A comparison of simple models for urban morphogenesis

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Abstract

The spatial distribution of population and activities within urban areas, or urban form at the mesoscopic scale, is the outcome of multiple antagonist processes. We propose in this paper to benchmark different models of urban morphogenesis, to systematically compare the urban forms they can produce. Different types of approaches are included, such as a reaction-diffusion model, a gravity-based model, and correlated percolation. Applying a diversity search algorithm, we estimate the feasible space of each model within a space of urban form indicators, in comparison of empirical values for worldwide urban areas. We find a complementarity of the different types of processes, advocating for a plurality of urban models.

Introduction

Understanding the dynamics of cities is an increasing issue for sustainability, since the proportion of the world population expected to live in cities will grow to a large majority in the next decades, and that cities combine both positive and negative externalities on most aspects. Their complexity implies that quantitative and qualitative predictions are not relevant, but planners can *invent future cities* [1], what requires though a knowledge of key urban processes which can be acted upon. In that context, the growth of *urban form* in its different definition and scales, is essential [2]. Considering urban form at a mesoscopic scale, i.e. roughly the scale of urban areas, it can be understood as the spatial distribution of activities. More particularly the distribution of population density has a strong impact on commuting, energy consumption and emissions [3]. Being able to link microscopic processes with the growth of different types of urban form is thus important for a long term planning of sustainable urban systems.

Urban modeling at the mesoscopic scale is the subject of diverse approaches and disciplines. Intra-urban urban economic models, building on works such as the Alonso-Mills-Muth model or the Fujita-Ogawa model Transportation and Urban Planning also have a long history in urban dynamics models, including Land-use transport interaction models [4] Spatial interaction models can also be used in a similar manner [5] At the interface of physics, artificial life and quantitative geography, a few approaches propose simple models to explain the growth of urban form. Although such models

[6]

[7]

Materials and methods

Urban morphogenesis models

Gravity-based model

[7]

Reaction-diffusion

[6]

Correlated percolation

[8]

The method to generate a spatial field exhibiting long range correlations was introduced for problems in physics by [9].

Kernel mixtures

Finally, to provide some kind of null model to understand the advantages of each approach compared to a simple description of population distribution, we also include urban forms generated as kernel mixtures. We consider in particular exponential mixtures [10], written as

Measures of urban form

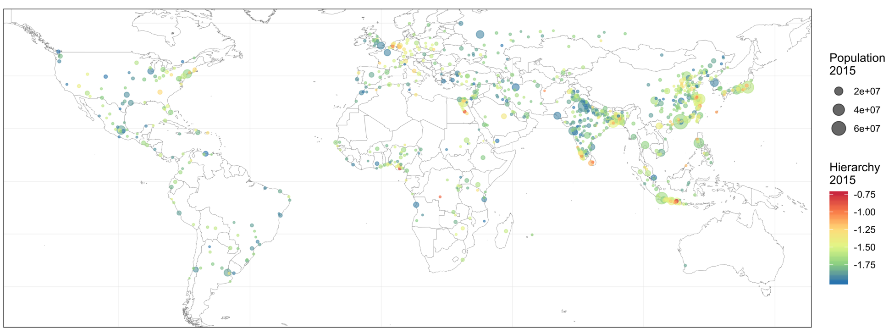
Quantitative measures of urban form

Results

Implementation

The models are implemented in `scala` and integrated into the `spatialdata` library for spatial sensitivity analysis [11]. The library is bundled as an OpenMOLE plugin for the numerical experiments. OpenMOLE is an open source software for model exploration and validation [12] combining model embedding with state-of-the-art exploration methods (including for example sensitivity analysis, design of experiments, calibration with genetic algorithms) and a transparent distribution of computations on high performance computing environments. In our case, we use its workflow system and an integrated algorithm to determine the feasible space of models.

Empirical data



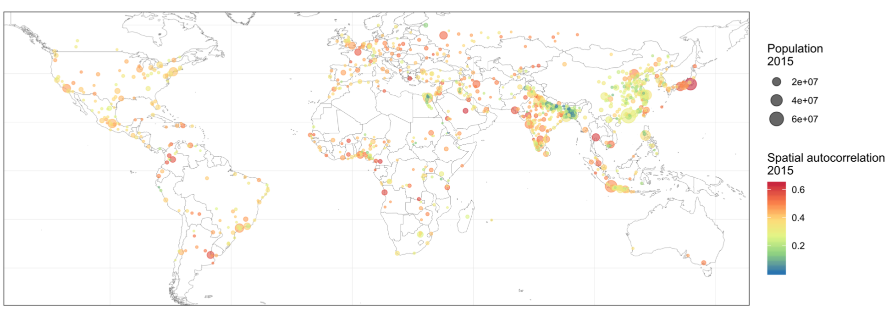


Fig 1. .

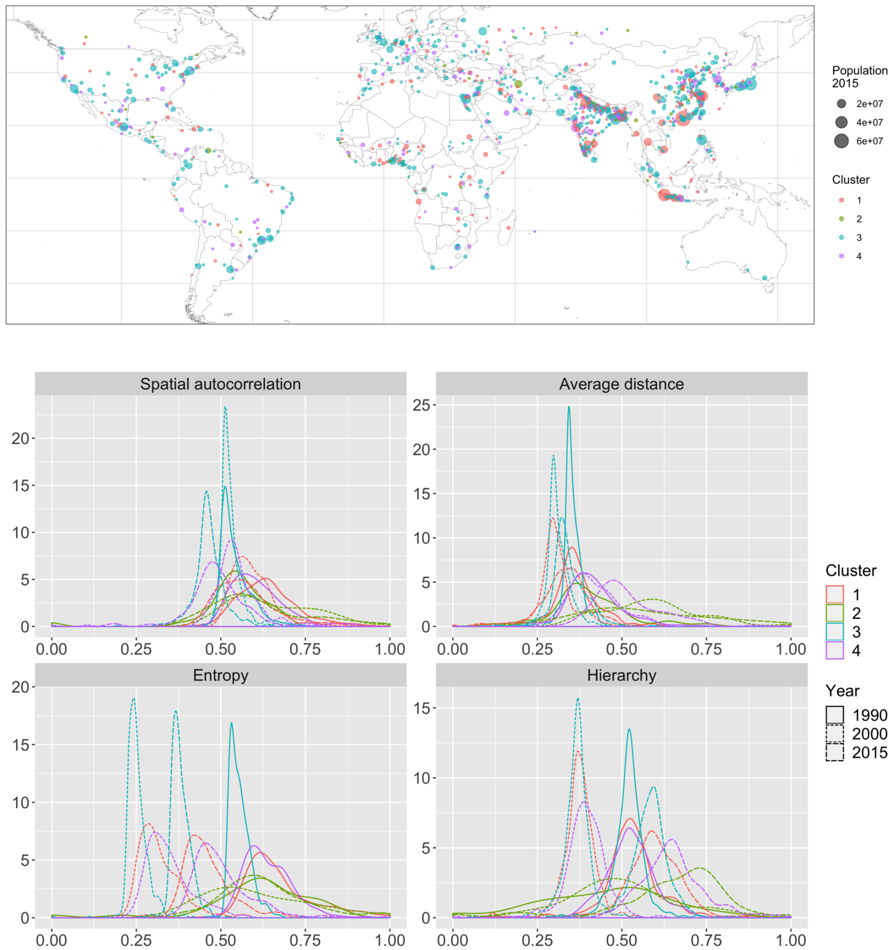


Fig 2. .

Feasible morphological spaces

Discussion

Conclusion

Acknowledgments

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