LULC in 1990 ($R^2 = 0.63$, $p < 0.05$) but not in subsequent periods. A similar model result was achieved for the NE of the amalgamated LULC wherein 60 % of model variance was explained by sales and real output in 1990 ($p < 0.05$). Real output tends to be the strongest underlying driver that contributed to increased fragmentation of LULC within these development districts in 1990. Model results for PC and NE for all LULC was not statistically significant beyond 1990.

Multiple linear regression results for the density of urban/built-up land demonstrated a statistically significant relationship with sales and construction cost in 2010 ($R^2 = 0.70$, $p < 0.05$) but not for the previous time-steps of the study. The model suggested that the influence of sales on the density of urban/built-up land in development districts is stronger than construction cost, which displayed a negative statistically significant relationship. The NE of residential LULC was positively influenced by sales in 1990 ($R^2 = 0.80$, $p < 0.05$) but not for subsequent time periods, even though the coefficients of determination were very similar. Spatial analysis of change in NE of residential LULC within development districts over the study period shows greater increase within districts to the south and east of Tulsa County between 2000 and 2010 compared with the previous time-step. Development districts that encapsulate other major cities in the TMSA demonstrated only marginal increase in NE of residential land over the entire study period with the exception of Claremore in Rogers County, which showed notable increase between 2000 and 2010. When changes in the NE of residential LULC were examined within intensity corridors, the intensity of increase tended to consistently reduce the father away from a highway for all but Rogers and Osage Counties. Rate of increase in NE of residential LULC within intensity corridors was more pronounced between 2000 and 2010 compared with the previous time-step. Tulsa and Washington counties demonstrated the greatest increase in NE of residential LULC within intensity corridors. Analysis of the trend of NE of industrial/commercial LULC between 1990 and 2000 shows that the latter developed significantly within the first two zones.

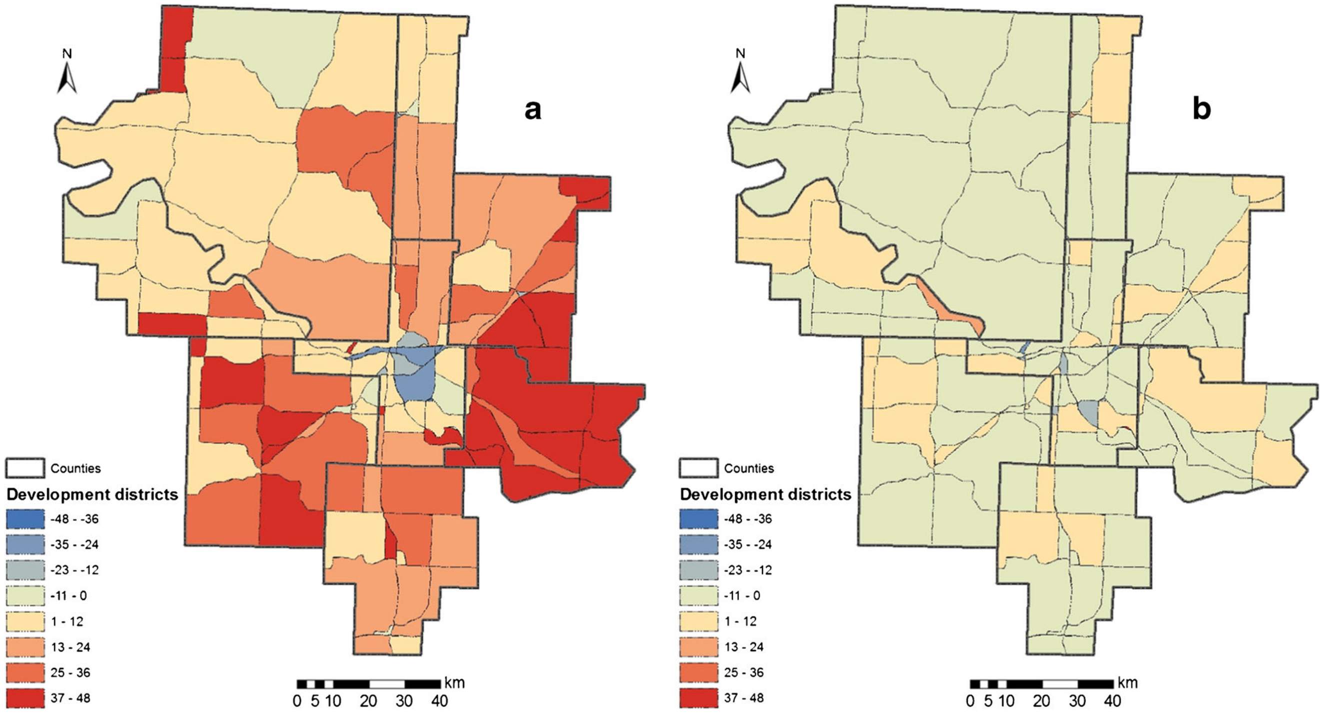

Fig. 9 Percentage change in patch compactness of all LULC for development districts, 1990–2000 (**a**) and 2000–2010 (**b**)

Discussion

Tulsa's MSA Balanced Growth Policy: a Space-Time Rejoinder

When compared with the spatial patterns of LULC displayed in the GIRAS data for the 1970s, the growth in urban landscape that occurred between 1974 and the periods of ex-post facto land use evaluation conducted in this study does not demonstrate an overall balanced growth in urban development. The proposed broad-based policy for equalized growth within development districts in the TMSA tend to be skewed towards the nerve centers and proximate locations of the City of Tulsa with the exception of Bartlesville in Washington County. This shows notable variation between plan objectives in the 1974 comprehensive plan of the region and outcomes of spatial patterns of development. In assessing the relationship between plan outcome and objectives for wetland development in Florida, Brody and Highfield (2005) observed significant deviations between plan objectives and outcomes in certain areas. Using the conformance-based approach for land use evaluation, Alterman and Hill (1978) reported 33 % conformity between planning objectives and outcomes and concluded that the plan had significant impact on land use outcome while political and economic forces are responsible for deviations between plan objectives and outcomes. In the TMSA, growth patterns within development districts for residential and industrial/commercial lands were found to be highly inconsistent with prescriptions outlined in the 1974 comprehensive plans of the region compared to the other LULC types examined in this study. This significant deviation between plan objectives and outcome for residential and industrial/commercial LULC can be partly ascribed to the intensification of sprawl, especially between 1990 and 2010, a phenomenon which is largely outside that envisioned for the region in the 1974 plan. Moreover, such an aberration from the balanced growth model can be primarily attributed to changing socioeconomic conditions. An upward mobility in the financial status of people in the City of Tulsa, especially during the period 1990 to 2000, triggered movement to suburban locations such as Sapulpa and Broken Arrow. The relocation is prompted by perceptions of better quality of life, better school districts, and lower crime rates in the suburbs. From a political standpoint, although the politicians recognized the economic forces stimulating sprawl, their lack of will to fight back those trends also contributed to further expansion of residential and industrial/commercial lands that are at variance to the balanced growth in urban development prescribed in the 1974 Comprehensive Plan (Senior Planning Officer, TMA, personal communications, August 8, 2015). The extension of roads and infrastructure also facilitated sprawl in the affected areas.

Within Tulsa County, high-density development in intensity corridors occurred as prescribed in the TMSA 1974 comprehensive plan. This spatial pattern was also observed in Washington County and to some extent in Wagoner County. Development patterns within intensity corridors in other counties were not as conspicuous as that exemplified by those

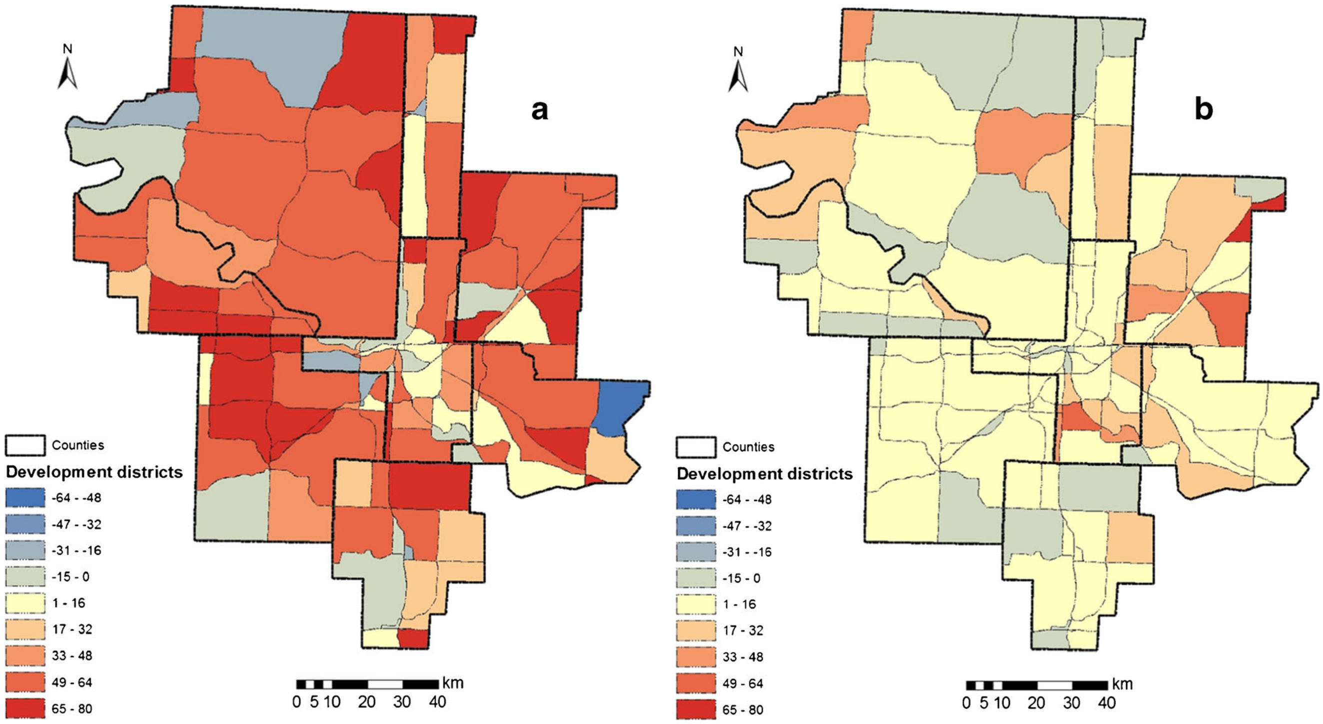

Fig. 10 Percentage change in normalized entropy of all LULC for development districts, 1990–2000 (**a**) and 2000–2010 (**b**)

three counties even though they illustrated intensification over time in the first two zones. This spatial pattern of development within intensity corridors is somewhat consistent with other studies even though the spatial scales are different. Gennaio *et al.* (2009) reported successful implementation of Switzerland's UGB plan over a 40-year period. In evaluating the influence of local urban plans and statewide growth management policies in the United States, Wassmer (2006) observed that most plans were successful in reducing urban sprawl although with different levels of success. Nelson and Moore (1996) found mixed results on the outcome of Oregon's urban growth management policies within and outside urban growth boundaries (UGBs). In appraising the efficacies of Oregon's land use plan on the preservation of forest and farm lands, Kline and Alig (1999) echoed some of the finding of Nelson and Moore (1996) by concluding that development has been mostly restricted within UGBs but some conversion of resource lands to developed lands outside the boundary is expected. From a plan evaluation perspective, the dynamics of LULC within the intensity corridors greatly conform to the objectives laid out in the 1974 plan.

Anthropogenic Driving Forces of Urban Growth in TMSA

This study shows that in the TMSA, the density of urban/built-up land is influenced mostly by population density, median household income, sales, construction cost, and to a lesser extent the number of housing units. Similar scenarios have been observed in other metropolitan areas. For example, Lo and Yang (2002) reported significant influence of per capita income and population growth on the expansion of the Atlanta Metropolitan Area (see also Deng *et al.* 2008; Wilson 2014, 2015). Population growth has been highlighted as instrumental in triggering the expansion of urban land (Thapa and Murayama 2010; Veldkamp and Fresco 1997). Seto *et al.* (2011) in a meta-analysis of global urban land expansion noted that population increase and growth in GDP per capita among other factors, are integral in urban LULC changes. Within the TMSA, areas with medium median household income contributed more towards sprawling growth of the urban area compared to low and high income areas especially from 2000 onwards. One would have expected infilling to occur in urban/built-up land rather than a sprawling type of development. Real output emerged as the strongest underlying driver that contributed to fragmentation of LULC in 1990; while sales played a greater role than construction cost on the density of urban/built-up land in subsequent periods. As construction cost increased, the density of urban/built-up land reduced.

In compartmentalizing the urban/built-up area into more distinct LULC types, median household income emerged as a fundamental driver shaping the structural integrity of residential lands within the TMSA. Block groups with high median household income displayed minimum fragmented and greater share of residential lands per unit area compared with low-income areas. However, few high-income areas slightly deviated from this trend pointing towards mixed use type of development. Mixed urban land use pattern is characteristic of some form of gentrification where average income is relatively moderate to high (Mckinnish *et al.* 2010). Areas of moderate to high income within cities are normally equipped with a larger number of amenities like parks and other paraphernalia, while disproportionately lower services are found in low income communities. A study by Talen and Anselin (1998) illustrated disproportionately lower urban public services in low-income areas within the City of Tulsa, Oklahoma. In areas of low population densities within the TMSA, residential lands were found to be more fragmented compared to highly populated centers (see also Irwin and Geoghegan 2001; Schneider and Woodcock 2008). Notwithstanding, Aguilera *et al.* (2011) reported contrasting results for Metropolitan Granada, Spain, where low-density populated residential areas were found to be more compact compared with high-density residential zones. These differences can be attributed to variations in land use planning and zoning between Granada and Tulsa.

Median household income is the most effective proximate driver that determines the configuration of industrial/commercial lands in the TMSA throughout the study period. Verburg *et al.* (2004) case study that distance to major cities determines land allocation for industrial/commercial use does not particularly resonate with the TMSA, where median household income appears more influential in the allocation and structural integrity of this LULC type. In general, low population centers outside the major cities exhibited more fragmented and less industrial/commercial lands per unit area compared with high population areas within the City of Tulsa. Median household income is also the strongest proximate driver determining the structural integrity and per unit area of forested lands in TMSA. Relatively high but non-alarming fragmented forest lands were found in some high-income block groups close to major cities compared to low income zones. Analysis of the LULC and transition maps within these zones shows that forest was encroached for the development of new residential areas. This rather peculiar finding can be ascribed to the massive unplanned growth triggered by sprawl, together with the lack of political will to combat it, as noted above. These new development areas became attractive because of lower crime rates, better school districts, and potential for upward social mobility. This is in contrast to the finding of Iverson and Cook (2000) that high-income areas within the Chicago Metropolitan Statistical Area displayed higher density of forest cover compared with low-income zones. Nevertheless, a plethora of studies have related the development of new residential areas to loss in forest cover within proximate zones of urban areas (Deng *et al.* 2008; Foresman *et al.* 1997; Lo and Yang 2002). In a related study, Wang and Moskovits (2001) reported that sprawl rather than population growth was responsible for forest and other vegetation loss in the Chicago Metropolitan Area between 1970 and 1990. However, DeFries *et al.* (2010) attributed forest cover loss to growth in urban population. Such differential findings might be attributed to variation in population dynamics between cities in developed versus developing countries. However, the role of population density on forest fragmentation in the TMSA is minimal compared with that of median household income.

Population density and median household income demonstrated significant associations with the structural integrity of agricultural lands in the TMSA over the study period. High population densities around major cities in the TMSA resulted in more compact but proportionally smaller areal distribution of agricultural land compared to areas farther away. This finding is partially similar to that observed in urban areas within Costa Rica where population pressures resulted in intensification of agricultural lands in cities (Veldkamp and Fresco 1997). Median household income resulted in low to moderately low disruption in the structural integrity of agricultural lands mostly outside but in proximate distance of the City of Tulsa and in portions of Okmulgee County characterized by mostly low and few medium level incomes.

By 2000 the influence of median household income on agricultural land fragmentation was more pronounced compared with the other study periods. A number of studies have reported the negative influence of urban growth on peri-urban agricultural lands (Long *et al.* 2008; Seto and kaufmann 2003; Tan *et al.* 2005). The analysis shows that despite the transformation of agricultural lands to non-agricultural uses, fragmentation of agricultural land is not alarming in the TMSA.

Conclusion

The study reveals that the spatial and temporal growth patterns within development districts mostly deviated from that envisioned in the TMSA 1974 comprehensive plan. At the intensity corridor scale of analysis, the spatiotemporal patterns of development largely mirrored that proposed in the 1974 comprehensive plan of the region. Deviations between plan objectives and outcomes within development districts can be predominantly attributed to financial upward mobility of residents, market growth, and the lack of political will to forestall urban sprawl. We have shown that in the future, additional efforts should be directed in achieving plan objectives at the development district or similar levels rather than within intensity corridors. Our results further demonstrate how remote sensing, GIS, and spatial statistical modeling techniques can provide adequate spatial information in monitoring and evaluating urban LULC dynamics within a metropolitan area. Our study shows that the TMSA witnessed significant changes in both LULC spatial extent and the structural characteristics of the landscape. Analysis of LULC trajectory shows that the urban/built-up land continually increased over the 21-year period with residential and industrial/commercial lands accounting for most of that growth, while forest and agricultural

LULC exemplified a reverse. Median household income, population density, sales and construction cost are the major drivers that condition the structural integrity of LULC within the TMSA. Sales and median household income are the two prominent underlying and proximate drivers respectively that accounted for most of the spatiotemporal patterns of LULC observed in the TMSA.

The most important contribution of this study is the integration of remote sensing, GIS, and spatial statistical modeling in understanding the major drivers of urban growth and more importantly in applying these modeling techniques in the ex-post facto evaluation of land use plans. The study also illustrates that this type of methodological approach can aid in filling some of the current methodological hiatus in evaluating land use comprehensive plans. The modeling framework we adopted in this study should be applicable to other metropolitan areas. It will be interesting to integrate other plan objectives if spatially quantifiable when conducting an ex-post facto land use plan evaluation within a geospatial modeling framework for a full understanding of the relationship between plan objectives and outcomes.

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Compliance with Ethical Standards

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Conflict of Interest The authors declare that they have no conflict of interest.

Human and Animal Rights This research does not involve human participants and/or animals.

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