A multi-scalar model for system of cities

J. Raimbault[1,2,3]*

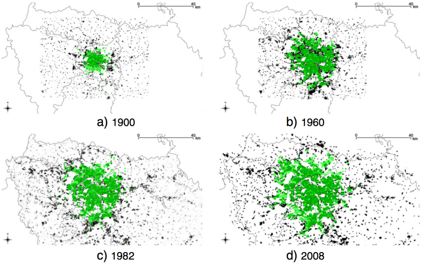
*j.raimbault@ucl.ac.uk

[1]CASA, UCL
[2]UPS CNRS 3611 Complex Systems Institute Paris
[3]UMR CNRS 8504 Géographie-cités

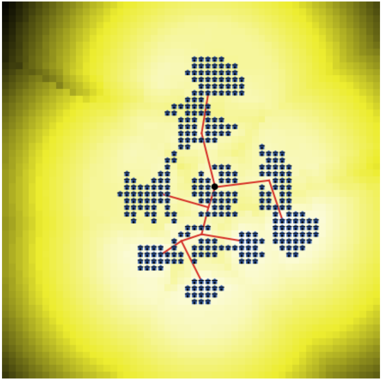
CCS 2019
Urban Complexity
October 1st 2019

Modeling urban growth

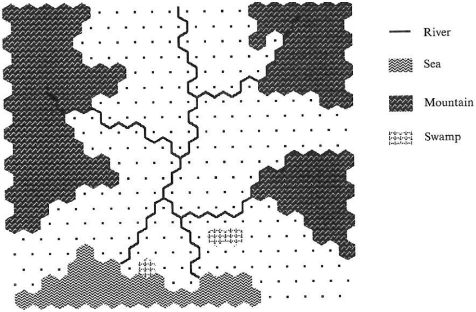
Growth models at the mesoscopic scale

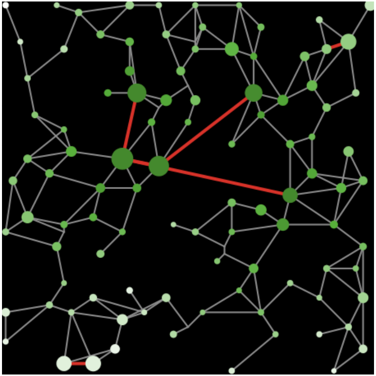


Land-use transport models
[Viguié et al., 2014]



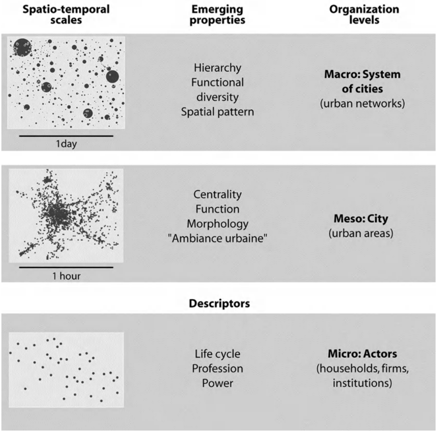
Hybrid urban morphogenesis model
[Raimbault et al., 2014]





The series of Simpop models: from Simpop1 [Sanders et al., 1997] to SimpopNet [Schmitt, 2014]

Towards multi-scalar models



Scales of urban systems of systems described by the evolutionary urban theory [Pumain, 2018]

Strong coupling and multi-scalarity

$\rightarrow$ Weak inter-scale coupling, such as progressive resolution for land-use model, does not considers emergence and autonomous scales

$\rightarrow$ An integrated model, or strongly coupled, would be *a new model extending the two coupled models in the sense that it includes them in some parameter settings or limit conditions*

Urban multi-scalar complexity must be capture by a strongly coupled model

Research objective

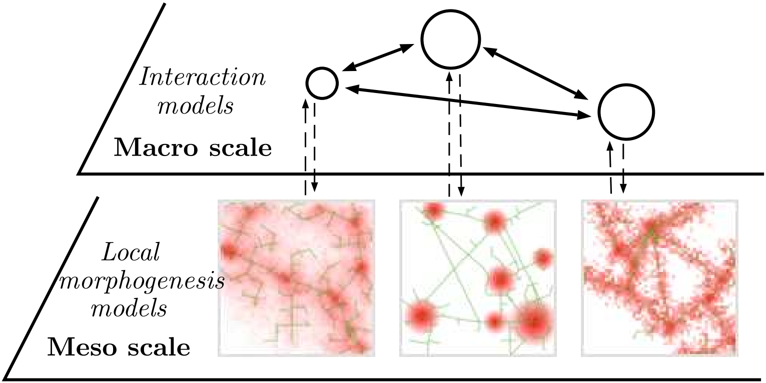
$\rightarrow$ no strongly coupled multi-scalar model in the literature

$\rightarrow$ need to however consider "simple" models to be able to understand their behavior and extract knowledge from them

Research objective:

Investigate a strong coupling of a simple urban system interaction network at the macroscopic scale with an urban morphogenesis model at the mesoscopic scale

Model rationale



Model scales and objects:

- Cities as agents at the macroscopic scale
- Cities as population density grids at the mesoscopic scale

Processes:

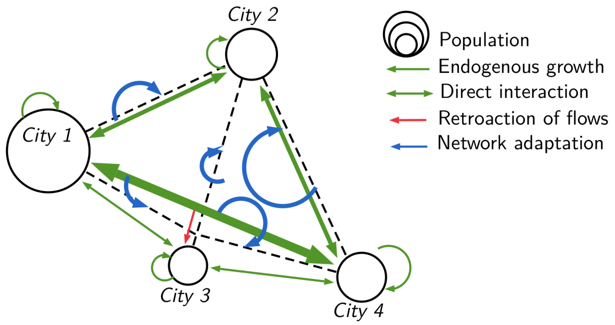
- Interaction flows between cities and endogenous growth
- Urban sprawl and aggregation within urban areas
- **Downward feedback** Adaptation of urban form parameters to population and accessibility growth (“policy response”)
- **Upward feedback** Adaptation of city interaction range depending on internal performance (congested flows)

Model formalization

At each time step:

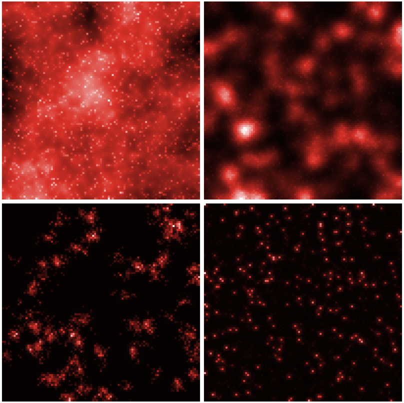
1. Macroscopic population are evolved with the interaction model
2. Population and accessibility differences modify the mesoscopic parameter of diffusion (sprawl) and aggregation (metropolization) ***(downward feedback)***
3. Urban forms are evolved for each city at the mesoscopic scale to match population increases
4. City interaction ranges are modified according to the internal performance of each city (congested flows) ***(upward feedback)***

System of cities interaction model including network evolution; production of multiple co-evolution regimes and calibration for France.
[Raimbault, 2018b]



Indicators at the macroscopic scale: distributions of population, accessibilities, centralities (summarized by average, hierarchy, entropy)

Aggregation-diffusion model at the mescoscopic scale, covering most existing urban forms in Europe [Raimbault, 2018a]



Indicators at the mesoscopic scale: urban form captured by Moran index, average distance, hierarchy, entropy

Model parameters

Type	Parameter	Process	Range
Macro	$g_i = g_0$	Endogenous growth	$[0; 0.05]$
	$w_i = w_G$	Interactions weight	$[0; 0.01]$
	$\gamma_i = \gamma_G$	Interactions hierarchy	$[0; 5]$
	d_i	Interactions decay	$[0; 1000]$
Meso	α_i	Aggregation	$[0; 5]$
	β_i	Diffusion	$[0; 0.1]$
	t_m	Urban growth speed	$\{1; 20\}$
	n_d	Diffusion steps	$[1; 5]$
Multiscale	$\delta\alpha$	Metropolization (downward)	$[-0.2; 0.2]$
	$\delta\beta$	Sprawl (downward)	$[-0.2; 0.2]$
	δd	Efficiency (upward)	$[-0.2; 0.2]$
	λ	Congestion cost (upward)	$[0; 10]$

Implementation

Performance constraints: simulate N mesoscopic morphogenesis models in parallel (macroscopic interactions are efficient as based on matrices)

→ model implemented in `scala` and integrated within a broader library (including implementations of [Raimbault, 2018b] [Raimbault, 2018a] [Favaro and Pumain, 2011] [Cottineau et al., 2015])

Large number of parameters and output indicators

→ integration into the OpenMOLE model exploration open source software [Reuillon et al., 2013]

Enables seamlessly (i) model embedding; (ii) access to HPC resources; (iii) exploration and optimization algorithms

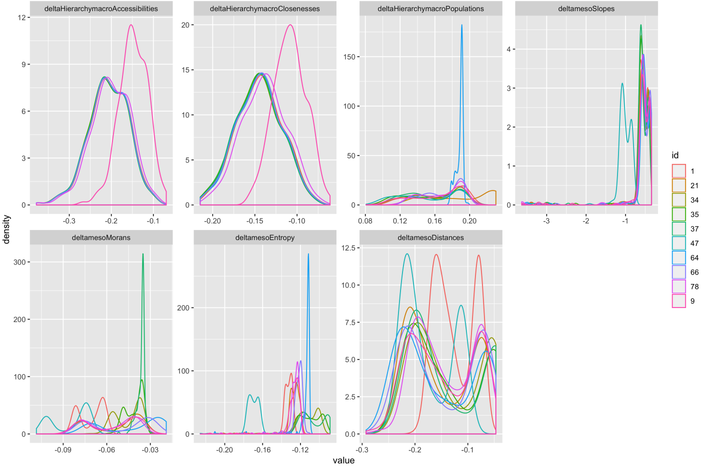
Come to the satellite *New Methods and Epistemologies to Explore Simulation Models* tomorrow afternoon in LHN-TR+05

Synthetic configuration

Model applied on synthetic systems of cities:

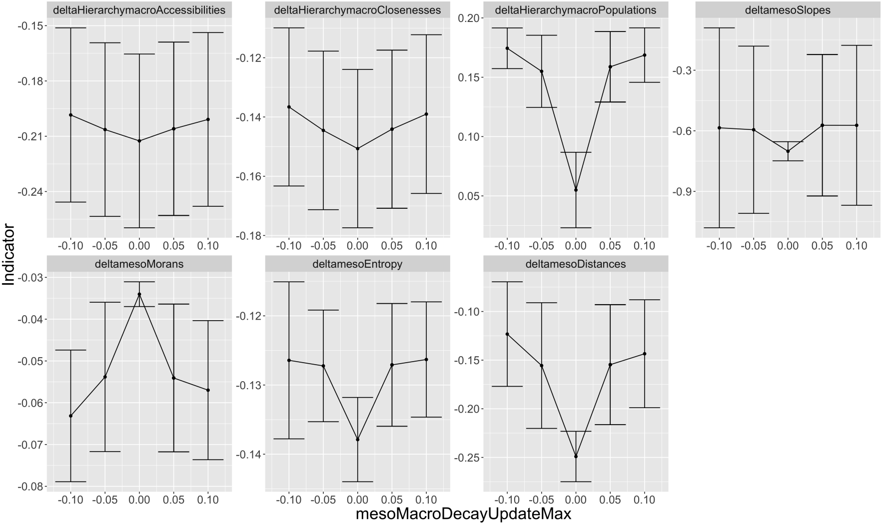
- random positions and rank-size hierarchy ($\alpha = 1.0$ and $P_0 = 100,000$)
- countrywide urban system scale: 500km and 20 cities
- initial population grids as monocentric (grid of size 50 and center cell density 1000 units)
- simulated for 20 macroscopic time steps (order of magnitude of half a century)

Statistical consistency



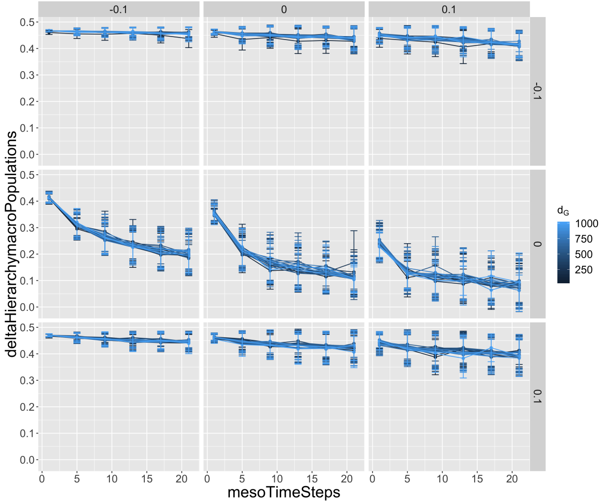
For all indicators, median sharpe ratios computing for a parameter point across repetitions are all larger than 1.6

Model exploration



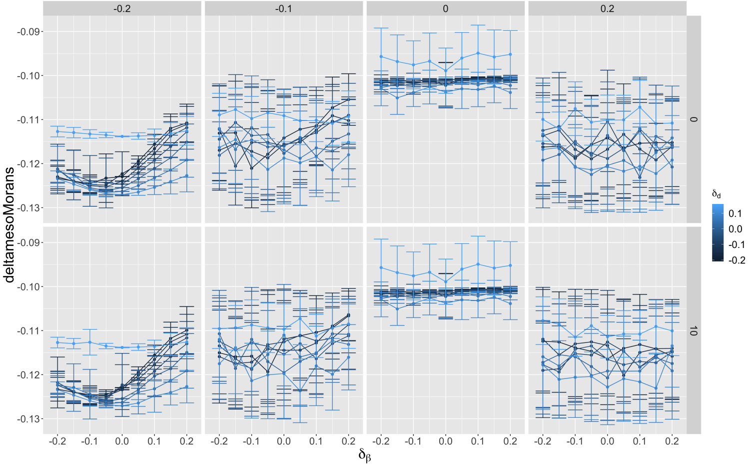
U-shape behavior of both macroscopic and mesoscopic indicators as a function of δd

Model exploration



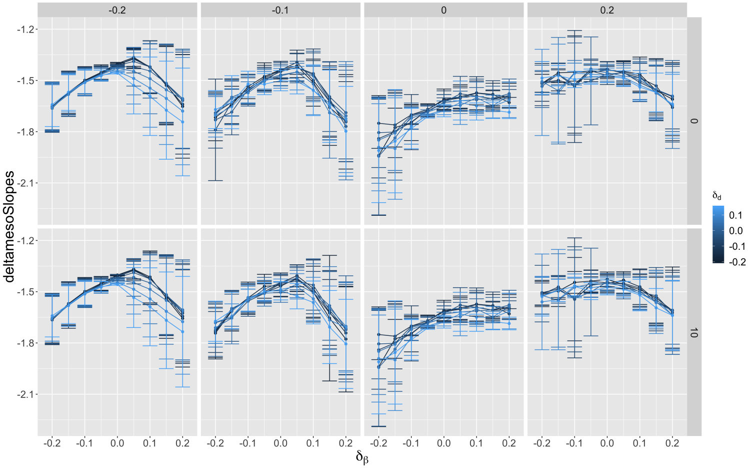
Non-trivial influence of coupled feedbacks on the different scales

Impact of policy parameters



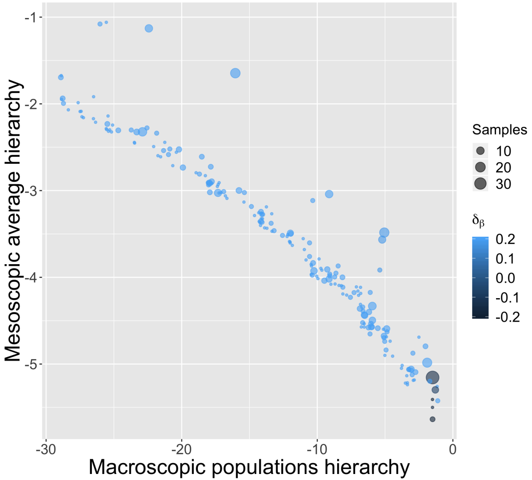
Mesoscopic centralization appears at a $\delta\beta$ critical value for low $\delta\alpha$; influenced by upward feedback

Impact of policy parameters



Mesoscopic hierarchy has a U-shape of $\delta\beta$ in negative $\delta\alpha$, but has a plateau for positive values

Multiscale optimization



Pareto front obtained with Genetic Algorithm optimization for two contradictory objective of macrosopic and mesoscopic hierarchies

Discussion

Theoretical and practical implications

$\rightarrow$ model effectively captures an interaction between downward and upward feedback: weak emergence [Bedau, 2002]

$\rightarrow$ coupling “simple three parameters models” yield a complicated and complex simulation model: necessity of complexity and simulation models to understand urban complexity?

$\rightarrow$ progressive integration towards models for policy?

Developments

$\rightarrow$ diversity search algorithm to find e.g. regimes with the strongest effect of feedback

$\rightarrow$ parametrization on real systems; possibly calibration
(see [Raimbault, 2019] forthcoming presentation at ILUS)

Conclusion

$\rightarrow$ A first step towards *strongly* multi-scalar models to capture urban complexity towards policy models

$\rightarrow$ Towards integrative models and theories for urban systems [Raimbault and Pumain, 2019]

Open repositories for

- Model: `https://github.com/JusteRaimbault/UrbanGrowth-model`
- Project: `https://github.com/JusteRaimbault/UrbanGrowth`
- Simulation data:

Acknowledgments: thanks to the *European Grid Infrastructure* for access to the infrastructure.

Reserve Slides

$\rightarrow$ Grid world with cell populations $\left(P_i\left(t\right)\right)_{1\leq i\leq N^2}$.

$\rightarrow$ At each time step:

1. Population growth with exogenous rate N_G, attributed independently to a cell following a preferential attachment of strength α
2. Population is diffused n_d times with strength β

$\rightarrow$ Stopping criterion: fixed maximal population P_m.

$\rightarrow$ Output measured by morphological indicators: Moran index, average distance, rank-size hierarchy, entropy.

Model formalization

Macroscopic interactions

$$P_i\left(t+1\right) = P_i\left(t\right)\left(1 + \Delta t \cdot \left(g_i + \frac{w_i}{N}\cdot\sum_j \frac{V_{ij}}{< V_{ij} >}\right)\right) \tag{1}$$

where the gravity interaction potential is given by

$$V_{ij} = \left(\frac{P_i P_j}{\sum_k {p_k}^2}\right)^{\gamma_G}\cdot\exp\left(-\frac{d_{ij}}{d_i}\right) \tag{2}$$

Accessibility given by

$$Z_i = \sum_j \frac{P_j}{\sum_k P_k}\cdot\exp - d_{ij}/d_i \tag{3}$$

Model formalization

- Mesoscopic growth rate $N_G^{(i)}\left(t+1\right)\ \Delta P_i/t_m$
- Sprawl parameter (population pressure)

$$\beta_i\left(t+1\right) = \beta_i\left(t\right)\cdot\left(1+\delta\beta\cdot\frac{\Delta P_i t}{\max_k \Delta P_k\left(t\right)}\right) \tag{4}$$

- Aggregation parameter (metropolization process)

$$\alpha_i\left(t+1\right) = \alpha_i\left(t\right)\cdot\left(1+\delta\alpha\cdot\frac{\Delta Z_i t}{\max_k \Delta Z_k\left(t\right)}\right) \tag{5}$$

Model formalization

Congested flows within the mesoscopic zones:

$$U_i = \sum_{kl} \left(\frac{P_k P_l}{P^2} \cdot \frac{1}{d_{kl}} - \lambda \left(\frac{P_k P_l}{P^2} \cdot \frac{1}{d_{kl}} \right)^2 \right) \tag{6}$$

Update the macroscopic interaction distance accordingly

$$d_i\left(t+1\right) = d_i\left(t\right)\left(1 + \delta d \cdot \frac{U_i}{\max_k \left|U_k\right|}\right) \tag{7}$$

Morphological indicators

1. Rank-size slope γ, given by $\ln\left(P_{\tilde{i}}/P_0\right) \sim k\ \gamma \cdot \ln\left(\tilde{i}/i_0\right)$ where $\tilde{i}$ are the indexes of the distribution sorted in decreasing order.
2. Entropy of the distribution:

$$\mathscr{E}\ \ \sum_{i1}^{M} \frac{P_i}{P} \cdot \ln \frac{P_i}{P} \tag{8}$$

   $\mathscr{E}\ \ 0$ means that all the population is in one cell whereas $\mathscr{E}\ \ 0$ means that the population is uniformly distributed.
3. Spatial-autocorrelation given by Moran index, with simple spatial weights given by $w_{ij}\ \ 1/d_{ij}$

$$I\ \ M \cdot \frac{\sum_{ij/} w_{ij}\left(P_i - \bar{P}\right) \cdot \left(P_j - \bar{P}\right)}{\sum_{ij/} w_{ij} \sum_i \left(P_i - \bar{P}\right)^2}$$

4. Mean distance between individuals

$$\bar{d}\ \ \frac{1}{d_M} \cdot \sum_{i<j} \frac{P_i P_j}{P^2} \cdot d_{ij}$$

References I

Bedau, M. (2002).
Downward causation and the autonomy of weak emergence.
Principia: an international journal of epistemology, 6(1):5–50.

Cottineau, C., Reuillon, R., Chapron, P., Rey-Coyrehourcq, S., and Pumain, D. (2015).
A modular modelling framework for hypotheses testing in the simulation of urbanisation.
Systems, 3(4):348–377.

Favaro, J.-M. and Pumain, D. (2011).
Gibrat revisited: An urban growth model incorporating spatial interaction and innovation cycles.
Geographical Analysis, 43(3):261–286.

References II

Pumain, D. (2018).
An evolutionary theory of urban systems.
In *International and Transnational Perspectives on Urban Systems*, pages 3–18. Springer.

Raimbault, J. (2018a).
Calibration of a density-based model of urban morphogenesis.
PloS one, 13(9):e0203516.

Raimbault, J. (2018b).
Indirect evidence of network effects in a system of cities.
Environment and Planning B: Urban Analytics and City Science, page 2399808318774335.

Raimbault, J. (2019).
Worldwide estimation of parameters for a simple reaction-diffusion model of urban growth.
In *International Land-Use Symposium 2019*.

Raimbault, J., Banos, A., and Doursat, R. (2014).
A hybrid network/grid model of urban morphogenesis and optimization.
In *4th International Conference on Complex Systems and Applications*, pages 51–60.

Raimbault, J. and Pumain, D. (2019).
Exploration methods for simulation models.

Reuillon, R., Leclaire, M., and Rey-Coyrehourcq, S. (2013).
Openmole, a workflow engine specifically tailored for the distributed exploration of simulation models.
Future Generation Computer Systems, 29(8):1981–1990.

Sanders, L., Pumain, D., Mathian, H., Guérin-Pace, F., and Bura, S. (1997).
Simpop: a multiagent system for the study of urbanism.
Environment and Planning B, 24:287–306.

Schmitt, C. (2014).
Modélisation de la dynamique des systèmes de peuplement: de SimpopLocal à SimpopNet.
PhD thesis, Paris 1.

Viguié, V., Hallegatte, S., and Rozenberg, J. (2014).
Downscaling long term socio-economic scenarios at city scale: A case study on paris.
Technological forecasting and social change, 87:305–324.