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Spatiotemporal variability of urban growth factors: A global and local perspective on the megacity of Mumbai

Hossein Shafizadeh-Moghadam[a,b,*], Marco Helbich[a,c,1]

[a] Institute of Geography, University of Heidelberg, Germany
[b] Tarbiat Modares University, Department of GIS and Remote Sensing, Tehran, Iran
[c] Department of Human Geography and Spatial Planning, Utrecht University, Netherlands

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ABSTRACT

The rapid growth of megacities requires special attention among urban planners worldwide, and particularly in Mumbai, India, where growth is very pronounced. To cope with the planning challenges this will bring, developing a retrospective understanding of urban land-use dynamics and the underlying driving-forces behind urban growth is a key prerequisite. This research uses regression-based land-use change models – and in particular non-spatial logistic regression models (LR) and auto-logistic regression models (ALR) – for the Mumbai region over the period 1973–2010, in order to determine the drivers behind spatiotemporal urban expansion. Both global models are complemented by a local, spatial model, the so-called geographically weighted logistic regression (GWLR) model, one that explicitly permits variations in driving-forces across space. The study comes to two main conclusions. First, both global models suggest similar driving-forces behind urban growth over time, revealing that LRs and ALRs result in estimated coefficients with comparable magnitudes. Second, all the local coefficients show distinctive temporal and spatial variations. It is therefore concluded that GWLR aids our understanding of urban growth processes, and so can assist context-related planning and policymaking activities when seeking to secure a sustainable urban future.

Introduction

Over the past few decades, urban expansion in India, mainly driven by globalization, privatization and liberalization, has resulted in rapid economic, social and environmental change taking place in the country (Van Ginkel, 2008; Tv et al., 2012). Excessive and uncoordinated urban growth has led to a loss of agricultural and forest land, as well as environmental resources, and has led to irreversible land-use conversion (e.g., Bhatta, 2009; Kumar et al., 2011; Punia and Singh, 2012; Munshi et al., 2014). Such rapid urban growth is of particular concern within the megacity[2] of Mumbai. Shafizadeh Moghadam and Helbich (2013) report that Mumbai experienced a 40% decrease in arable and open land in favor of built-up areas between 1973 and 2010. Moreover, additional and unbalanced urban growth is predicted to occur up to 2030, which will put a severe strain on sanitation services and basic infrastructure (e.g., public transportation systems and sewers), and lead to environmental damage and increasing social tensions. In this respect, Van Ginkel (2008) has highlighted how ill-prepared policymakers are for dealing with the outcomes related to this increase of urban living. As a consequence, Mumbai's policymakers face challenges with regard to land-use management, governance and urban planning. A crucial prerequisite for formulating sustainable future planning strategies and policies is to understand the past spatial developments of physical urban structures and the driving-forces behind urban growth (Cheng, 2011; Jokar Arsanjani et al., 2013a; Patino and Duque, 2013), as doing so can support the development of purposeful and goal-oriented planning strategies (Pethe et al., 2014).

Land-use change models (Verburg et al., 2004) based on geospatial technologies, multi-temporal remote sensing and spatial analysis, have proven to be valuable, efficient and technologically sound ways to analyze land conversion activities across space and over time. As well as being able to monitor urban growth (e.g., Bhatta, 2009; Kumar et al., 2011; Basawaraja et al., 2011;

* Corresponding author at: Berliner Straße 48, D-69120 Heidelberg, Germany. Tel.: +49 6221 54 4370.
E-mail addresses: shafeezadeh@uni-heidelberg.de, Hossein.shafeezadeh@geog.uni-heidelberg.de (H. Shafizadeh-Moghadam), m.helbich@uu.nl (M. Helbich).
1 Heidelberglaan 2, 3584 CS Utrecht, Netherlands.
2 According to the United Nations (2012), the term 'megacity' refers to an urban area with more than 10 million inhabitants.

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Taubenböck et al., 2012), a key advantage of land-use change models is their ability to determine and quantify the driving-forces behind spatiotemporal land-use transitions (e.g., Poelmans and Van Rompaey, 2010; Jokar Arsanjani et al., 2013a; Tayyebi and Pijanowski, 2014). Verburg et al. (2004) split these driving-forces into five categories: (a) environmental characteristics, (b) social factors, (c) economic factors, (d) spatial policies, and (e) spatial neighborhood interactions. Neighborhood variables link urban growth models to economic theories (e.g., the core-periphery model by Krugman, 1991, cited in Dendoncker et al., 2007). In spite of the large number of possible drivers, the majority of empirical studies operationalize environmental (e.g., distance to transportation infrastructures) and, if available, socio-economic determinants (e.g., household incomes), in order to explain urban growth processes (e.g., Hu and Lo, 2007; Poelmans and Van Rompaey, 2010; Cheng, 2011).

A wide-range of advanced methods have been developed to analyze urban expansion processes (Jokar Arsanjani et al., 2014), and these can be divided into descriptive approaches, simulation-based models and statistical urban growth models. Descriptive approaches aim to quantify spatiotemporal urban patterns by means of spatial landscape matrices. For example, Tv et al. (2012) and Punia and Singh (2012) describe the shape, "clumpiness" and "patchiness" of urban growth patterns over time. In contrast to landscape matrices, cellular automata (CA) models focus on the prediction of future urban extents rather than on the characterization of urban patterns (Aljoufie et al., 2013; Jokar Arsanjani et al., 2013a). These bottom-up, cell-based approaches use site-specific rules to simulate urban dynamics over discrete time steps. While both approaches have contributed substantially to our knowledge of urban growth processes, they lack the ability to determine the underlying driving-forces behind such growth (Cheng and Masser, 2003), so instead regression models (e.g., Dubovyk et al., 2011), support vector machines (e.g., Huang et al., 2009), and artificial neural networks (ANN; e.g., Chu et al., 2013) are commonly applied for that purpose. However, the majority of studies have applied non-spatial logistic regression (LR) models (McCullagh and Nelder, 1989) to explain complex urban growth patterns, using a set of predictors (e.g., Hu and Lo, 2007; Poelmans and Van Rompaey, 2010; Dubovyk et al., 2011). While Cheng and Masser (2003) focus on the effectiveness of LR at being able to determine driving-forces, and stress its extensive explanatory power, Hu and Lo (2007) emphasize the multi-scale calibration abilities of LR; so reducing the computational burden. In comparison to the large number of LR applications in existence, spatial autocorrelation (SAC) has received relatively little attention (Dendoncker et al., 2007), and even less research has sought to spatially varying relationships. SAC refers to the coincidence between locational and attribute similarities (Anselin, 2009), the presence of which denotes that non-built-up areas adjacent to existing built-up areas are more likely to themselves become built-up than those areas further away. As SAC violates model assumptions, the parameters estimated may not be reliable (e.g., Augustin et al., 1996; Anselin, 2009).

To account for SAC, spatial sampling can be used, which causes a significant loss of information and makes parameter estimations less reliable (Cheng and Masser, 2003). Alternatively, a spatially explicit model like autologistic regression (ALR) can be applied (Augustin et al., 1996; Huang et al., 2009). ALR assumes that an autocovariate term absorbs SAC and that parts of the variance can be explained through neighborhood effects, by relating a cell's transition to its surroundings (Overmars et al., 2003). While Lin et al. (2011) report a higher level of accuracy for ALR when compared to LR, Dendoncker et al. (2007) highlight the efficiency of ALR when accounting for SAC. In contrast, Dormann (2007) shows that ALR tends to underestimate the true model parameters when compared to aspatial LR, and recommends coupling ALR with alternative models. More recently, Lin et al. (2011) tested the predictive accuracy of LR, ALR and ANN, finding that both the ALR and ANN models perform better than LR, while the difference between ALR and ANN is marginal. In addition, regression-based techniques are easier to interpret than ANNs, which require additional algorithms to be used to derive a variable's importance (Hagenauer and Helbich, 2012).

Despite the fact that ALR appeals for use with land-use modeling, it assumes that a single equation represents land-use transitions and, thus, disregards local variations as potential driving-forces behind spatial characteristics (e.g., Fotheringham et al., 2002). Such a global perspective is too simplistic for Mumbai, and tends to over generalize growth, resulting in invalid policies on a local level. Therefore, it is rational to explore the spatial variability of the driving-forces using geographically weighted logistic regression (GWLR; Brunsdon et al., 1996; Atkinson et al., 2003). When compared to LR and ALR, GWLR has received less attention within urban growth modeling circles, even though the approach examines local land-use conditions based on the spatial variation of drivers (Luo and Wei, 2009), while simultaneously reducing SAC and having appealing visualization capacities for policy-oriented research (Ogneva-Himmelberger et al., 2009).

To conclude, global non-spatial and spatial regression models currently dominate land-use modeling. In this respect, the main objective of this research is to investigate local urban growth drivers of growth in Mumbai. The city's rapid urban expansion makes it an excellent case study for exploring and retrospectively cross-comparing urban growth drivers over the periods 1973–1990, 1990–2001 and 2001–2010. The following questions will be addressed:

- What are the main driving-forces behind Mumbai's urban land-use transition?
- Have these driving-forces been constant over different time periods and across space?
- Does the GWLR model out-perform the global non-spatial LR and spatial ALR models?

Materials

Study area

As the country's commercial and financial center, Mumbai represents one of India's key megacities. The city lies in the state of Maharashtra and is located on the west coast, next to the Arabian Sea (Fig. 1). Mumbai covers an area of 430 km^2 and can be characterized as a poly-nuclear region with emerging sub-centers (Pacione, 2006).

Between 1971 and 2011, Mumbai's population increased steadily, from approximately 5,971,000 to more than 12,478,000 inhabitants. The United Nations (2012) has predicted that the population will continue to increase to 27 million inhabitants by 2025. This growth in population has been accompanied by a massive growth in the number of condominiums and office towers, shopping malls and multiplexes being built, as well as motorways. These large investments have polarized Mumbai; it is becoming both an emerging global city and a place full of informal settlements – a predominant part of the urban landscape (Pethe et al., 2014).

Data and pre-processing

As the world's oldest data archive – available free of charge to users and constantly being updated – Landsat imagery offers efficient mid-resolution remote sensing products, those which can be