

Enhanced cellular automata model for the simulation of electricity demand at the urban scale Study case: Guadalajara, Mexico

Anahi Molar-Cruz, Thomas Hamacher

Technical University of Munich

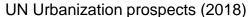
Chair of Renewable and Sustainable Energy Systems

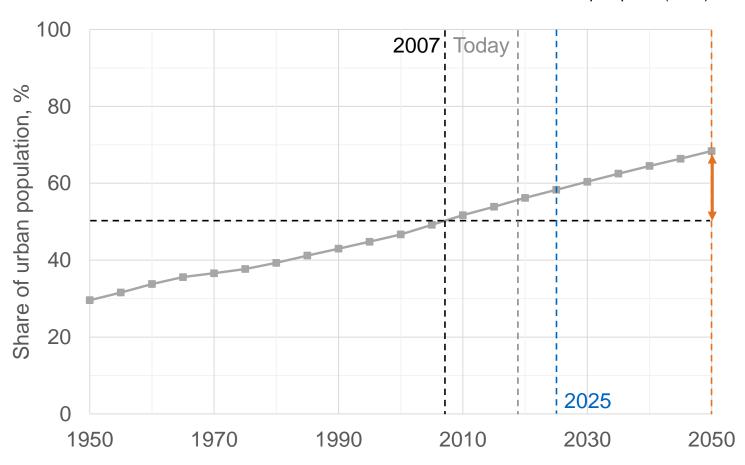
Conference on Complex Systems 2019

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Our urban world





Cities are responsible of 75% of the global **primary energy** consumption and 50-60% of the total **GHG emissions**.

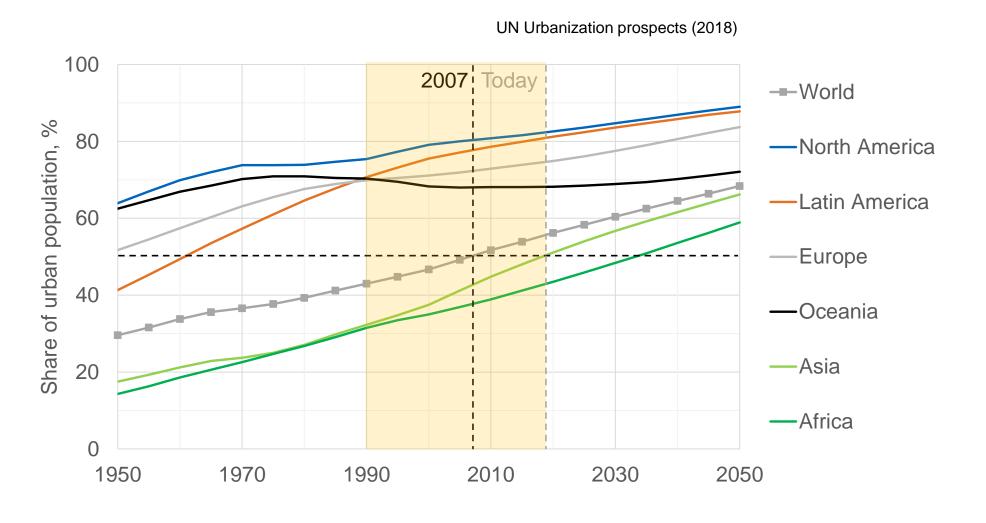
1 billion new inh. in the "consuming class"

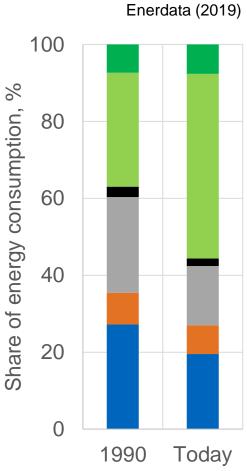
1 in 8 people will live in one of the 43 megacities

2.5 billion **new urban** inhabitants

50% of the population are expected to live in medium-sized cities

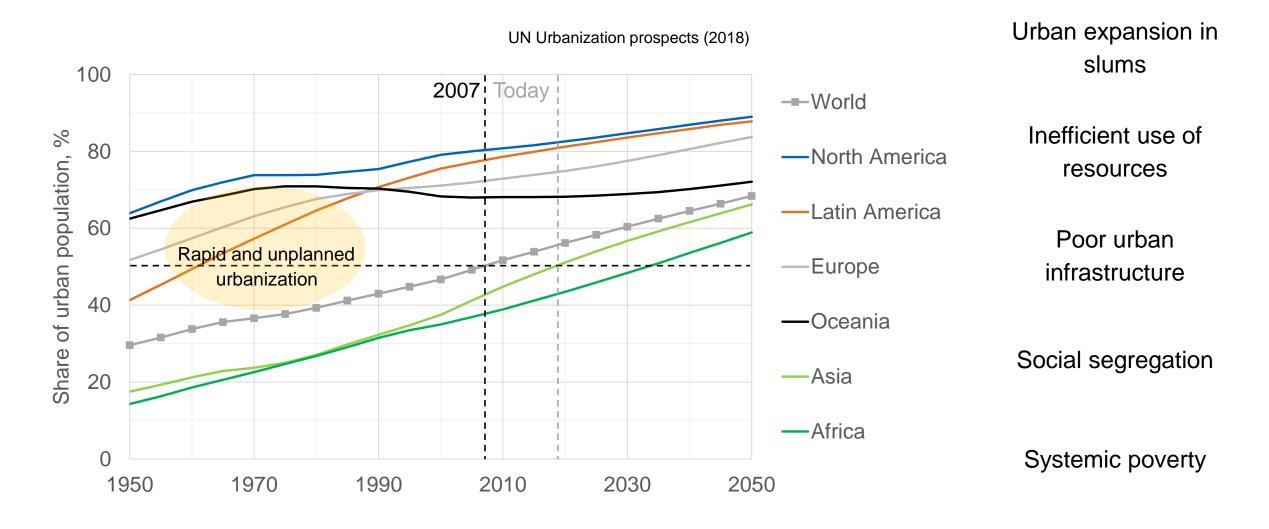
Our urban world



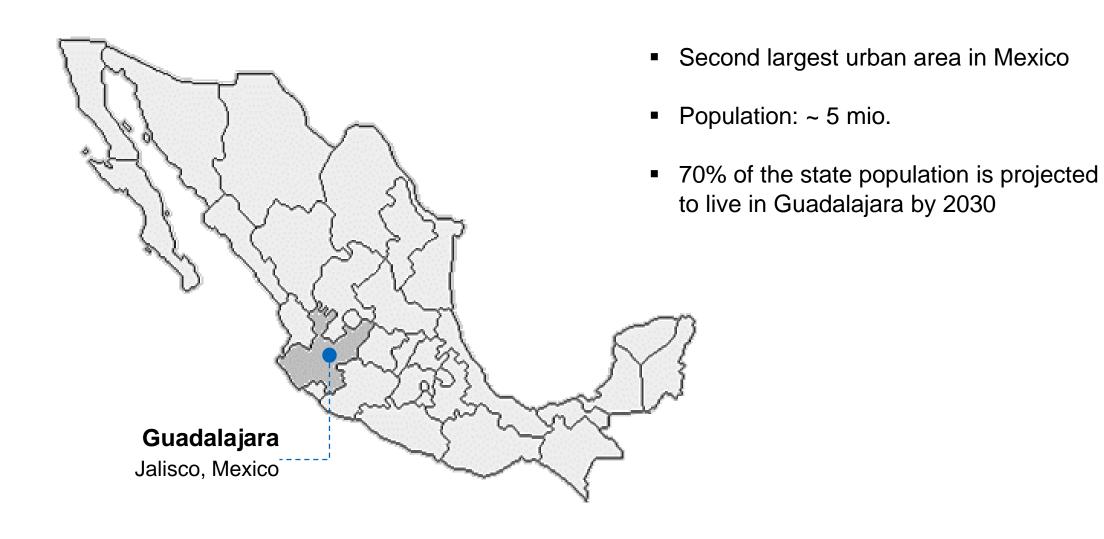


E = f(P, K, I, C)

Our urban world



Study case

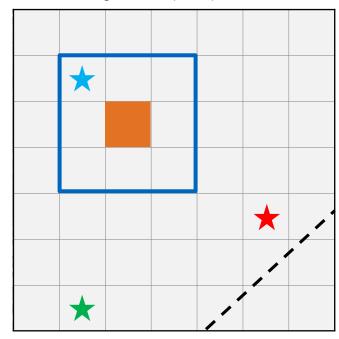


Cities as complex systems: urban growth

Cellular automata + agent-based simulation

Guadalajara, Mexico

Source: Google Earth (2016)



Cells

Environment

$$C_t = \sum c_{i,j,t} \qquad c_i \in N_i$$

$$c_{i,j,t} = [c_{i,j,t}^{D_1}, c_{i,j,t}^{D_2}, ..., c_{i,j,t}^{D_n}]$$

$$D_{x} = [d_1, d_2, \dots, d_m]$$

- Geographic features
- - Urban infrastructure

Agents

Drivers of urbanization

- ★ Industry
- **★** Commerce
- ★ High-income residential

Modeling urban energy demand

Growth cycle, g_i

$$E = f(P, K, I, C)$$

 Accessibility matrices (land value) for agents and cells

 ABM Location of key urbanization drivers

 CA Local urban growth rules

Distribution of wealth

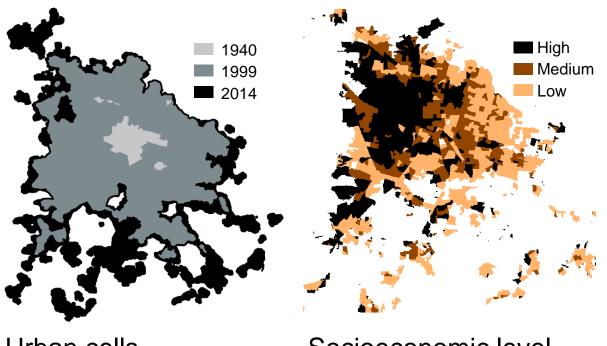
Energy demand

1. Accessibility matrices: learning the value of land **Urbanization** (residential) X

Machine learning (Random Forest Regressor)

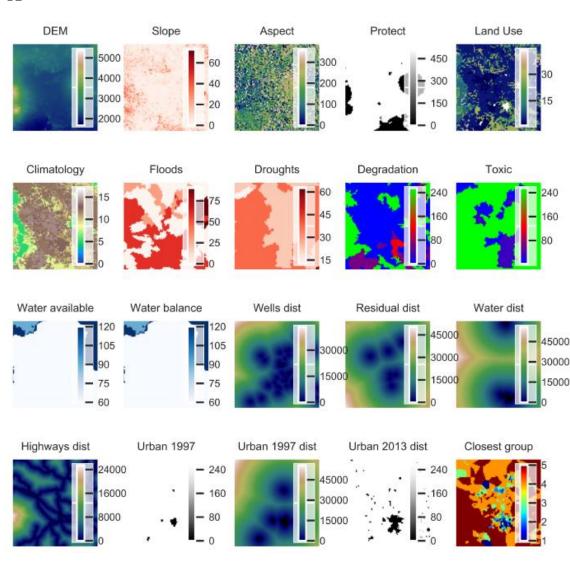
$$Y = f(X) + \varepsilon$$

- *Y* response or dependent
- *X* causative factors or features

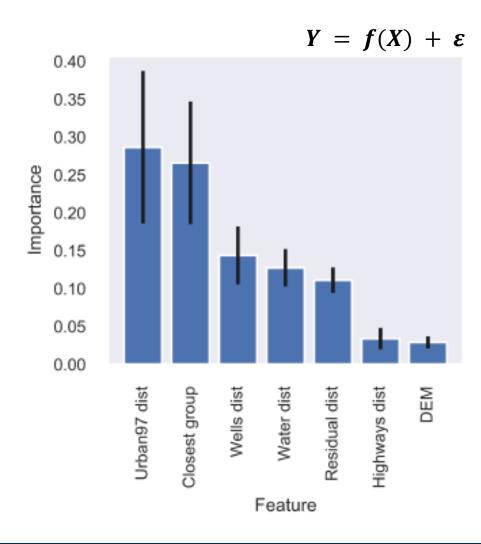


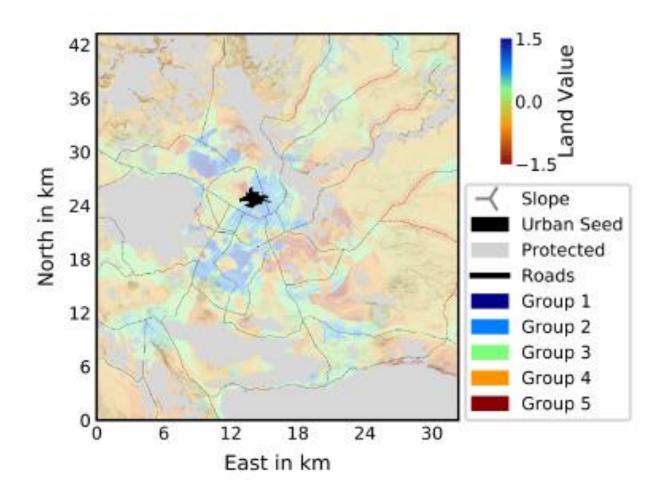
Urban cells

Socioeconomic level



1. Accessibility matrices: learning the value of land Urbanization (residential)

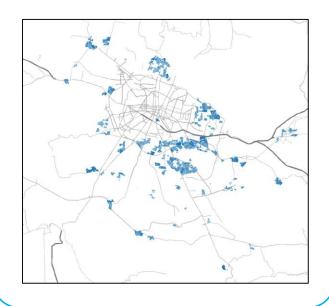




2. ABM: Location of key urbanization drivers

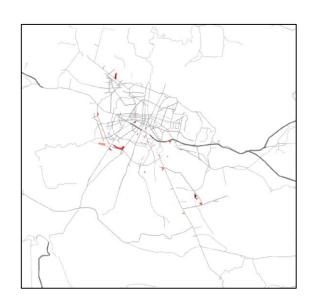
High-income residential

- (-) Distance to high-income residential
- (-) Distance to main roads
- (+) Urban infrastructure
- (-) Distance to green areas



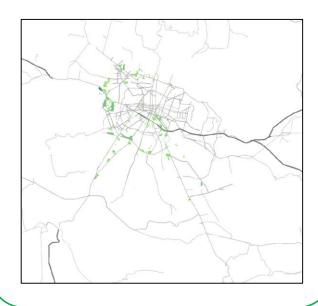
Industry

- (+) Area
- (-) Distance to transport infrastructure



Commerce

- (-) Distance to main roads
- (-) Distance to high-income residential
- (+) Area

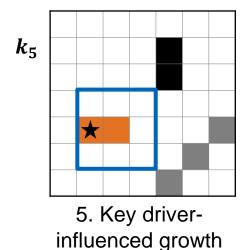


3. CA: local urban growth rules

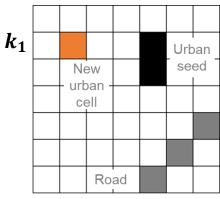
Probabilistic cellular automata model

Dimensions:

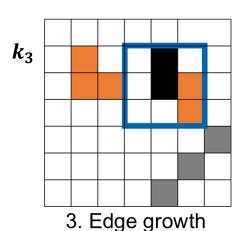
- Land use [urban, not urban]
- Land value (-1.5, 1.5)
- Infrastructure [with road, without road]
- Urbanization driver [high-income, industry, commerce)

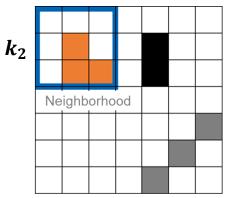


SLEUTH model (Clark et al, 1997)

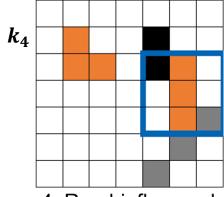


1. Spontaneous growth



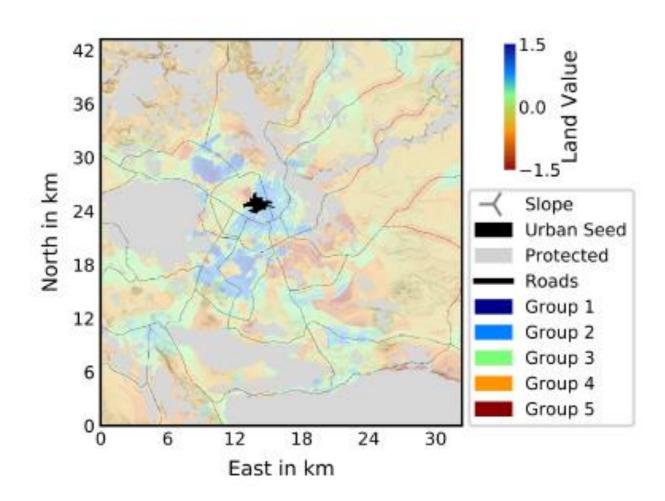


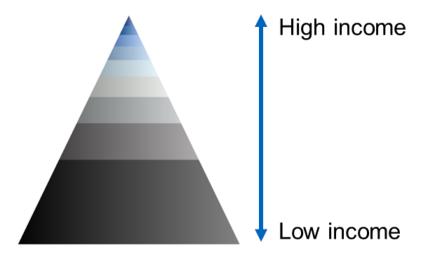
2. Growth of new spreading center



4. Road-influenced growth

4. Distribution of wealth

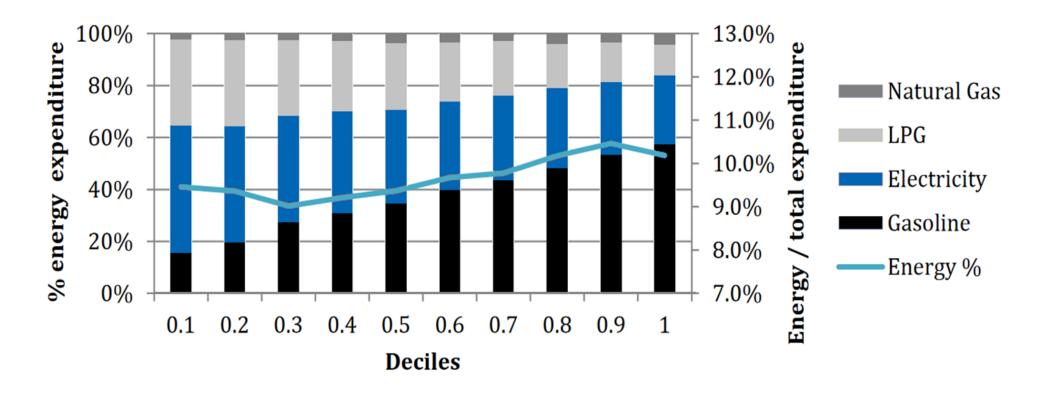




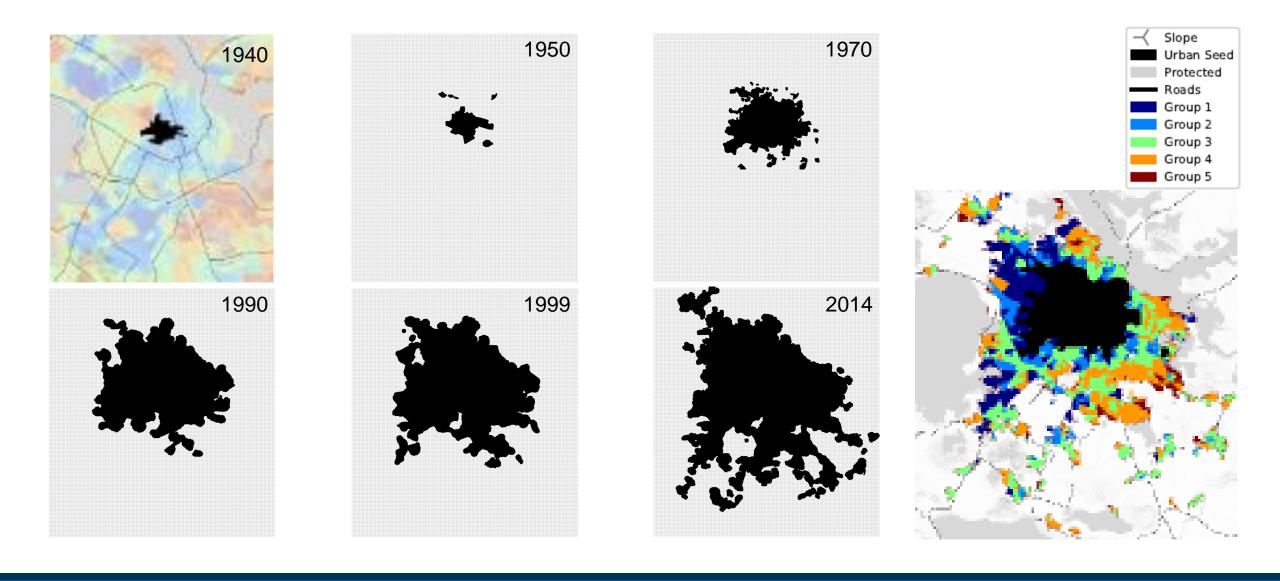
5. Urban energy demand Residential

Statistical model to calculate energy consumption for every cel

Expenses on energy services in Mexican households (Rodríguez-Oreggia & Yepez-García 2014)

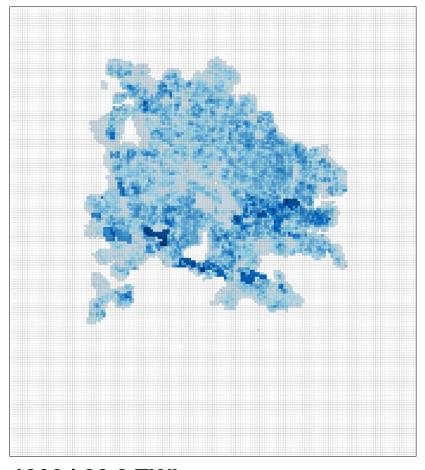


Urban growth: 1940-2014

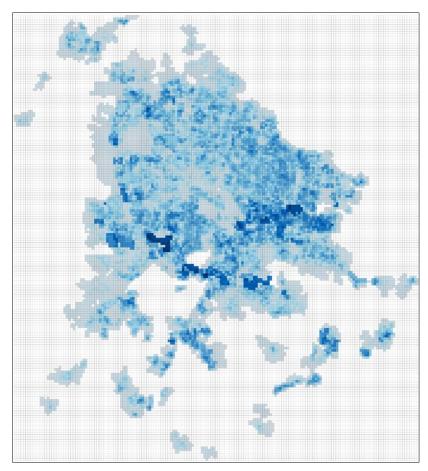


Electricity demand in MWh/a

1 10 000 15 000 20 000 25 000 30 000



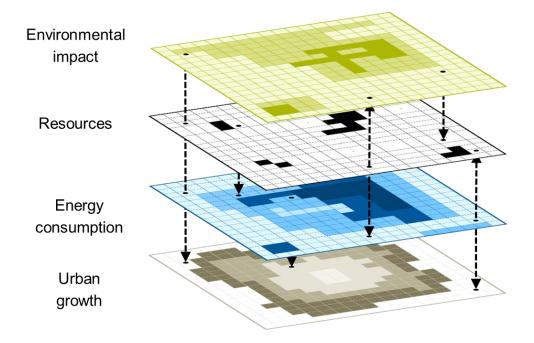
1999 | 22.8 TWh



2014 | 27.1 TWh

Key messages

- CA + ABM + machine learning were used to simulate the urban energy demand. Coupling urban growth and energy demand models allows a better understanding of the energy use patterns in cities.
- 2. Integrated modeling is necessary to capture the complexity of cities.
- 3. The inclusion of the spatially explicit urban transformations expands the possibilities for incorporating other dynamic urban processes: transport, technology adoption
- 4. The development of integrated urban planning tools is crucial for the successful management of emerging cities and the shaping of a sustainable future.



Anahi Molar-Cruz

Technical University of Munich
Chair of Renewable and
Sustainable Energy Systems

anahi.molar-cruz@tum.de