



HAL
open science

Impact of Spatial Scale on Mobility Parameters

Rachit Agarwal, Nikolaos Georgantas, Valérie Issarny

► **To cite this version:**

Rachit Agarwal, Nikolaos Georgantas, Valérie Issarny. Impact of Spatial Scale on Mobility Parameters. NetSci 2018 - International Conference on Network Science, Jun 2018, Paris, France. Netsci 2018: Book of Abstracts (Posters - Social). hal-01923856

HAL Id: hal-01923856

<https://inria.hal.science/hal-01923856v1>

Submitted on 15 Nov 2018

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

MOTIVATION

- Huge body of work focusing on the understanding of human mobility characteristics [1] utilizing various types of data [2]
- How spatial scale affect the human mobility parameters is still the question?

DATA COLLECTION

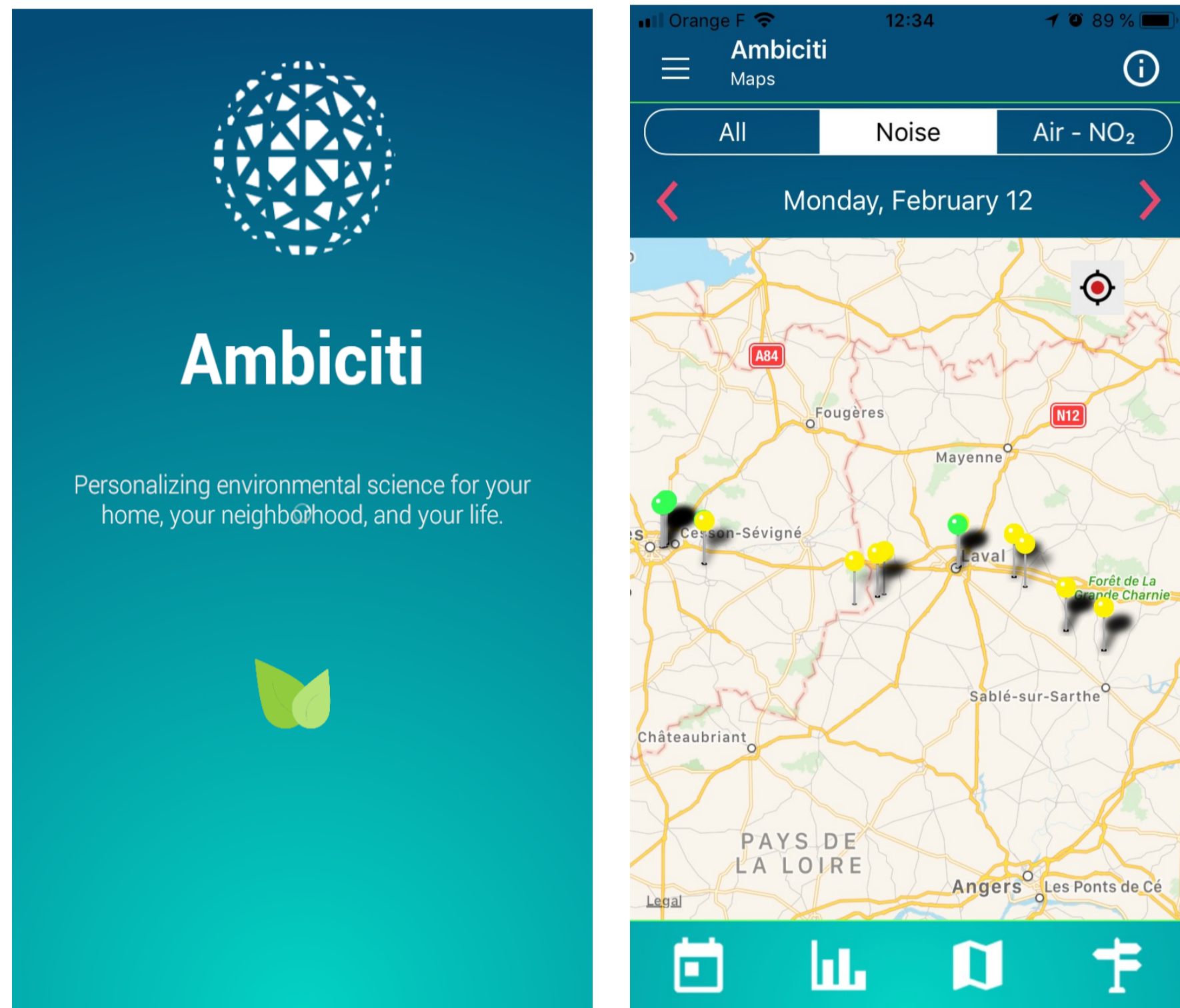


FIGURE 1: Ambiciti application (formerly called as SoundCity) monitors the environmental pollution the user is exposed to [3].

DATA PROCESSING

- Perform data cleaning and labeling:
 - Clean by removing data points having location as (0,0) identified in private mode.
 - Associate each data point to arrondissements and cities in France towards spatial scales.
 - Generate paths at three scales using cleaned data. The cleaned dataset has 5629 user with 25,787,201 valid samples collected from 01/07/2015 to 30/09/2017
- Identify PDF for Jump length and Radius of Gyration (R_g) [4].
- Identify best fit using KS test
- Identify KL divergence between distributions identified at different scales.

RESULTS

- Positive lognormal distribution fits best (See Figure 2 and Table 1) both jump length and R_g
- As expected spatial scale affects the distribution parameters
- Other results:
 - Pause time also follow positive lognormal distribution but bias present due to nature of the dataset (crowdsourced dataset) used.
 - Distribution of max and min jump length from users also follow positive lognormal distribution with parameters $\mu=9.95$ $\sigma=2.75$ and $\mu=3.68$ $\sigma=1.70$ respectively at fine grain scale.

CONCLUSION/FUTURE WORK

The findings reported here will be leveraged for revisiting the identified parameters, based on further analysis using complementary datasets.

BIBLIOGRAPHY

- [1] L. Alessandretti, P. Sapiezynski, S. Lehmann, and A. Baronchelli, "Multi-scale Spatio-Temporal Analysis of Human Mobility," PLOS ONE, vol. 12, pp. 1–17, 02 2017.
- [2] D. Karamshuk, C. Boldrini, M. Conti, and A. Passarella, "Human Mobility Models for Opportunistic Networks," IEEE Communications Magazine, vol. 49, pp. 157–165, December 2011.
- [3] V. Issarny, V. Mallet, K. Nguyen, P. Raverdy, F. Rebhi, and R. Ventura, "Do's and Don'ts in Mobile Phone Sensing Middleware: Learning from a Large-Scale Experiment," in Proceedings of the 17th International Middleware Conference, (Trento), pp. 17:1–17:13, December 2016.
- [4] M. Gonzalez, C. Hidalgo, and A. L. Barabasi, "Understanding Individual Human Mobility Patterns," Nature, vol. 453, pp. 779–782, June 2008.

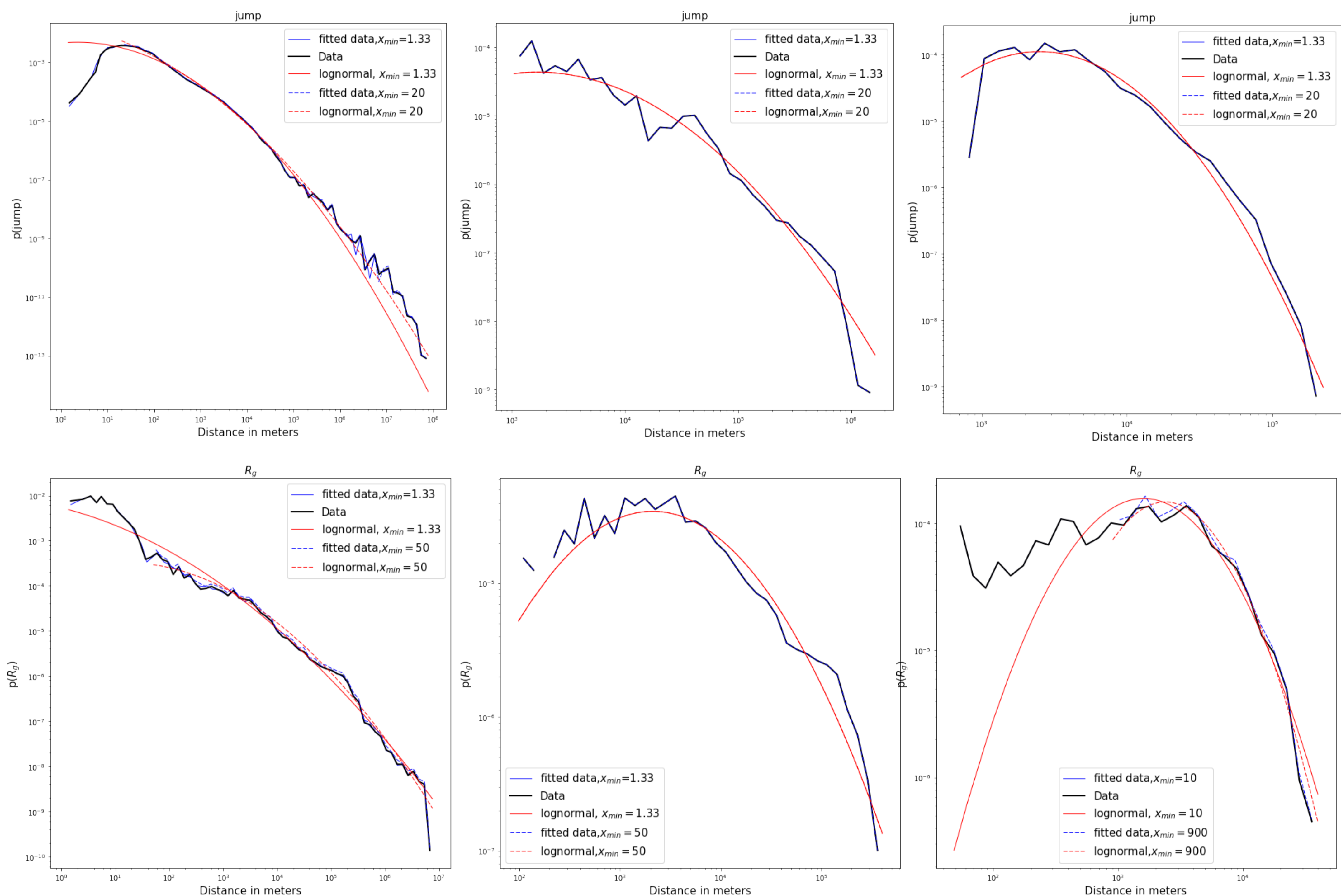


FIGURE 2: Log-Log plot of best fit distribution for jump-length and R_g at different spatial scales with different values of x_{min} . Top row (Jump length): (a) fine grain samples, (b) samples mapped to arrondissements, (c) samples mapped to Ile-de-France cities. Bottom row (R_g): (d) fine grain samples, (e) samples mapped to arrondissements, (f) samples mapped to Ile-de-France cities.

TABLE 1: Distribution fit with identified parameters.

	x_{min} in meters	power law		positive log-normal			exponential		truncated power law			
		α	D	μ	σ	D	λ	D	α	β in km	D	
Jump length	fine grain	1.33	1.16499	0.32032	6.31135	2.34599	0.04968	0.383×10^{-4}	0.65465	1.00000000047	307	0.18570
		20	1.28349	0.13633	5.67313	2.79791	0.02119	0.366×10^{-4}	0.65156	1.18549609894	760	0.08300
	arrondissements	1.33	1.10381	0.49939	9.917793	1.57635	0.073776	1.550×10^{-5}	0.23363	1.00000000008	823	0.52336
		20	1.14447	0.43674	9.917795	1.57641	0.073770	1.551×10^{-5}	0.23379	1.00000000081	630	0.41185
	cities	10	1.15651	0.51625	8.69207	0.93215	0.056347	1.033×10^{-4}	0.10579	1.00000000011	81	0.55626
		125	1.25882	0.43681	8.69201	0.93232	0.056319	1.045×10^{-4}	0.10689	1.00000000188	53	0.40801
R_g	fine grain	1.33	1.11777	0.30689	8.69591	3.51229	0.06945	5.695×10^{-6}	0.47778	1.00000000733	2430	0.24018
		50	1.17299	0.27522	9.59149	2.61934	0.05053	5.004×10^{-6}	0.43508	1.00000000109	2004	0.16950
	arrondissements	1.33	1.10143	0.46931	10.14405	1.57791	0.076356	1.568×10^{-5}	0.16348	1.00000000649	812	0.51268
		50	1.16046	0.38631	10.14373	1.57844	0.076347	1.571×10^{-5}	0.16376	1.00000004508	557	0.36802
	cities	10	1.16549	0.46070	8.34509	0.98044	0.05847	1.599×10^{-4}	0.08637	1.00000000545	49	0.50714
		900	1.58662	0.25364	8.46224	0.82646	0.02251	1.733×10^{-4}	0.04724	1.00000007368	16	0.19361

TABLE 2: KL divergence between identified distributions at different spatial scale.

		fine grain	arrondissements	cities	x_{min} in meters
		Jump length	0	4.12646616206	
	arrondissements	7.7901952234	0	1.26852900653	20
	cities	1.23656465376	0.502427101463	0	125
R_g	fine grain	0	0.431600843735	4.30231619411	50
	arrondissements	0.210279300944	0	2.74652057699	50
	cities	0.79623349401	0.851536328754	0	900