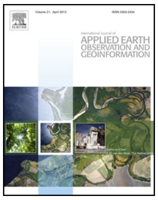
International Journal of Applied Earth Observation and Geoinformation 35 (2015) 161–174

Contents lists available at ScienceDirect

International Journal of Applied Earth Observation and Geoinformation

journal homepage: www.elsevier.com/locate/jag



Drivers of land cover and land use changes in St. Louis metropolitan area over the past 40 years characterized by remote sensing and census population data

Maitiniyazi Maimaitijiang[a,c], Abduwasit Ghulam[a,*], J.S. Onésimo Sandoval[b], Matthew Maimaitiyiming[a]

[a] Center for Sustainability, Saint Louis University, St. Louis, MO 63108, USA
[b] Department of Sociology and Anthropology, Saint Louis University, St. Louis, MO 63108, USA
[c] College of Management, Xinjiang Agricultural University, Urumqi, Xinjiang 830052, China

ARTICLE INFO

Article history:
Received 3 April 2014
Accepted 26 August 2014
Available online 29 September 2014

Keywords:
Urban growth
Land cover and land use
Geographically weighted regression

ABSTRACT

In this study, we explored the spatial and temporal patterns of land cover and land use (LCLU) and population change dynamics in the St. Louis Metropolitan Statistical Area. The goal of this paper was to quantify the drivers of LCLU using long-term Landsat data from 1972 to 2010. First, we produced LCLU maps by using Landsat images from 1972, 1982, 1990, 2000, and 2010. Next, tract level population data of 1970, 1980, 1990, 2000, and 2010 were converted to 1-km square grid cells. Then, the LCLU maps were integrated with basic grid cell data to represent the proportion of each land cover category within a grid cell area. Finally, the proportional land cover maps and population census data were combined to investigate the relationship between land cover and population change based on grid cells using Pearson's correlation coefficient, ordinary least square (OLS), and local level geographically weighted regression (GWR). Land cover changes in terms of the percentage of area affected and rates of change were compared with population census data with a focus on the analysis of the spatial-temporal dynamics of urban growth patterns. The correlation coefficients of land cover categories and population changes were calculated for two decadal intervals between 1970 and 2010. Our results showed a causal relationship between LCLU changes and population dynamics over the last 40 years. Urban sprawl was positively correlated with population change. However, the relationship was not linear over space and time. Spatial heterogeneity and variations in the relationship demonstrate that urban sprawl was positively correlated with population changes in suburban area and negatively correlated in urban core and inner suburban area of the St. Louis Metropolitan Statistical Area. These results suggest that the imagery reflects processes of urban growth, inner-city decline, population migration, and social spatial inequality. The implications provide guidance for sustainable urban planning and development. We also demonstrate that grid cells allow robust synthesis of remote sensing and socioeconomic data to advance our knowledge of urban growth dynamics from both spatial and temporal scales and its association with population change.

Introduction

With the growth of urbanization around the world, today, more than half of the world's population lives in urban regions, and this trend is projected to continue in the future decades (United Nations, 2014). Land cover and land use change (LCLUC) with urban growth is a global issue with paramount socioeconomic and environmental implications (Bhatta et al., 2010; De Freitas et al., 2013; Lopez et al., 2001; Xian and Crane, 2005). For example, LCLUC leads to a number of environmental problems including water quality degradation, air pollution, loss of biodiversity, urban heat island effects, social-economic disparities, social fragmentation, and infrastructure costs (Arnfield, 2003; Kalnay and Cai, 2003; Squires et al., 2002; Xian and Crane, 2005, 2006).

Post-industrial US cities have been experiencing urban sprawl growth spreading out over rural land at the periphery of urban area, while the population in the urban core is shrinking (Frumkin, 2002; Hasse and Lathrop, 2003). The St. Louis Metropolitan Statistical Area (STL) is an excellent example of urban sprawl where poverty, crime, and racial segregation are concentrated in inner city, while wealth

---

* Corresponding author. Tel.: +1 314 977 5156.
E-mail address: awulamu@slu.edu (A. Ghulam).

http://dx.doi.org/10.1016/j.jag.2014.08.020
0303-2434/

and environmentally rich resources are located in the suburban areas. The St. Louis City once was an industrial powerhouse of the Midwestern US with the 4th largest population in the nation in 1904. It has been undergoing urban sprawl with a shrinking urban core over the last several decades (Gordon, 2008).

Remote sensing, spatial statistics, and geo-informatics provide powerful tools to study urban environments (Griffiths et al., 2010; Sutton, 2003; Yang et al., 2003), urban growth modeling (Herold et al., 2003; Jat et al., 2008; Poelmans and Van Rompaey, 2009), and projecting socio-economical, environmental, and ecological effects of urban development (Gillies et al., 2003; Squires et al., 2002; Tu, 2013; Xian and Crane, 2006). Urban growth is a synthetic process, which includes not only biophysical change but also socioeconomic change (Lambin et al., 2003; Martinuzzi et al., 2007; Radeloff et al., 2000). Socioeconomic aspects are critical to further understand urban growth process and temporal and spatial patterns (Bagan and Yamagata, 2012; Banzhaf et al., 2013; De Freitas et al., 2013). Numerous studies have examined the relationship between LCLUC and socioeconomic data over the last two decades. Most of these studies were limited to regional scale socioeconomic data summarized for the metropolitan statistical area, city, or county level (Alperovich and Deutsch, 1992; Berry, 1990; Fox, 2003; Ma et al., 2008), which was unable to reveal the detailed spatial characteristics of LCLUC and socioeconomic factors. As these datasets became publicly available in recent years, census tract scale was also explored (De Freitas et al., 2013; Lo and Yang, 2002; Ryznar and Wagner, 2001; Xiao et al., 2006). However, many census tracts boundaries were not stable from the time period of study (Gallego, 2010; Martin, 1996; Small et al., 2011) and may not be suited for temporal statistical (Verburg et al., 2008). Most of these previous studies utilized global level statistical tools such as Pearson's correlation coefficient or Ordinary Least Square (OLS) to illustrate the relationship between LCLUC and socioeconomic data (Bagan and Yamagata, 2012; Lo and Yang, 2002). In fact, these statistical methods are based on two basic assumptions: (1) model residuals are uncorrelated with each other (no spatial autocorrelation) and (2) there is constant variance (homoscedasticity) (Fotheringham et al., 2003; Hamilton and Press, 1992). However, natural, social, and anthropogenic characteristics are not constant over space (Fortin, 1999; Tu, 2013), and some magnitude of spatial autocorrelation often are present in these data (De Freitas et al., 2013). Spatial autocorrelation has several implications for statistical inference testing (Fortin and Dale, 2009). For example, the presence of spatial autocorrelation in one or both variables may violate the assumption of independence among samples and thereby inflate the degrees of freedom in the traditional test of significance of a Pearson's correlation coefficient (Fortin and Payette, 2002). The efficiency of OLS would be reduced and the interpreted results would be misleading because of the existence of spatial autocorrelation (Bellehumeur and Legendre, 1998). In addition, global level statistics lack the ability to reveal and the varying relationships over space (Tu and Xia, 2008). For these reasons, geographically weighted regression (GWR), which is capable of capturing the spatial heterogeneity and variations in the relationships and account for spatial autocorrelation, has been suggested (Fotheringham et al., 2003).

The goal of this study was to identify the drivers of LCLUC in the STL region over the last 40 years by integrating remote sensing derived land use data with socioeconomic data. LCLU and census tract data were converted to 1-km grid cells. Global level and local level statistical approaches were employed to reveal the past and present patterns and processes and trends of urban growth. This paper contributes to our knowledge of urban developments in post-industrial US cities with comparative analysis of the role of various statistical tools on LCLUC studies. Other climate and environmental factors such as temperature and precipitation changes may influence LCLUC, but these factors were outside of the scope of this contribution. Climate change and its impacts on land use dynamics were discussed in recent publications (Jordan et al., 2012, 2014).

Study area and data

Study area

The St. Louis Metropolitan Statistical area is located at the junction of Missouri and Illinois and at the intersection area of the Missouri and Mississippi Rivers. In this study, we chose the East-West gateway region as our study area, which includes St. Louis City, St. Louis County, St. Charles County, Franklin County and Jefferson County for the Missouri part of the region and Madison County, St. Clair County and Monroe County for the Illinois part of the region (Fig. 1). The total area of this region is approximately 11,892 km^2, and much of the area is a fertile and gently rolling prairie that features low hills and broad, shallow valleys. The elevation of surface topography ranges from 68 m at Chester to 530 m at the hilly area of the south-west St. Louis County. It includes a diversity of land cover classes in the area such as forest, agriculture, and pasture and urban (Jordan et al., 2012). The climate of this region is continental type with distinct alteration of seasons characterized by wide ranges in temperature, and irregular annual and seasonal precipitation (NWS, 2014).

Data

Land use data

The Landsat program is significant in studying the earth's surface and associated change process (Cohen and Goward, 2004). We collected 17 Landsat MSS and TM images to generate LCLU maps for the study area from five separate dates (four MSS images for 1972 and 1982 respectively, three TM images for 1990, 2000, and 2010, respectively). Table 1 provides the detailed information about the images. These images were selected from relatively cloud-free acquisitions (<10%) and during the growing season. In addition, the time series of Landsat data were selected corresponding to the decadal census data (Banzhaf et al., 2013).

All Landsat images were geometrically rectified using ground control points (GCPs) from high resolution images to a common map reference system (UTM map projection Zoon 15 North, GCS_North_American_1983 Datum). The GCPs were dispersed throughout each scene and the registration accuracy was less than 0.5 pixels. Radiometric "bad" pixels on 1972 Landsat MSS images were identified visually and removed by on screen digitizing. Atmospheric correction was carried out using Quick Atmospheric Correction (QUAC) available with ENVI® image processing and analysis software from EXELIS Visual Information Solutions. The goal of atmospheric correction was to adjust the multi-temporal dataset to a common radiometric scale (Song et al., 2001).

Aerial photos, National Land Cover Dataset (NLCD) of 1992 and 2001 from United States Geological Survey, St. Louis Metropolitan Statistical Area LCLU data for 2010 ("Current Vegetation 2010") from Missouri Resource Assessment Partnership (MoRAP) and East-West Gateway Council of Governments were used to collect training samples and validate classification results.

Socioeconomic data

Socioeconomic data (i.e., population, race, and housing units) were obtained from US Census Bureau, Social Explorer Demographic Data center, and LTDB (Longitudinal Tract Data Base) of the US2010 project (http://www.s4.brown.edu/us2010/Researcher/Bridging.htm). US Census TIGER Products and National Historical Geographical Information System (NHGIS) shapefiles were joined with socioeconomic data.