Characterizing Urban Expansion Processes Using Dynamic Spatial Models – a European Application

Alex Hagen-Zanker
School of Sustainability, Civil and Environmental Engineering, University of Surrey, UK

Jingyan Yu
Institute of Geography and Sustainability (IGD), Faculty of Geosciences and Environment, University of Lausanne, Switzerland

Naratip Santitissadeekorn
Department of Mathematics and Physics, University of Surrey, UK

Susan Hughes
School of Sustainability, Civil and Environmental Engineering, University of Surrey, UK

Abstract

Characterisation of the urban expansion processes using time series of binary urban/non-urban land cover data is complex due to the need to account for the initial configuration and the rate of urban expansion over the analysed period. Failure to account for these factors makes the interpretation of landscape metrics for compactness, fragmentation, or clumpiness problematic and the comparison between geographical areas and time periods contentious. This paper presents an approach for characterisation using spatio-dynamic modelling which is data-centred using a process based model, Bayesian optimization, cluster identification, and maximum likelihood classification. An application of the approach across 652 functional urban areas in Europe (1975-2014) demonstrates the consistency of the approach and its ability to identify spatial and temporal trends in urban expansion processes.

2012 ACM Subject Classification Applied computing → Environmental sciences

Keywords and phrases Urban expansion, morphology, spatio-temporal dynamics, simulation, compactness

Digital Object Identifier 10.4230/LIPIcs.GIScience.2023.36

Category Short Paper

Funding NERC(UKRI) Landscape Decisions project NE/T004150/1.

1 Introduction

Urban expansion along with climate change is one of the major global challenges, affecting all pillars of sustainable development. Past processes of urban expansion are often characterised in terms of composition, for example by the rate of growth of built-up areas. However, it is also of relevance to understand the spatial structure, i.e. the spatial configuration and its process of change. In particular the compactness of urban areas is consequential as it affects the quality of both the natural (e.g. fragmentation of habitats) and urban (e.g. transport demand, walkability) environment.

Commonly, as in this paper, the source data for analysis of urban expansion is multi-temporal raster data classified into binary urban/non-urban classes. The methods that are widely used for the characterization of urban configuration include landscape metrics that were largely developed and applied in the field of landscape ecology. These metrics include the dispersion index, clumpiness index, fractal dimension and compactness index. These metrics can characterize temporal change when applied cross-sectionally for multiple moments in time. Few metrics exist that take a longitudinal perspective and characterize changes over time. Notable exceptions are the Landscape Expansion Index[3], which measures to what extent new urban land is adjacent to existing urban land and the classification of change events as infill, edge expansion, or leapfrogging[8].

The suitability of the landscape metrics to describe urban expansion *processes* is limited: the same observed changes in landscape metrics may be the result of different processes; Furthermore, the same process will have different effects on landscape metrics dependent on the initial configuration as well as the duration over which the processes are active. This paper investigates an alternative approach to characterizing urban expansion processes. The rationale is to characterize the urban expansion that occurs over a given period by the simulation model that best describes the observed changes. The initial configuration is exogenous to the model, as is the total area of expansion. Hence, the model – and classification – are exclusively about the change in urban configuration. The urban expansion model used is the recent model by Yu et al. [6] as is the clustering of parameter sets into four growth modes ranging from compact to dispersed [7]. This current paper extends this work by applying the classification method to 652 functional urban areas (FUAs) in OECD countries within Europea over the periods 1975-1990, 1990-2000 and 2000-2014. For a sample of FUAs the characterization will be compared to the well-established metrics of fractal dimension (FD)[2] and dispersion index (DI)[5] .

2 Methods and data

The model is a Constrained Cellular Automata urban expansion model. It is dynamic in the sense that it starts from an initial urban configuration and then steps through time to incrementally allocate new urban land to raster cells. The model takes the total urban land at each moment in time as an exogenous constraint. The model represents complex dynamics as the spatial configuration of existing urban land is the main factor determining the locations where new urban expansion takes place, causing a process of self-organisation. With just four parameters, representing processes of agglomeration and preservation of natural capital it is one of the most concise urban expansion models. The use of the model to characterise urban expansion patterns goes through several stages:

1. The first stage is calibration using a stochastic method based on Markov chain Monte Carlo with approximate Bayesian computation. For each FUA and time period it produces twenty different parameter sets representing the uncertainty of the calibration. Yu et al. [7] estimated the model for ten FUA across Europe and two time periods and thus produced 10 x 2 x 20 = 400 parameter sets.
2. In the second stage the generated parameter sets are applied to a common initial configuration and rate of urban expansion yielding 400 simulated urban configurations.
3. In the third stage all 400 simulated urban configurations are mutually compared and clustered into four groups based on their similarity . The four groups are considered urban expansion modes and were labelled 'compact', 'medium compact', 'medium dispersed' and 'dispersed'.
4. The fourth stage of the classification applies sample parameter sets from each of the urban expansion modes to a single FUA over a given period. A basic maximum likelihood classification takes place based on the urban expansion mode that most closely resembles the observed dynamics.

This paper uses the model and parameter clusters identified before and extends the analysis to the full set of 652 FUAs within European OECD countries. The built-up and functional urban area data that support the findings of this study are part of the Global Human Settlement Layer (GHSL)[1] [4]. All the models and analyses of this study are implemented in Python as open-source[1].

3 Results and discussion

The results, as seen in Fig. 1 present classification of urban expansion processes in Europe over time. The first period is from “0” to 1975, this classification is based on the urban expansion mode that best represents the expansion from urban genesis (a map void of urban land) to 1975. The results indicate that the processes that have historically shaped urban form in Europe could best be described as compact or medium compact. From 1975 onward however, a clear shift is visible and increasingly over time, more FUAs are becoming classified as undergoing dispersed or medium dispersed expansion processes. This does not imply that this shift occurred in 1975, but rather that it occurred sometime *before* 1975. Where in 1975-1990 58% of FUA could be classified as having a dispersed urban expansion process, in 2000-2014 this had increased to 88%. There is also a distinct spatial pattern, of more urban and industrialized areas turning towards a dispersed process of expansion first, and more rural areas following later.

For a sample of four FUAs we show four model realisations of urban expansion patterns (one for each mode), as well as the observed urban expansion pattern (Fig. 2). For each of the resulting maps the corresponding Dispersion Index and Fractal Dimension are also calculated. The results indicate that the four urban expansion modes reflect a variability of modelled expansion patterns that reflects actual variability across time and FUAs. The comparison of compactness metric by urban expansion mode (Fig. 3) shows that for each of the four FUAs individually the results are consistent, i.e. a more dispersed expansion mode is reflected in corresponding values for DI and FD. However between FUAs the results are not comparable: based on the metrics alone it is not possible to predict what expansion mode a FUA belongs to. Efforts to make the metrics more comparable, by considering the relative change of the metric over time, or by considering the relative metric value compared to that of the compact expansion scenario, did not effectively make the results more comparable (Fig. 3.) These results supports the assertion in the introduction that existing landscape metrics are ill-suited to give insight in urban expansion processes when there is variation in initial configuration or rate of expansion.

4 Conclusion

The proposed method for characterising urban expansion processes presents stark spatio-temporal patterns of changing urban expansion processes across Europe in recent decades. The method is complex and computationally intensive, but is more effective than widely used landscape metrics in characterizing urban expansion processes. The reason for this is that the simulation model based approach is inherently dynamic and independent of initial configuration and quantity or rate of expansion. Although specifically aimed at the process of urban expansion, the general framework should be applicable to a wider range of spatial dynamics.

[1] Available here: https://github.com/JingyanYu/LandUseDecisions

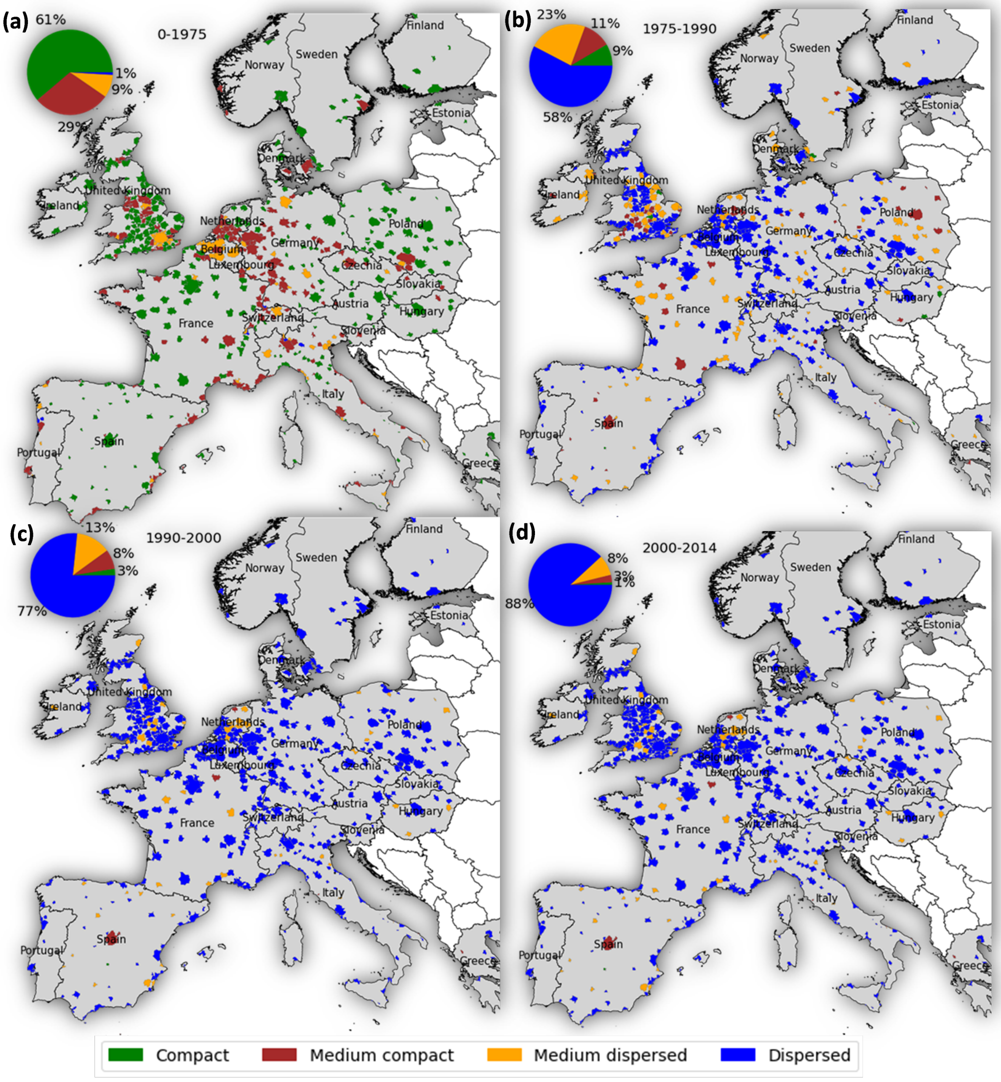

Figure 1 Classification of urban expansion processes for FUAs in Europe over time.

References

1. Christina Corbane, Aneta Florczyk, Martino Pesaresi, Panagiotis Politis, and Vasileios Syrris. GHS-BUILT R2018A - GHS built-up grid, derived from Landsat, multitemporal (1975-1990-2000-2014). *European Commission, Joint Research Centre (JRC)*, 2018. doi:10.2905/jrc-ghsl-10007.
2. Atilla R. Imre and Jan Bogaert. The Minkowski-Bouligand dimension and the interior-to-edge ratio of habitats. *Fractals*, 14(01):49–53, 2006. doi:10.1142/S0218348X06003027.
3. Xiaoping Liu, Xia Li, Yimin Chen, Zhangzhi Tan, Shaoying Li, and Bin Ai. A new landscape index for quantifying urban expansion using multi-temporal remotely sensed data. *Landscape ecology*, 25:671–682, 2010. doi:10.1007/s10980-010-9454-5.
4. Marcello Schiavina, Ana Moreno-Monroy, Luca Maffenini, and Paolo Veneri. GHS-FUA R2019A–GHS functional urban areas, derived from GHS-UCDB R2019A,(2015).

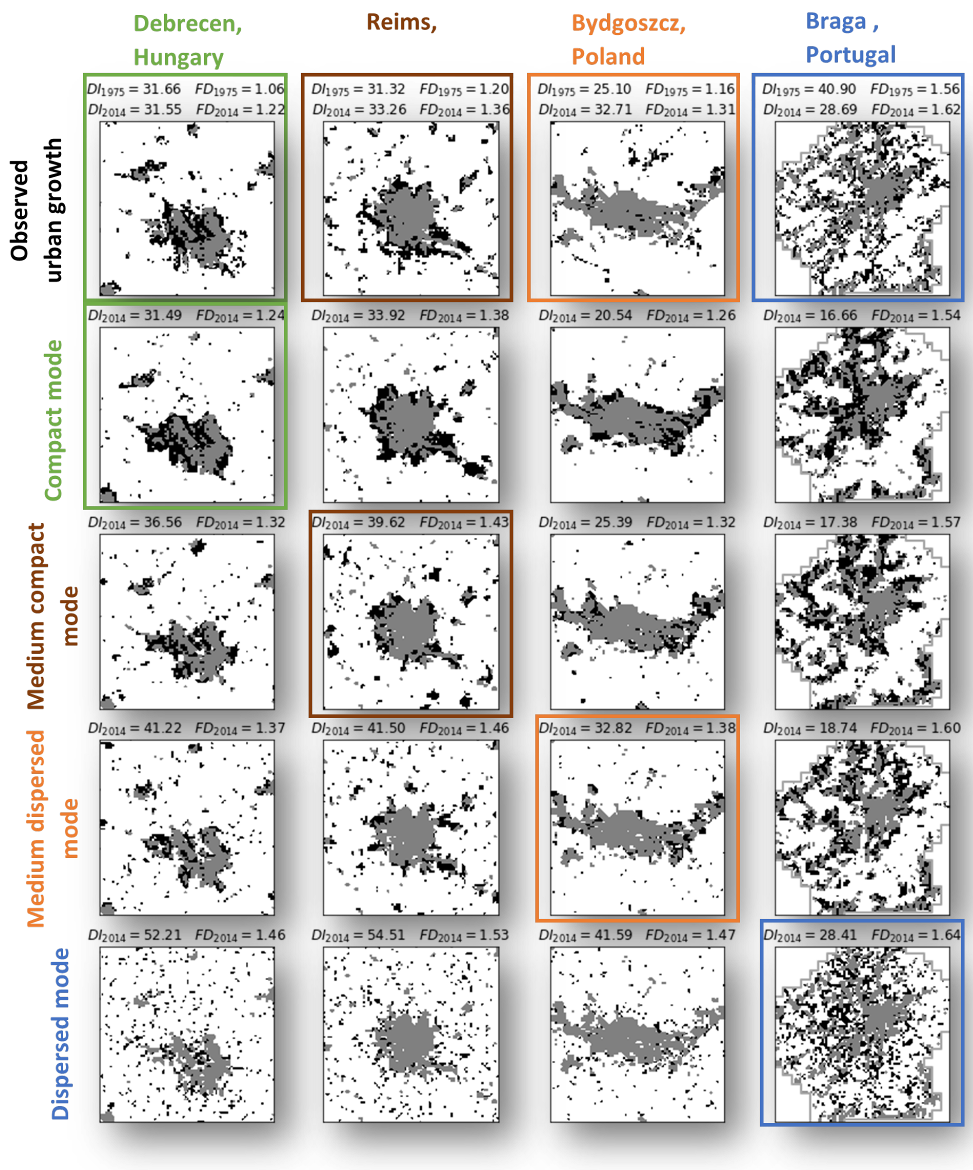

Figure 2 Model realisations for four sample FUAs for each growth mode, and observed expansion (1975-2014).

R2019A. edited by Joint Research Centre (JRC) European Commission, 2019. `doi:10.2905/347F0337-F2DA-4592-87B3-E25975EC2C95`.

5 Hannes Taubenböck, Michael Wurm, Christian Geiß, Stefan Dech, and Stefan Siedentop. Urbanization between compactness and dispersion: Designing a spatial model for measuring 2d binary settlement landscape configurations. *International Journal of Digital Earth*, 12(6):679–698, 2019. `doi:10.1080/17538947.2018.1474957`.

6 Jingyan Yu, Alex Hagen-Zanker, Naratip Santitissadeekorn, and Susan Hughes. Calibration of cellular automata urban growth models from urban genesis onwards-a novel application of Markov chain Monte Carlo approximate bayesian computation. *Computers, Environment and Urban Systems*, 90:101689, 2021. `doi:10.1016/j.compenvurbsys.2021.101689`.

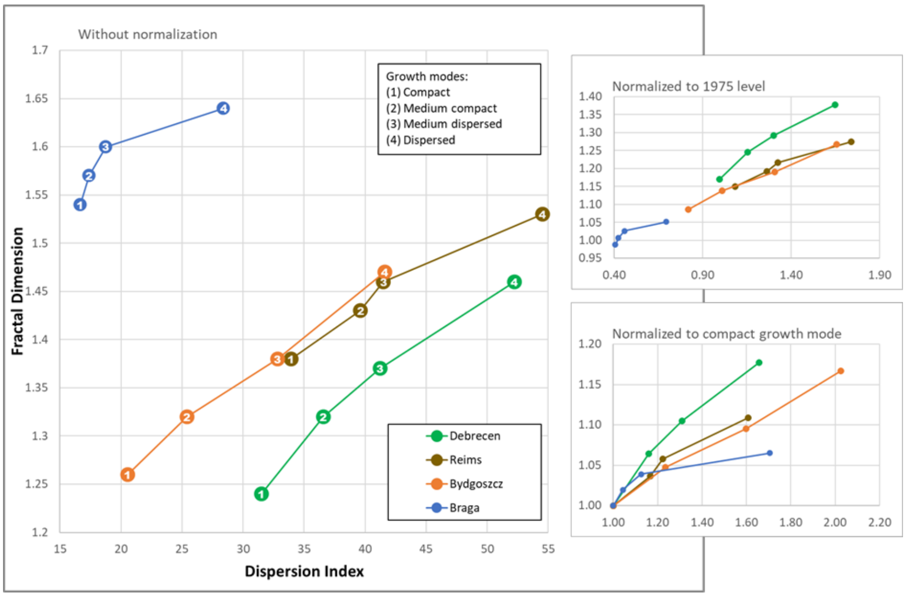

Figure 3 Comparison with widely used metrics of urban form.

7 Jingyan Yu, Alex Hagen-Zanker, Naratip Santitissadeekorn, and Susan Hughes. A data-driven framework to manage uncertainty due to limited transferability in urban growth models. *Computers, Environment and Urban Systems*, 98:101892, 2022. `doi:10.1016/j.compenvurbsys.2022.101892`.

8 Hui Zeng, Daniel Z. Sui, and Shujuan Li. Linking urban field theory with GIS and remote sensing to detect signatures of rapid urbanization on the landscape: Toward a new approach for characterizing urban sprawl. *Urban Geography*, 26(5):410–434, 2005. `doi:10.2747/0272-3638.26.5.410`.