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Urban driving forces and megacity expansion threats. Study case in the Mexico City periphery

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A B S T R A C T

The megacity proximity produces significant stress in the surrounding areas with fast changes in land conversion, mainly in the urban sprawl growth. The swiftness facilitates studies about land use changes to urban in short-term. The principal boosting urbanization factors, either socioeconomic or physical geographical, are usually identified as the driving forces (DF) to be considered in the regional planning programs and prospective urbanization modeling.

The land-use-change-to-urban (LUCU) phenomenon was studied by Landsat images along the 2000–2014 period in the Northern periphery of Mexico Megacity. The study case was delimited in the Pachuca-Tizayuca Valley, Hidalgo State. Municipalities and the whole area showed high annual urbanization growth rates (2.89%–4.14%) and 3.39%, respectively. The urban area's increase in each unit allowed calculation of three dependent variables as LUCU quantitative descriptors, which were further applied in three statistical approaches. In the first one, multivariate Ordinary Least Squares (OLS) was performed to evaluate the correlation coefficient (R) and the sensitivity factor (β) for the urbanization rate (δ_{14}) vs. each socioeconomic or physical factor. In the second one, the urbanization ratio ($U_{R_{14}}$) vs. independent variables mean values were used in spatial OLS and Geographically Weighted Regression (GWR) analysis. Finally, the third approach applied Cramer's V test based on the number of pixels converted to urban (PUc_{14}) as LUCU descriptor and all independent variables. Cramer test allowed the best factors' analyses, while not all fitted the OLS and GWR requirements. The whole process leads to a methodologic pathway to identify land change DFs to urban use.

The study case acknowledged the following main DF to urbanization: the welfare; the population growth rate; the population proportions of immigrants, scholar age, workers in second and third economic sector; and the distances to quarry stones, schools, urban areas and roads. Cramer's V reach 70.5 accuracy values in the urbanization modeling with the mentioned DFs by the Multi-Layer Perceptron of the Land Change Modeler (Idrisi). The spatial urban area increase in the 2029 year was predicted based on these DFs.

1. Introduction

Outcomes predictions in the human world are highly uncertain. Nevertheless, there are many approaches to do that, because the policy needs for the strategic foresight to adjust actions or make preventive plans (CONAPO, 2010a). Megacity nearness produces quick changes in surrounding areas. A useful methodology to describe, predict and prevent them is one, based on detecting the primary driving forces (DFs) which cause social, economic, environmental, health, and other effects (Bishop, Hines, & Collins, 2007).

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1.1. Driving forces associated with change to urban land (CUL)

Urbanization DFs are those that produce any change or influence the landscape processes (Bürgi, Hersperger, & Schneeberger, 2004) They can be classified in two factors: human and natural factors, (Hersperger, Gennaio, Verburg, & Bürgi, 2010). DF frameworks to study transitions on land use change in a period, and its causes (Álvarez Martínez, Suárez-Seoane, De, & Luis Calabuig, 2011).

DF's analysis can be spatially explicit or non-spatial (Seto & Kauffmann, 2003). Reports usually assess the impact of DFs conducting to a particular final use; such as urban growth (Shu, Zhang, Li, Qu, & Chen, 2014). Table 1 displays some state-of-the-art drivers described for land use change and accurately, for the transitions to urban (LUCU). Scientists explore the most representative modeling variables that trigger LUCU; such as population growth, altitude, and distances to roads, water bodies, and localities.

Reviewed methods of DF assessment about urbanization trends evaluate correlations between the quantified transformed area and some explanatory variables. The non-spatial statistical methods usually consider socioeconomic information obtained from surveys published by governments, which are databases with different levels of geography disaggregation (López, Bocco, Mendoza, Velázquez, & Rogelio Aguirre-Rivera, 2006; Newman, McLaren, & Wilson, 2014).

The spatial assessment process usually considers raster files which include geographic and socioeconomic data. The most common approaches are based on linear or logistic regressions (Serra, Pons, & Saurí, 2008; Shu et al., 2014) and automata cellular models (Burinskiene & Rudzkiene, 2009; Guan et al., 2011).

Both frameworks are valuable, non-spatial is effective describing a general trend, and spatial data is useful describing the regional importance of variables and its correlations with changed land.

The DF analysis for land use change is a valuable tool for territorial planning (Long, Tang, Li, & Heilig, 2007); and to understand processes related to urban land system dynamics (Qasim, Hubacek, & Termansen, 2013). Few studies combine physical-geographic and socioeconomic data to find the main DFs that better simulate land use changes (Guan et al., 2011).

More research is required, mostly in developing countries, and at smaller scales. It has been demonstrated that the unit analysis size plays a significant role in detecting DFs for land use change (Du, Wang, & Guo, 2014). Also, there is a rapid and uncontrolled urban growth reported for cities in all the world. However, in emerging countries, data is frequently unavailable or untrustworthy; therefore, innovative socioeconomic, environmental and physical ways are scientific challenges to assessing land-use-change to-urban-drivers.

Latin-American cities growth have been thoroughly analyzed on the socioeconomic basis by several authors. Some reports are The influence of high-tech industry and universities in Sao Paulo (Lencioni, 2011; Sposito & Jurado-da Silva, 2014); politics and inequity in Buenos Aires (Ciccolella, 2012); the compilation of social outlook related to governments in Santiago, Buenos Aires and Mexico City (Hidalgo and Janochka, 2014); Los Angeles and Chillan in Chile (Henríquez, Azocar, & Romero, 2006); San Luis Potosi (Rivera-Gonzalez, 2009), peri-urbanization, politics and sustainability in Guadalajara, Monterrey and Puebla-Tlaxcala and Mexico (Arroyo and Corvera, 2011); poverty in the Central Mexico Valley (Vieyra and Escamilla, 2004).

In Mexico, Geographic Informational Systems (GIS) has been reported in limited land-use change to urban studies. Nevertheless, socioeconomic data has used mainly in choropleths and continuous raster data (Burinskiene & Rudzkiene, 2009; García-Frapolli, Ayala-Orozco, Bonilla-Moheno, Espadas-Manrique, & Ramos-Fernández, 2007; Inouye, de Sousa, de Freitas, & Simões, 2015; López, Bocco, Mendoza, & Duhau, 2001; Pérez-Vega, Mas, & Ligmann-Zielinska, 2012; Pineda Jaimes, Bosque-Sendra, Gómez Delgado, & Franco Plata, 2010).

Land use change in megacities context is particularly interesting because urbanization has an enormous ecological footprint, due to the massive goods consumptions associated with the intense anthropogenic activities, their significant Greenhouse Gas (GHG) emissions (Ali et al., 2012) and ecosystem degradation effects (Mendoza-González, Martínez, Lithgow, Pérez-Maqueo, & Simonin, 2012).

Land use/land cover is primarily associated with anthropogenic activities and population dynamics (Dihkan, Karsli, Guneroglu & Guneroglu, 2015), and also strongly determined by geographic conditions. However, in each megacity and its peripheral cities, urbanization DF are different (Kuang, Chi, Lu, & Dou, 2014).

Megacities are those metropolitan areas having more than 10 million people. Mexico City reached this magnitude since 1975 (Sorensen & Okata, 2010), and it exceeds 18 million (INEGI, 2010)

Table 1
Previously reported driving forces.

Driving forces for urban land use	Reported/Applied by	Exploration methods
Territorial policies, market, economic development, planning on development, population, Gross domestic product (GDP), industrial production value.	(Kuang, Liu, Dong, Chi, & Zhang, 2016)**	Exploratory data analysis and correlation matrix. (Non-Spatial)
GDP, urban land rent, urban wages.	(Jiang, Deng, & Seto, 2012)**	Multi-level model. (Non-Spatial)
Population age, car ownership, settlement rurality.	(Mann, 2009)**	Exploratory data analysis.(Non-Spatial)
Population change.	(Maimaitijiang, Ghulam, Sandoval, & Maimaitiyiming, 2015)**	Geographically weighted regression (GWR) (Spatially explicit)
Cost distance, income, infrastructure.	(Ghosh & Manson, 2008)**	GWR
Distance to geologic formations.	(Álvarez Martínez et al., 2011)*	Binary logistic regression (Non-Spatial)
GDP, land price, elevation, population density, distance to nearest river.	(Guan et al, 2011)**	Markov and cellular automata integrated evaluation model (Spatially explicit)
Population and employment	(Burinskiene & Rudzkiene, 2009)**	Cellular automata modified method. (Spatially explicit)
Technology in agriculture.	(Qasim et al., 2013)*	Exploratory data analysis (Non-spatial).
Diversity, landscape fragmentation.	(Serra et al., 2008)*	Spatial logistic multiple regression model (Spatially explicit)
Ecological sensitivity, prime to croplands, distance to town centers, neighbourhood factors	(Shu et al., 2014)**	Spatial logistic multiple regression model
Population income, industrialization, population features, economic measures.	(Long et al., 2007)**	Exploratory data analysis and correlation matrix. (Non-spatial)
	(Fukushima, Takahashi, Matsushita, & Okanishi, 2007)	Bivariate analysis (Spatially explicit) (Fukushima et al., 2007)

*Study about general land use change ** Study about CUL.