Spatial sensitivity of the evolutionary swarm chemistry model

J. Raimbault[1,2,3,4,*]

* juste.raimbault@ign.fr

[1] LASTIG, IGN-ENSG
[2]CASA, UCL
[3]UPS CNRS 3611 ISC-PIF
[4]UMR CNRS 8504 Géographie-cités

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Evolution and space

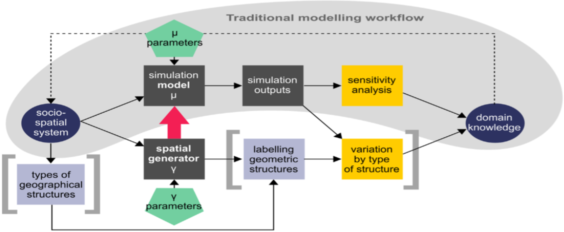
→ role of spatial structure and dynamics in evolution [Lion and Baalen, 2008]

→ niche construction linked to spatial effects [Silver and Di Paolo, 2006]

→ [Holland, 2012]'s theory for complex adaptive systems links spatial boundaries with niches

→ biogeography optimisation algorithms rely on island geography [Simon, 2008]

Spatial sensitivity of social simulation models



Raimbault, J., Cottineau, C., Le Texier, M., Le Nechet, F., Reuillon, R. (2019). Space Matters: Extending Sensitivity Analysis to Initial Spatial Conditions in Geosimulation Models. *Journal of Artificial Societies and Social Simulation*, *22*(4).

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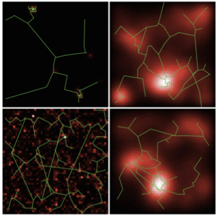
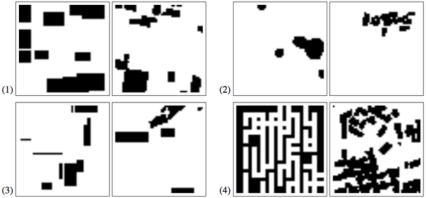


Raimbault, J. (2019). Second-order control of complex systems with correlated synthetic data. *Complex Adaptive Systems Modeling*, *7*(1), 1-19.



Raimbault, J., Perret, J. (2019). Generating urban morphologies at large scales. In *Artificial Life Conference Proceedings* (pp. 179-186).

Research objective

→ Does the role of space in socio-spatial systems transfer to other disciplines?

→ ALife as an interdisciplinary field to investigate spatial effects in various models.

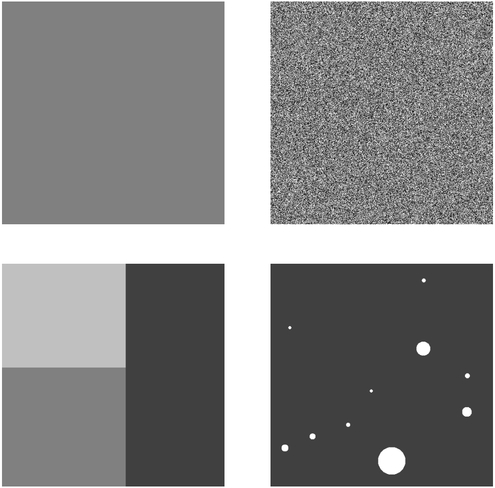
Contribution: considering Swarm Chemistry as an iconic model in ALife [Sayama, 2009], we investigate how different types of spatial structures for selection rules influence outcomes in the evolutionary swarm chemistry model [Sayama, 2018].

Evolutionary swarm chemistry

- "Static" swarm chemistry model [Sayama, 2009]: self-propelled particles with kinetic parameters (c_1 cohesion, c_2 alignement, c_3 separation), self-organise into spatial patterns
- Evolutionary dynamics on long times [Sayama, 2018] induced by mutation in particle parameters and transmission occurring at particle collision
- Different rules for parameters transmission: faster transmits, slower, local majority, behind, ...
- Rules can be changed in space and time to foster evolutionary dynamics: in [Sayama, 2018], particles in half of the space switch their rule (faster/slower) during a time window

Spatial generators

$\rightarrow$ introducing an heterogeneous spatial context for evolutionary rules (random among "Faster", "Slower", "Behind", "Majority" and "Majority Relative"), randomly generated: (i) uniform (baseline), (ii) random, (iii) four quadrant split, (iv) polycentric with Zipf's law inspired by urban systems [Pumain et al., 2006] [Lemoy and Caruso, 2020]



Indicators and experimental setup

Indicators : summary statistics on main kinetic parameters on the swarm $\bar{c_1}, \bar{c_2}, \bar{c_3}, \sigma(c_1), \sigma(c_2), \sigma(c_3)$

Swarm parameters at default values [Sayama, 2018]; swarm size $N = 200$ and final time $t_f = 10000$; initialised with 20 random and 180 inactive particles.

Application of the **PSE diversity search algorithm** [Chérel et al., 2015] to obtain a feasible space maximising diversity for indicators, with free parameters random seed and type of spatial generator.

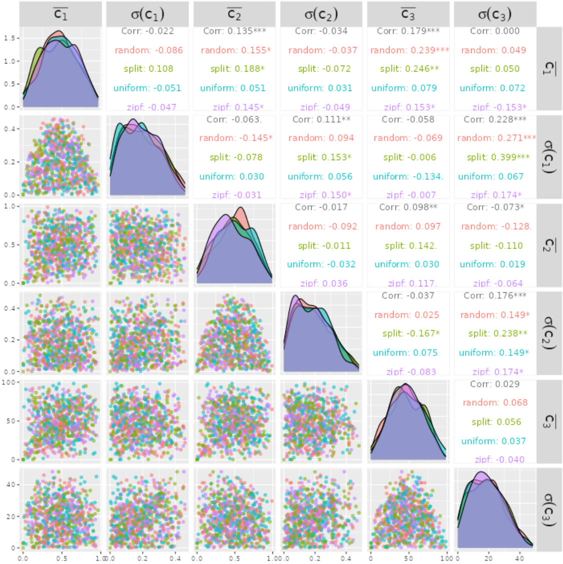
Model implementation

Model reimplemented in scala, based on the open source java implementation by [Sayama, 2018]

Open git repository: `https://github.com/JusteRaimbault/SwarmChemistrySpatialSensitivity`

Coupled with the spatial structure generators from [Raimbault et al., 2020] and integrated into the OpenMOLE platform for **model exploration and validation** [Reuillon et al., 2013]

Results: feasible spaces



Indicator cloud points obtained running the PSE algorithm for 2100 generations

Results: statistical analysis

$\rightarrow$ t-tests to compare statistical distributions of each generator on each indicator.

Significant differences:

- $\sigma(c_1)$: zipf - uniform, $p = 0.055$
- $\bar{c_2}$: split - uniform, $p = 0.057$
- $\bar{c_2}$: random - zipf : $p = 0.017$
- $\bar{c_2}$: zipf - uniform : $p = 0.005$

$\rightarrow$ average alignement is the parameter which is the most influenced by the spatial structure of evolution; Zipf's law spatial context has the strongest effect.

Discussion

Main result: proof-of-concept of spatial sensitivity in the swarm chemistry model, and more generally in ALife models.

Next steps:

- more experiments to link type of spatial structure to swarm typology
- better qualitative understanding of spatial evolutionary dynamics and of the emerging biogeography
- other types of spatial generators

Conclusion: spatial sensitivity across disciplines; application to more realistic evolutionary processes?

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