

# **Optimising geospatial vector data matching algorithms for change detection with synthetic data**

Paul Guardiola, Juste Rimbault, Ana-Maria Olteanu-Raimond, Julien Perret

CCS 2024

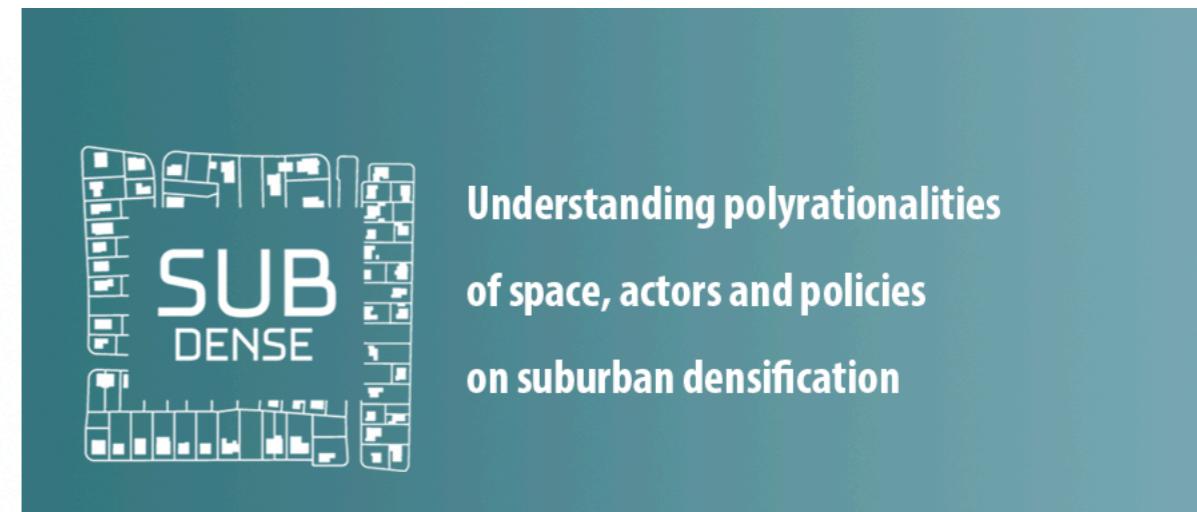
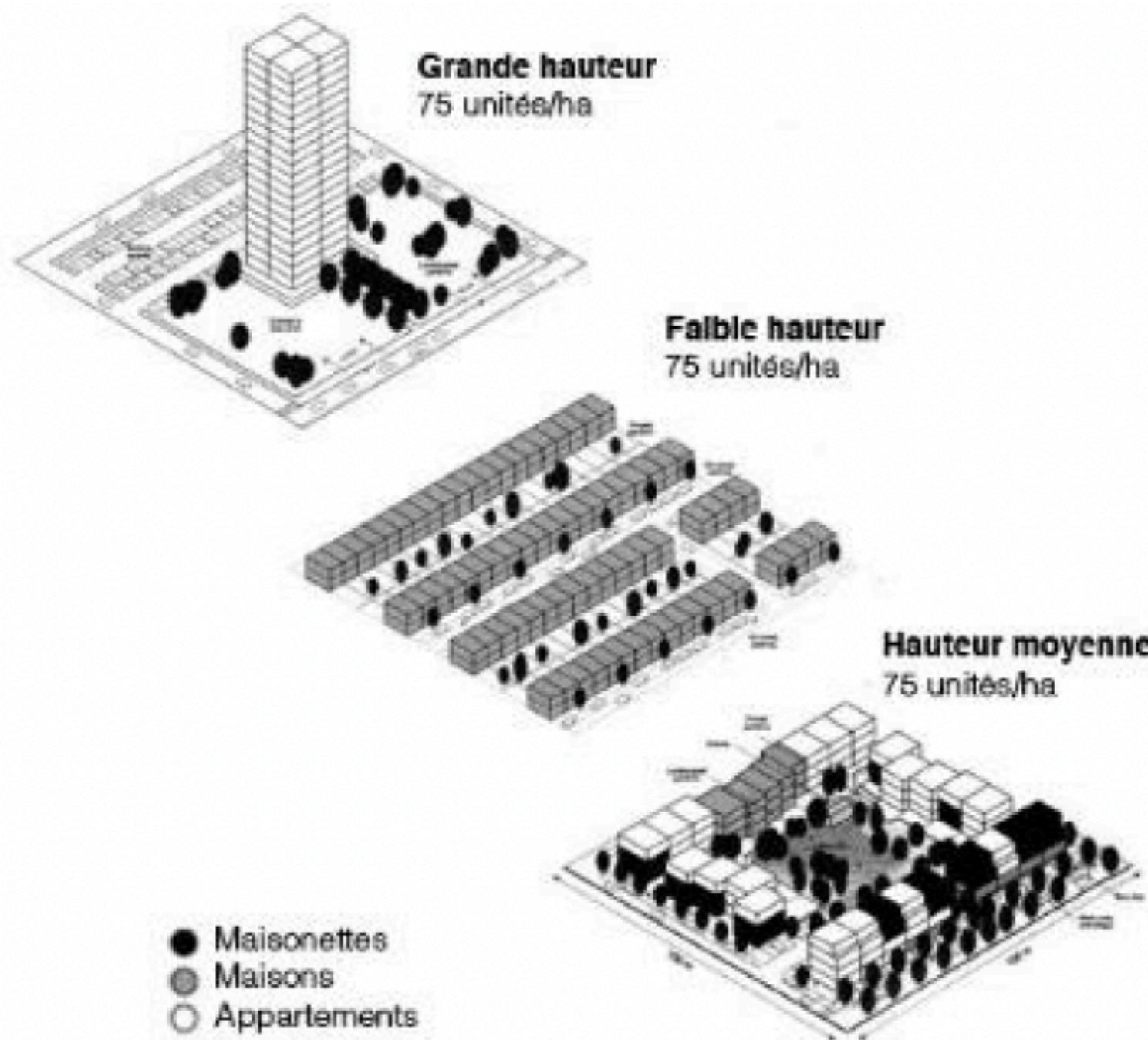
# 1 CONTEXT

## CONTEXT

## ALGORITHM

## G.TRUTH

## OPTIMISATION



## ■ Quantification of urban dynamics :

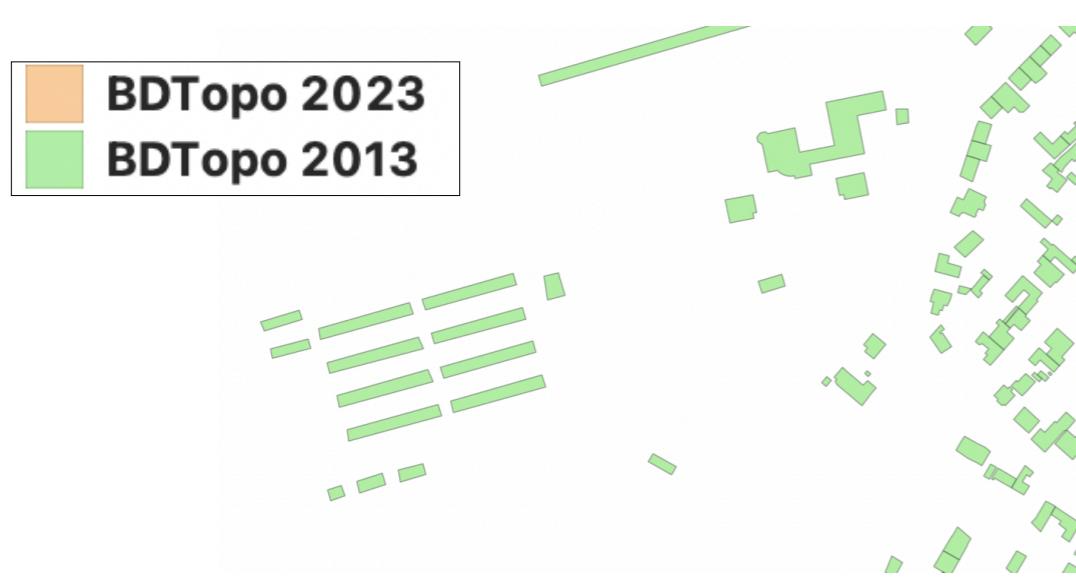
- Buildings stability assessment at different dates



Oblique image in 2014



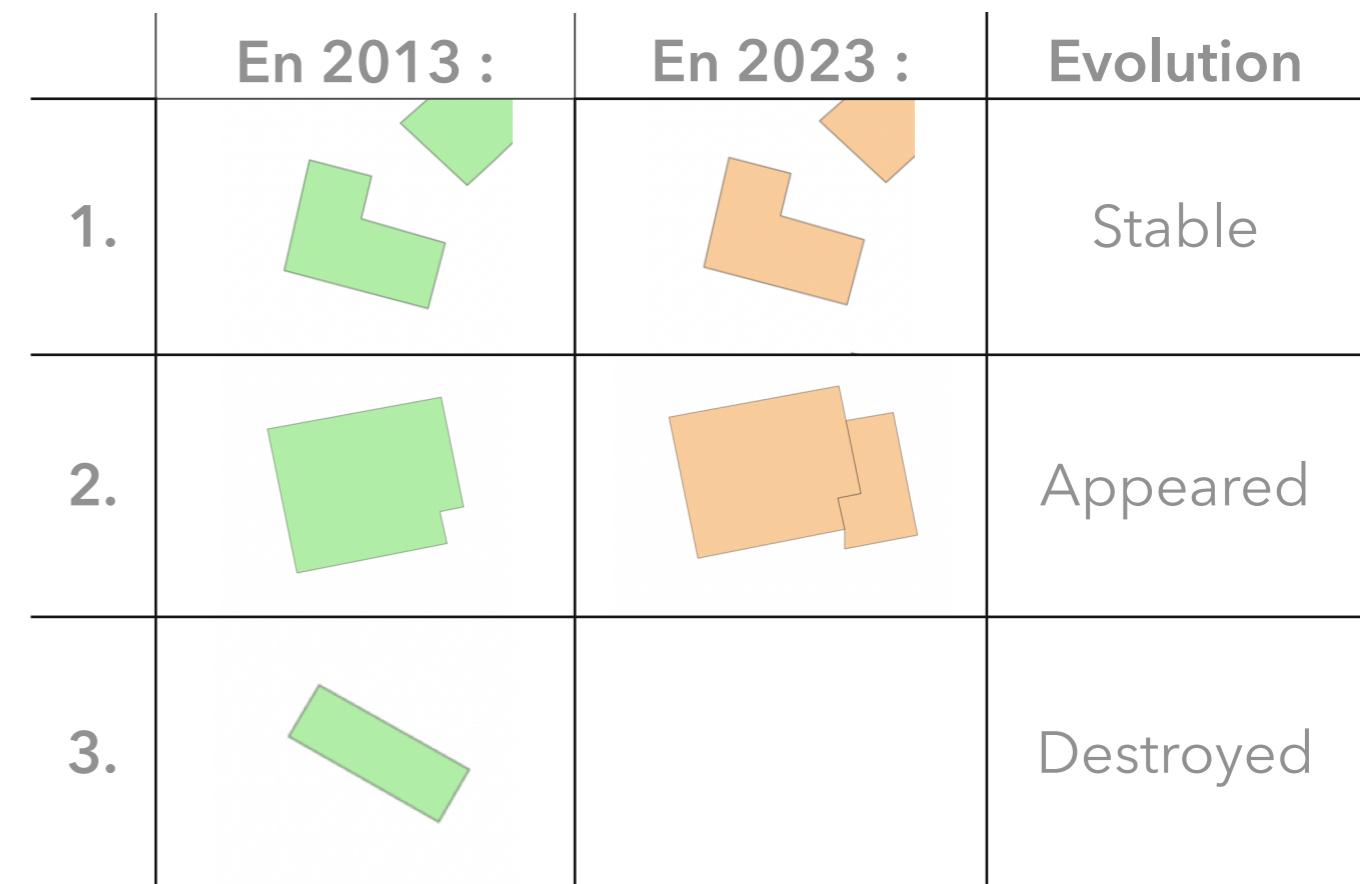
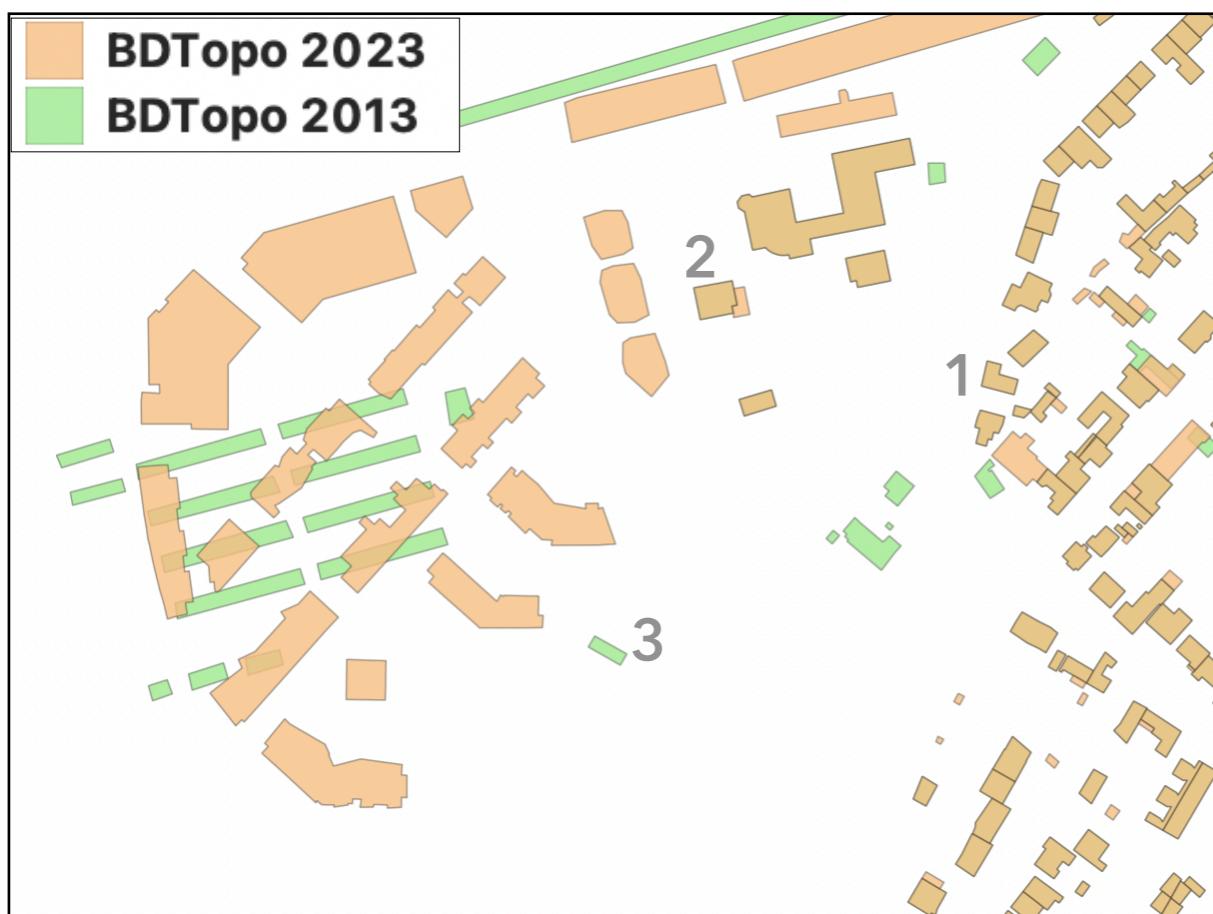
Oblique image in 2023



Example : BDTopo 2013 and 2023 in peripheral area to the north of Rennes

## ■ Quantification of urban dynamics :

- Establish the types of evolution possible for territorial dynamics



**Example : BDTopo 2013 and 2023 in peripheral area to the north of Rennes with types of evolution for several buildings**

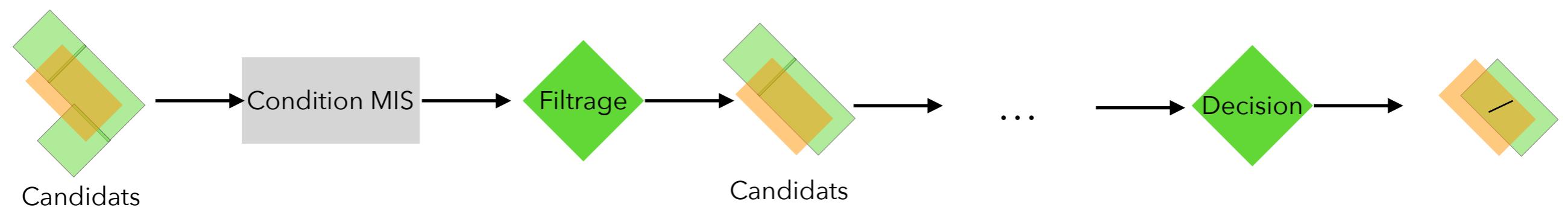
# 2 ALGORITHMS

CONTEXT

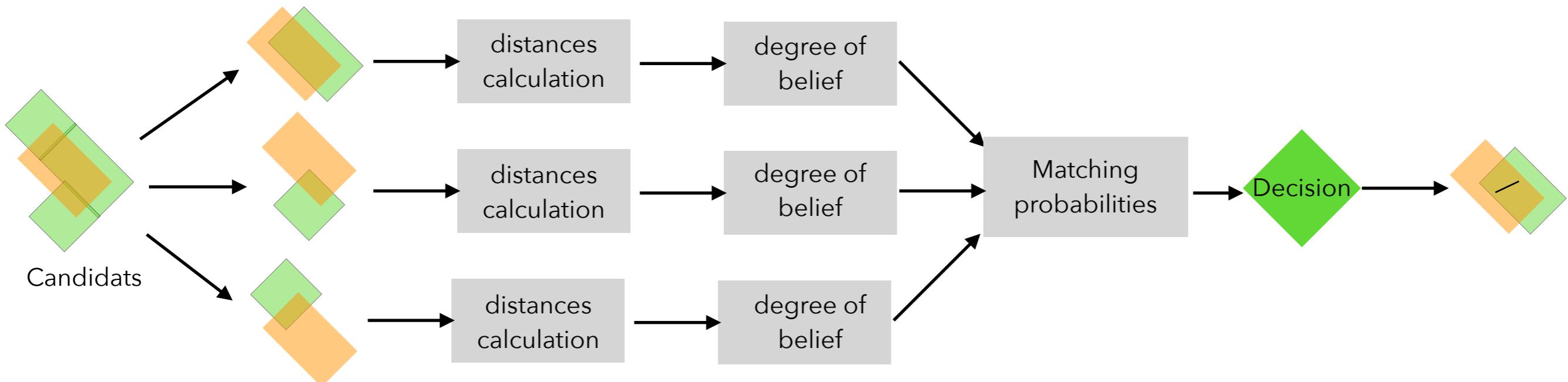
ALGORITHM

G.TRUTH

OPTIMISATION

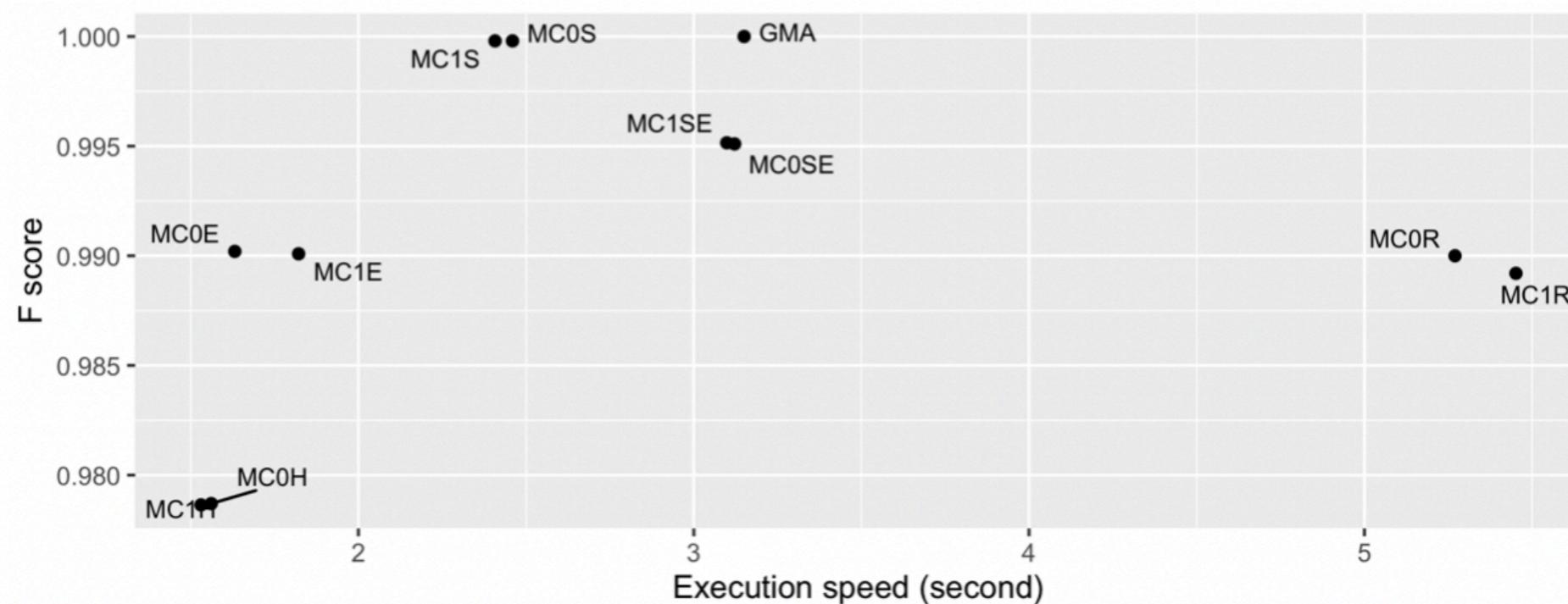


### Workflow of Geometric Matching of Areas algorithm (GMA)



### Workflow of Multi Criteria Algorithm algorithm (MCA)

- Paul Guardiola and alt, Benchmarking algorithms for matching geospatial vector data, French Regional Conference Complex System 2024, <https://zenodo.org/records/11267401> page 277 - 280



Optimal GMA parameters:  $MIS = 1$ ,  $MIP = 1$ ,  $PIS = 0.8$ ,  $MSD = 0.25$ ,  $MCCF = 0.8$ ; MC0SE: Multi-Criteria ( $d_b = 0$ ) with Surface and Euclidian criteria

### Pareto comparison of optimal instantiations of the matching algorithms

- Repeat for different study areas

# 3 Synthetic data generator

- Method : We develop a synthetic data generator, which starts from real-world building data, and perturbs the dataset to generate a virtual future state

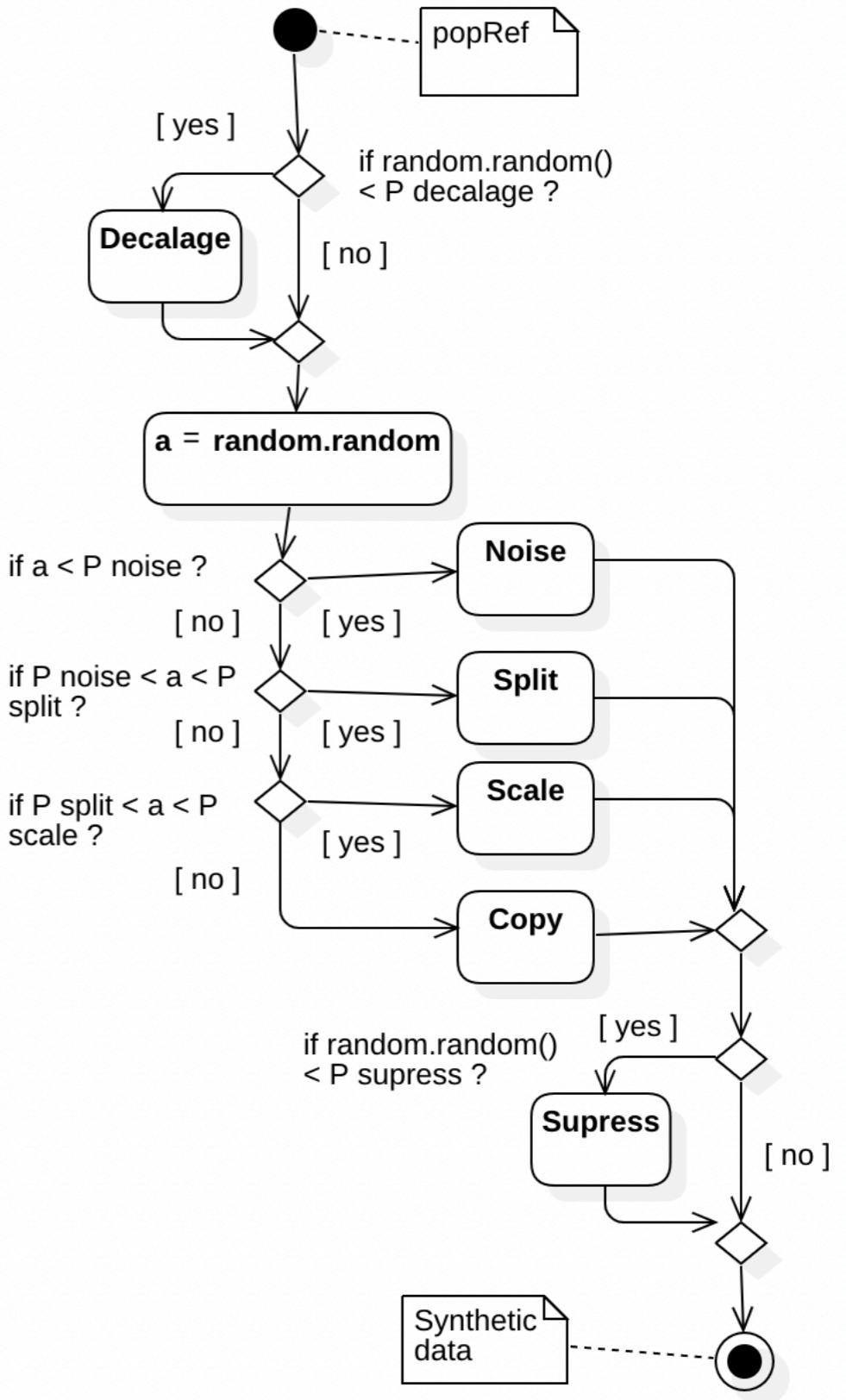
	popRef	popCreate
Decalage		
Noise		
Split		
Scale		
Copy		
Suppress		

**Table of synthetic data generation**

## ■ Construction of a synthetic data generator

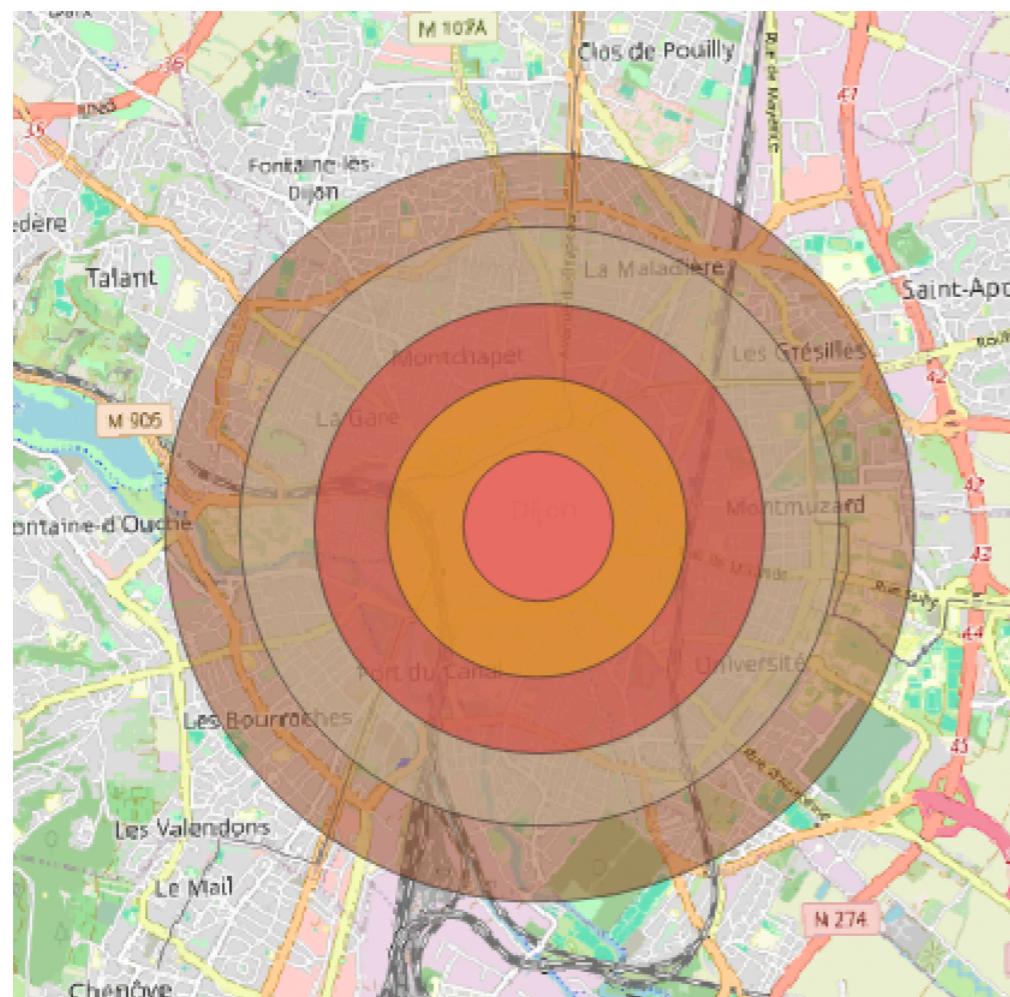
- Use of probabilities to choose to apply a noise or other changement in data specification
- Decalage and supress intervene during the beginning and at the end of the process to be used on all the data

**Exemple : Workflow synthetic data generator**

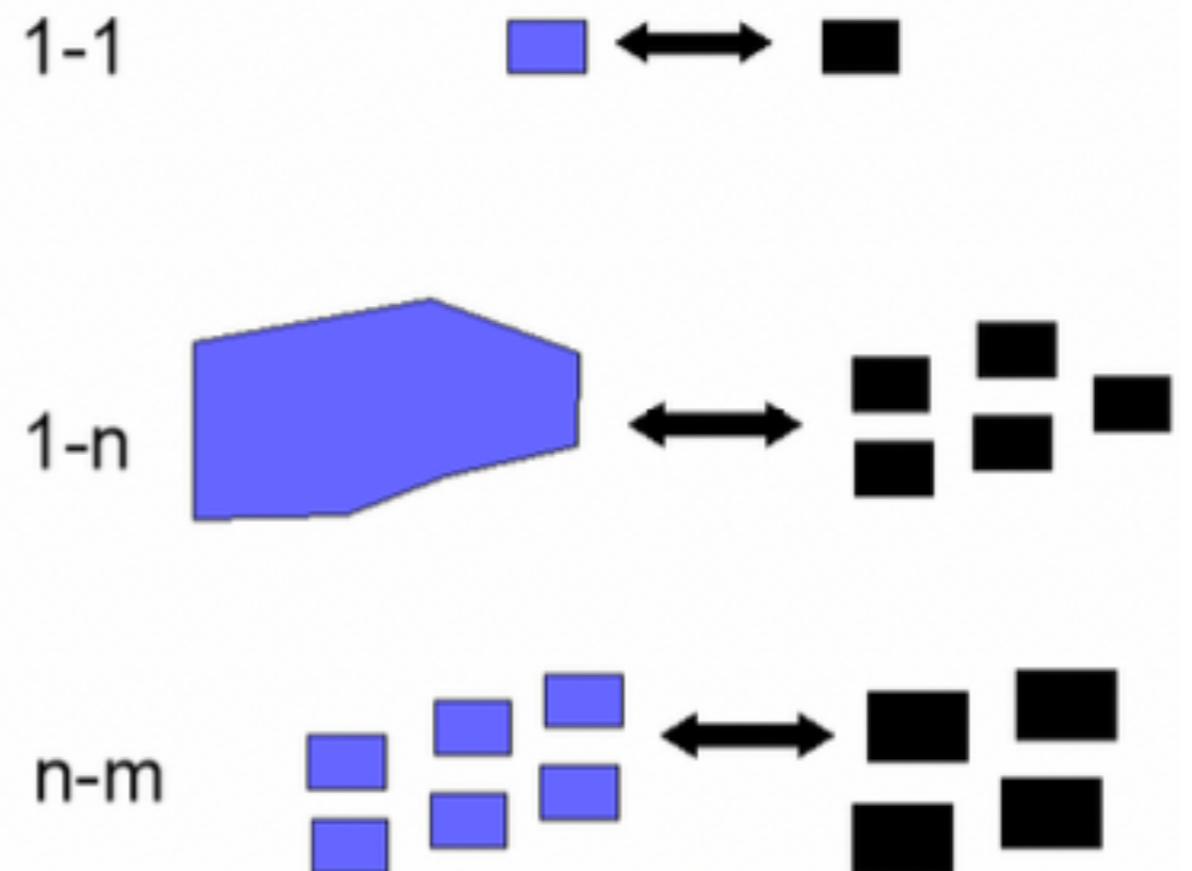


## ■ The problem is to fix the different probabilities

- Recreate urban dynamics



**Density of surface distance  
between popRef and popComp On  
Dijon on annulus with a radius of 1  
km**

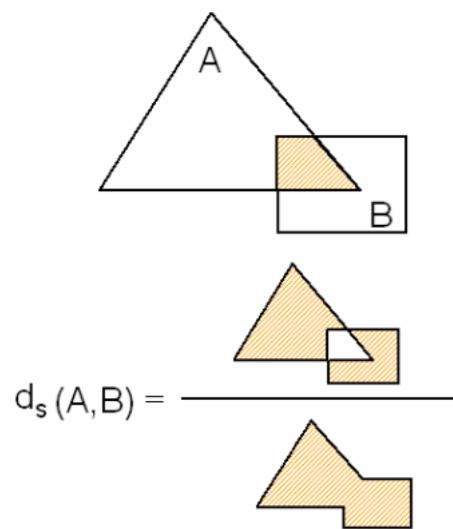


**Types of matching links**

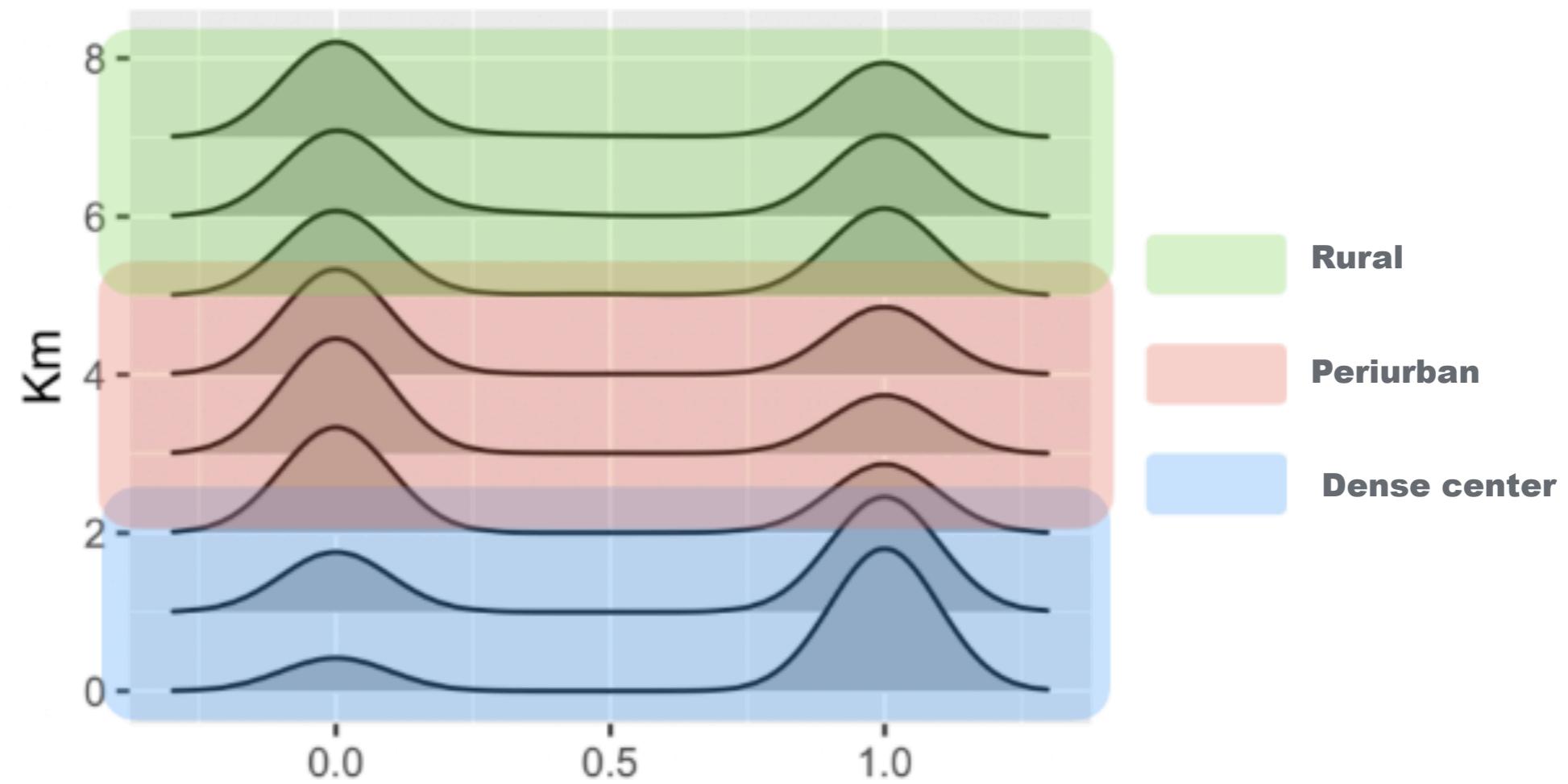
## ■ The problem is to fix the different probabilities

- Recreate urban dynamics

**Reminder : Surface distance**



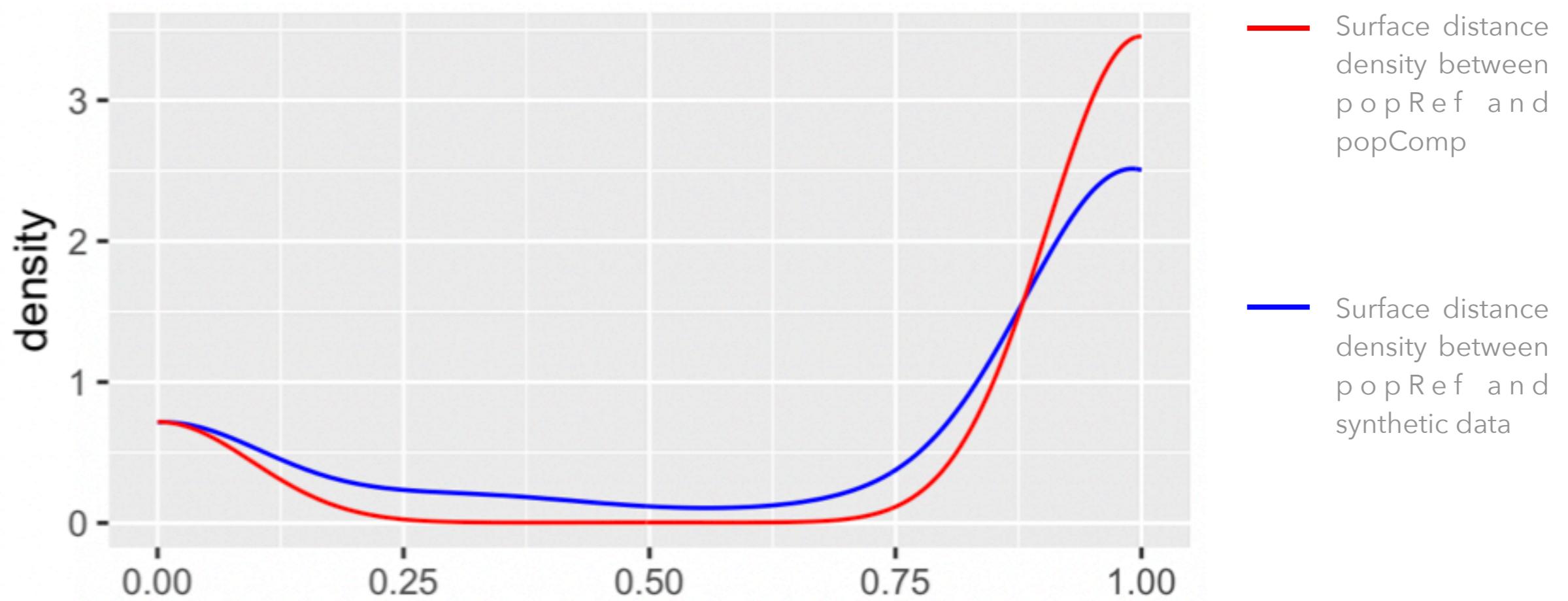
Ana-Maria Olteanu. Fusion de connaissances imparfaites pour l'appariement de données géographiques: proposition d'une approche s'appuyant sur la théorie des fonctions de croyance. Autre [cs.OH]. Université Paris-Est, 2008. Français. NNT : 2008PEST0252 . tel-00469407



**Density of surface distance between popRef and popComp On Dijon on annulus with a radius of 1 km**

## ■ The problem is to fix the different probabilities

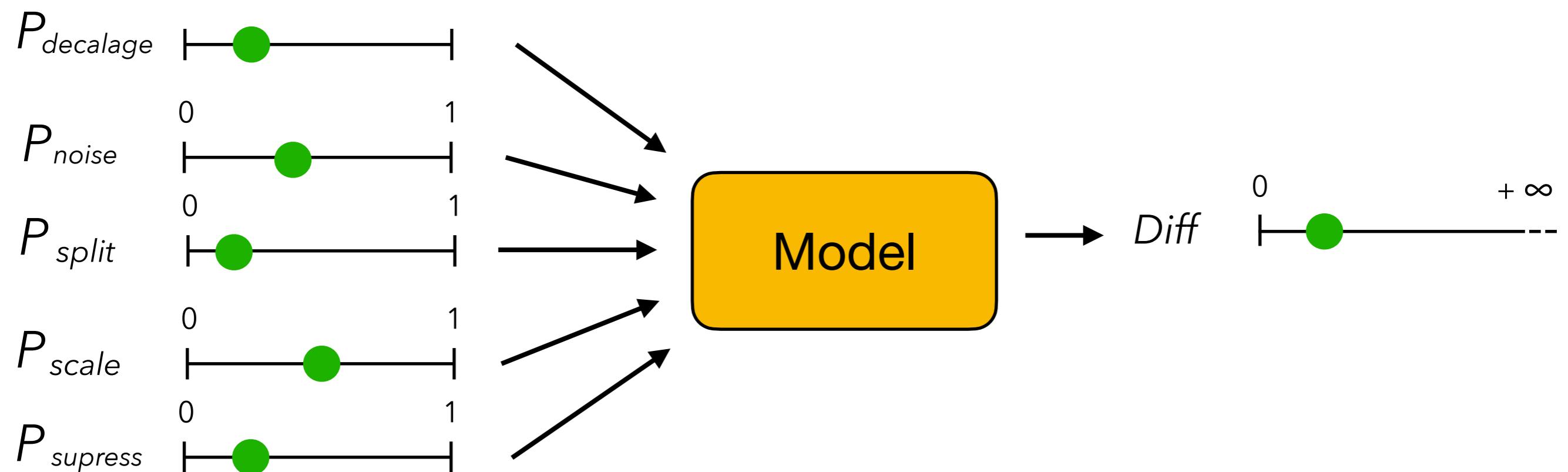
### ■ Recreate urban dynamics



$$Diff = \int (density(test(dS)) - density(reference(dS)))^2 ddS$$

## ■ The problem is to fix the different probabilities

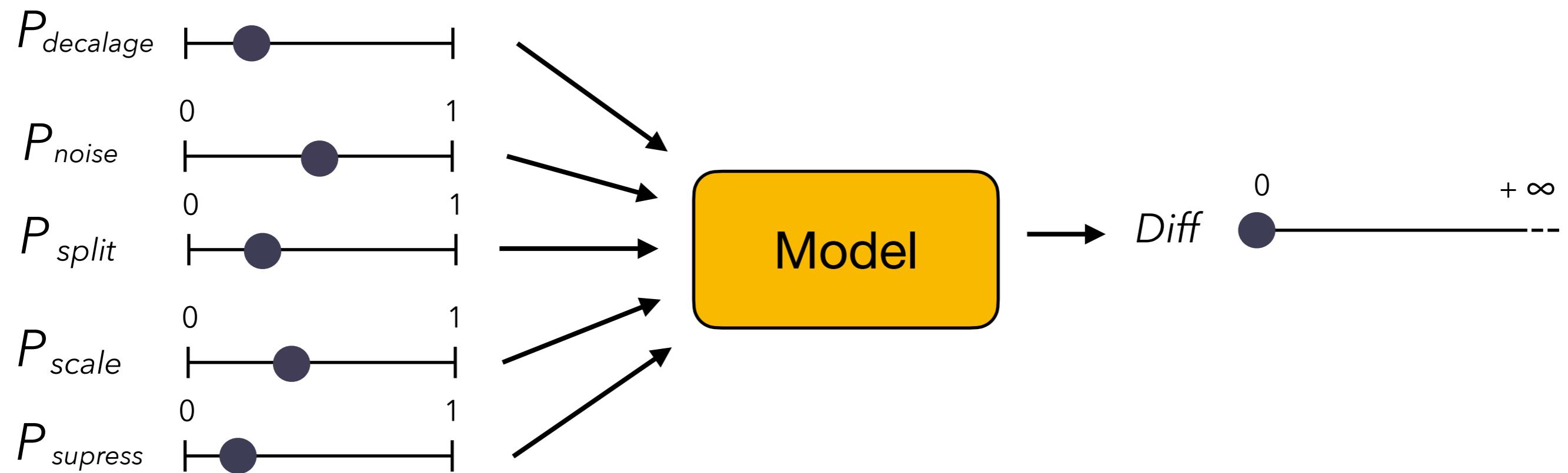
### ■ Recreate urban dynamics



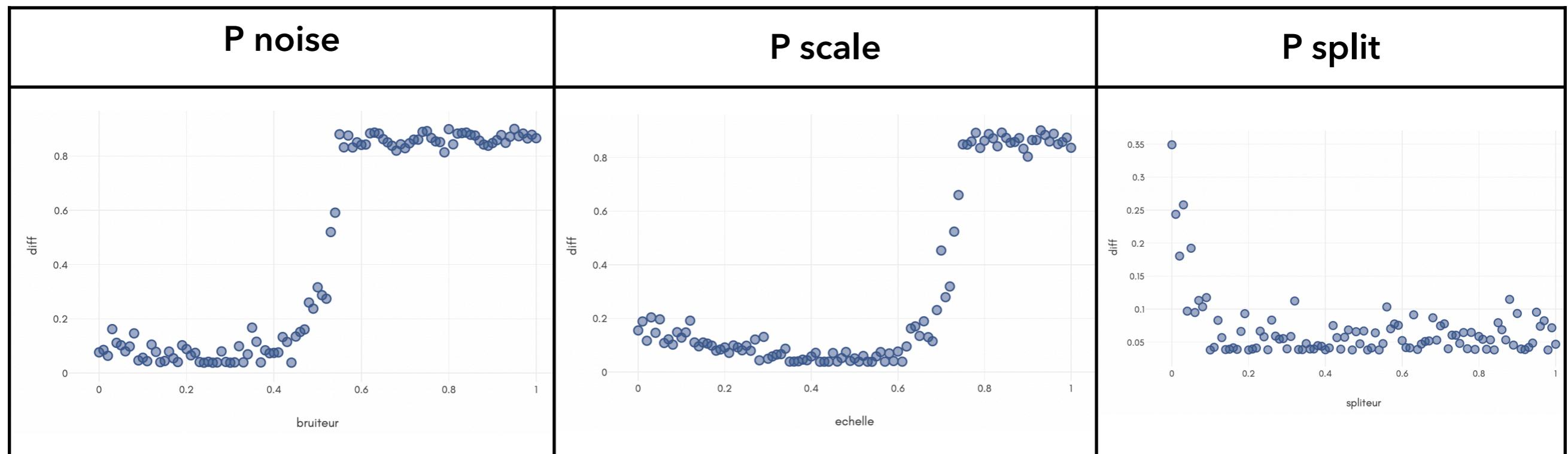
**Synthetic data generator inputs and output**

## ■ Use of OpenMOLE calibration

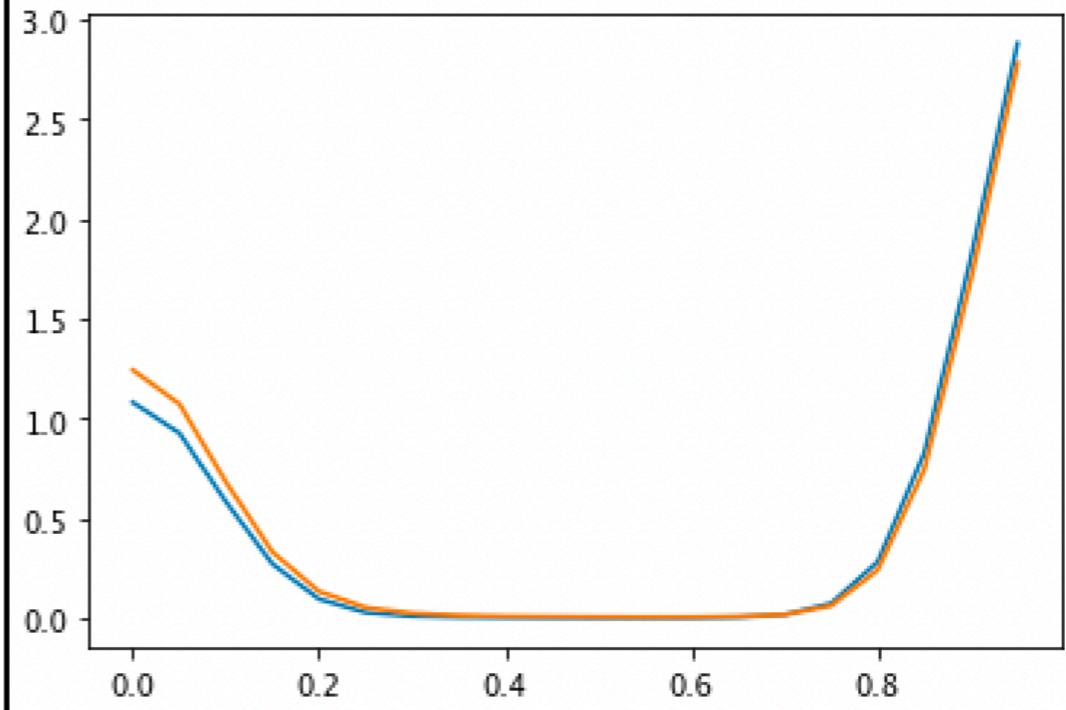
## ■ Use of OpenMOLE calibration



	Calibration 1	Calibration 2	Confidence interval
Input	$P_{\text{noise}} = 0.26$ $P_{\text{scale}} = 0.46$ $P_{\text{split}} = 0.24$ $P_{\text{copy}} = 0.04$	$P_{\text{noise}} = 0.23$ $P_{\text{scale}} = 0.49$ $P_{\text{split}} = 0.11$ $P_{\text{copy}} = 0.16$	$I_{\text{noise}} = [0.20, 0.30]$ $I_{\text{scale}} = [0.40, 0.50]$ $I_{\text{split}} = [0.05, 0.25]$ $I_{\text{copy}} = [0, 0.20]$



## ■ Résultats de la calibration d'OpenMOLE pour différentes types de zone sur Rennes

Urban morphologies	Optimized probabilities	Surface distance density between popRef and synthetic data
Dense center	Decalage= 0.05 Noise = 0.45 Scale = 0.20 Split = 0.25 Copy = 0.10 Supress = 0.10	

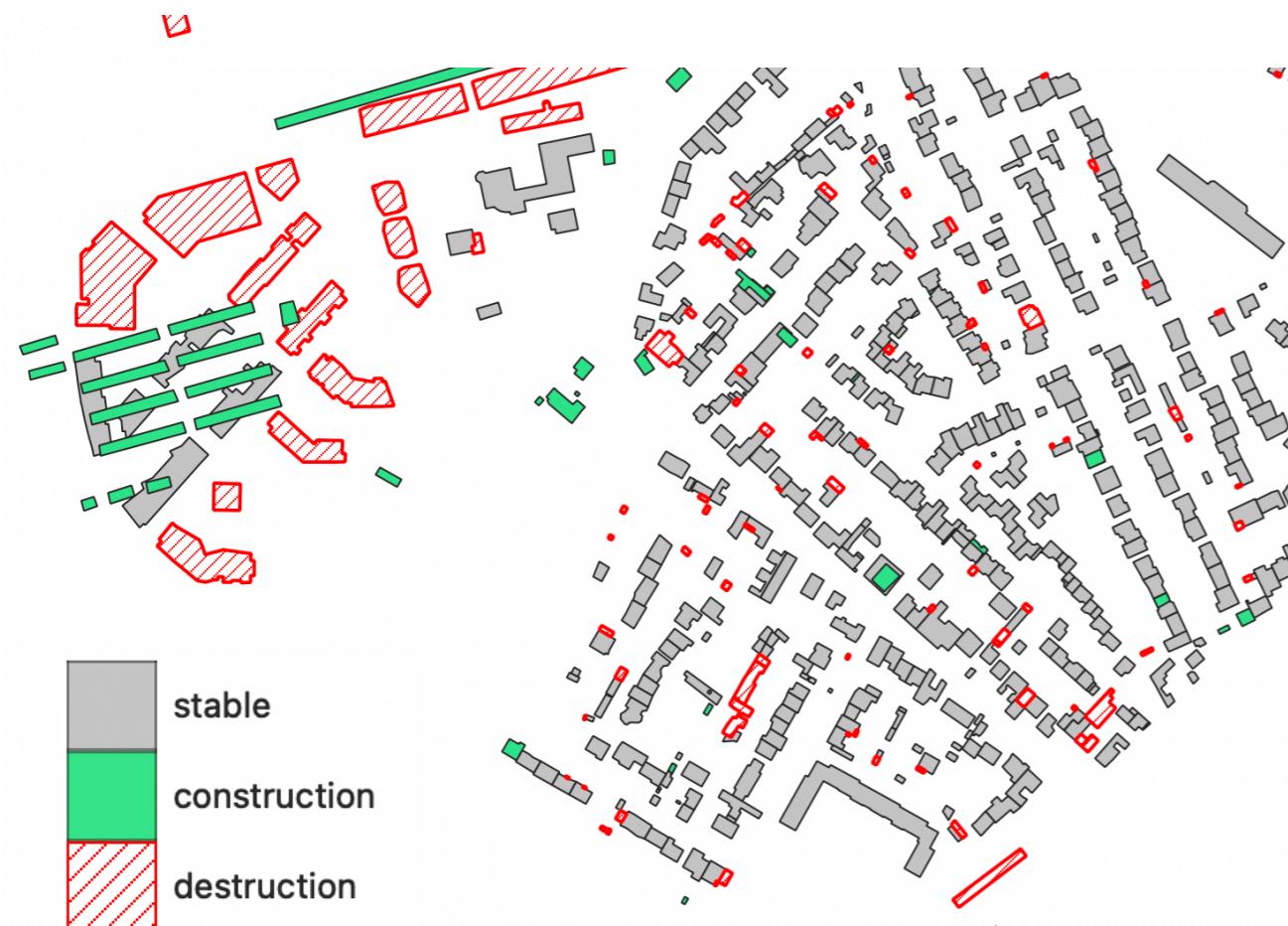
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■ Matching algorithm classification with GMA and MCA



Result for MCA classification



Result for GMA classification

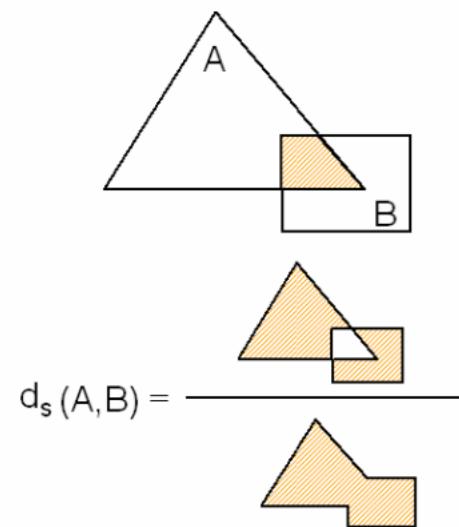
- We find an under-detection for the GMA and an over-detection for MCA
- GMA is a well method for n-m links rather than MCA is better for 1-1 links

# 4 Optimisation

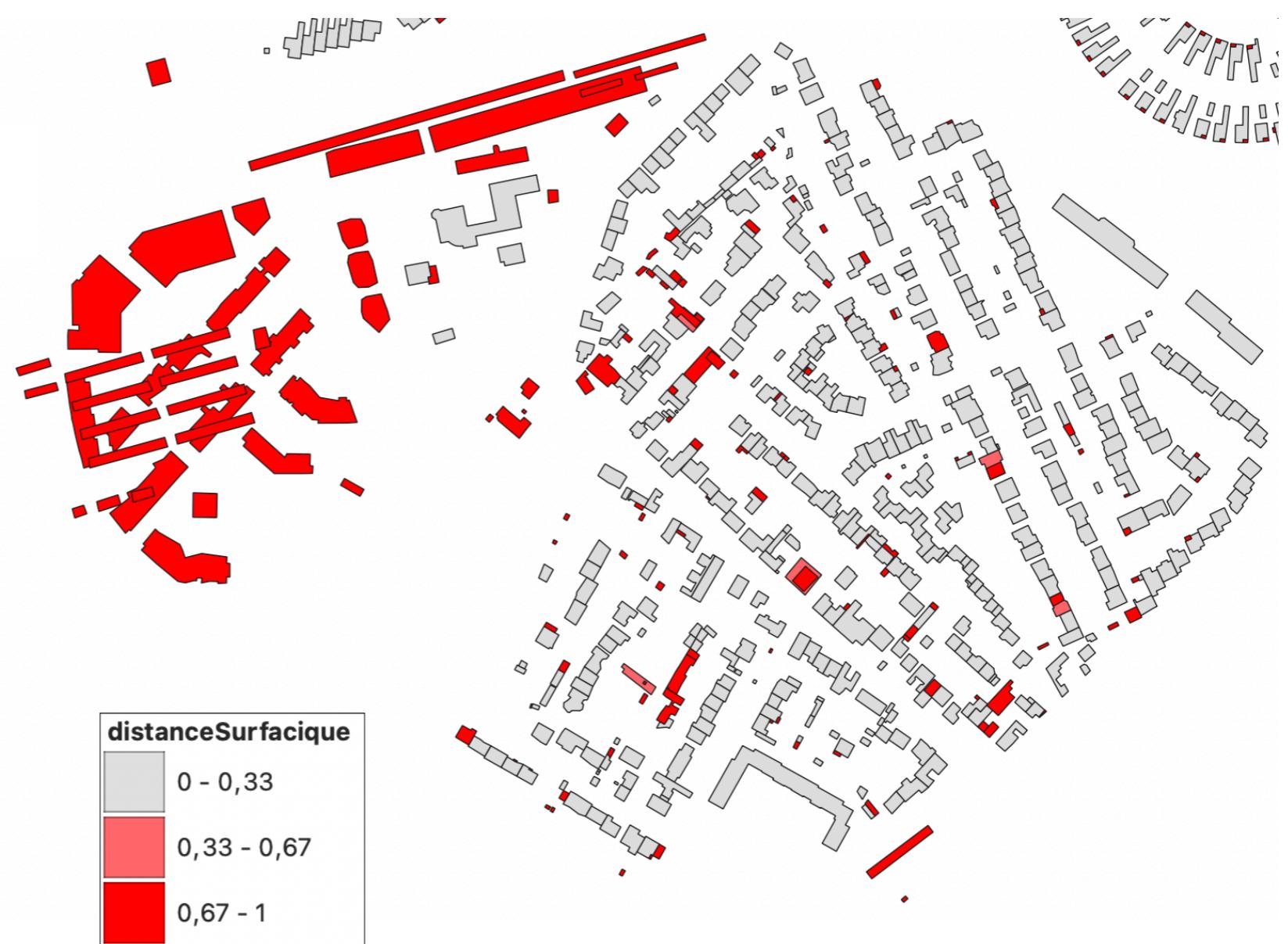
## ■ Multi-modeling

- Apply different Matching algorithm according their zone of predilection

**Reminder : Surface distance**

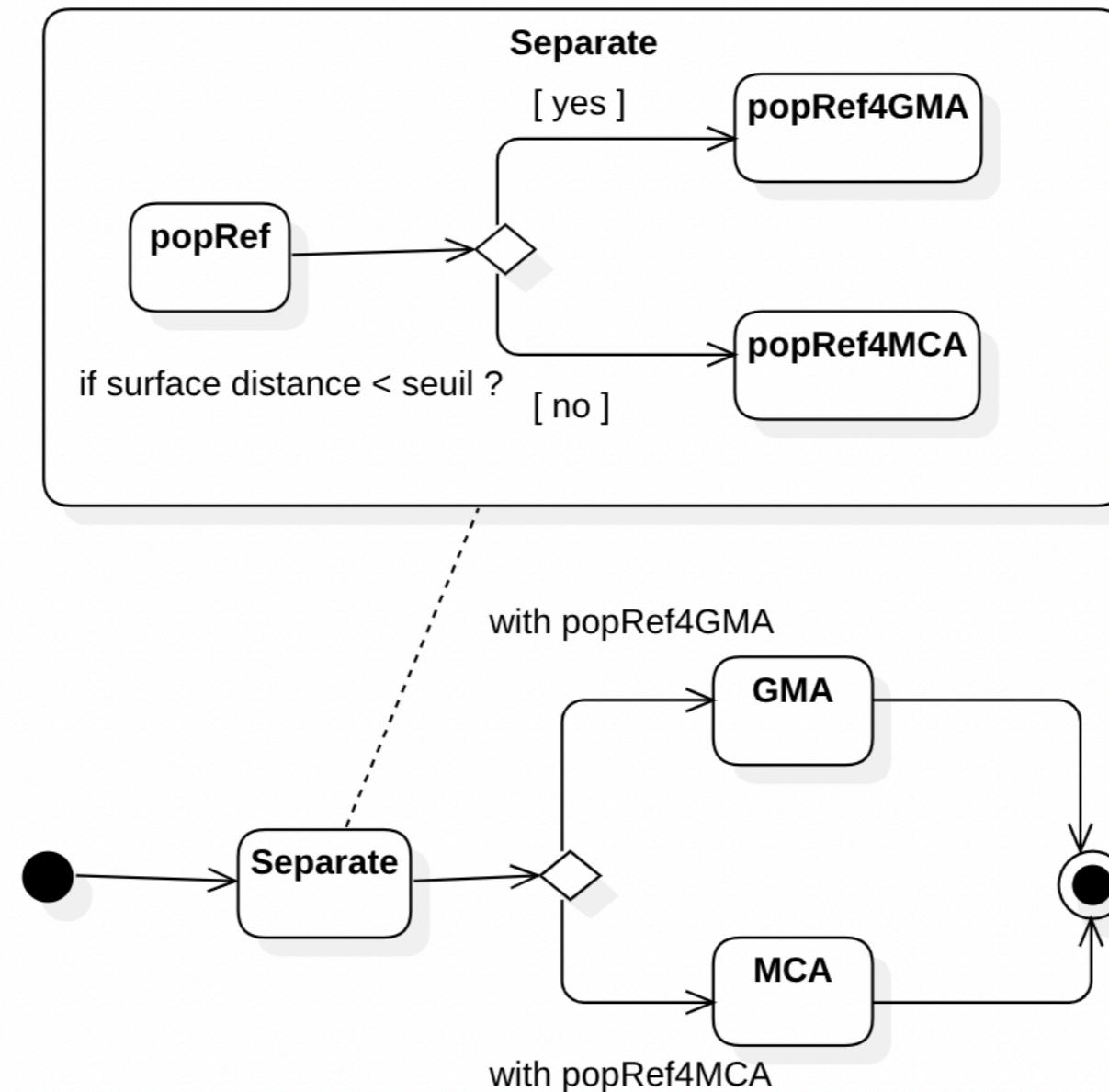


Ana-Maria Olteanu. Fusion de connaissances imparfaites pour l'appariement de données géo-graphiques: proposition d'une approche s'appuyant sur la théorie des fonctions de croyance. Autre [cs.OH]. Université Paris-Est, 2008. Français. NNT : 2008PEST0252 . tel-00469407



**popRef with surface distance**

## ■ Apply different Matching algorithm according their zone of predilection



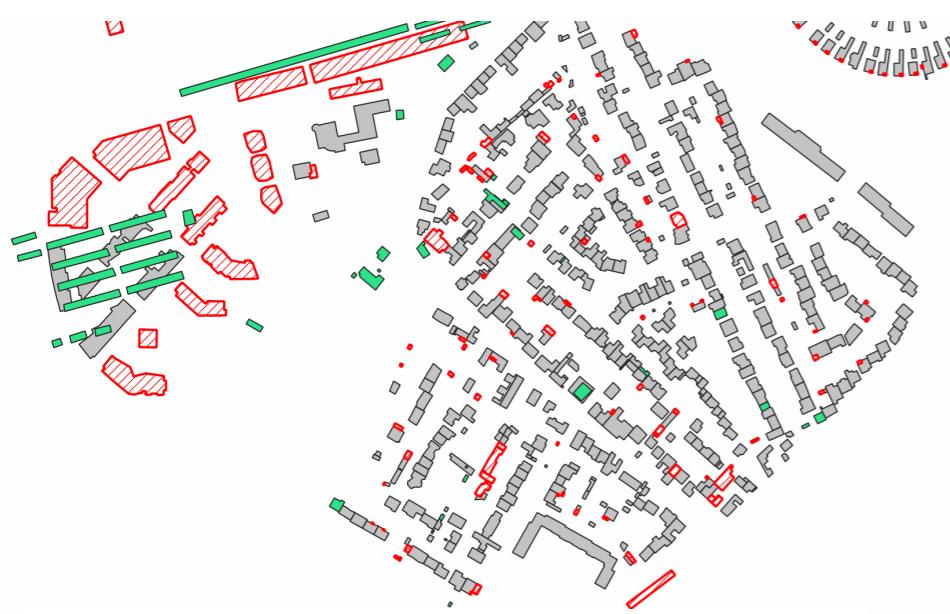
**Worflow du modèle pour séparer la population de référence**

CONTEXT

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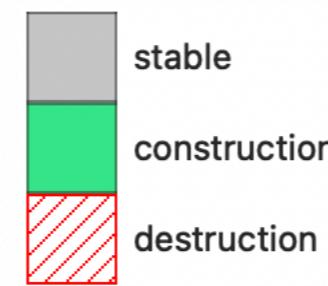
**Result for MCA classification**



**Result for GMA classification**



**Result for multi-modeling classification in peripheral area to the north of Rennes**



## Future works :

- to test this work to other European countries
- to test other matching algorithms
- to compare change detection results with machine learning results on remote sensing images

While our results are quite specific to geospatial data and the case of building change detection, they provide some insights into the broader question of spatial sensitivity analysis for complex systems, since we describe a methodology to generate synthetic data by introducing noise into a real world dataset, a research direction that was remaining to be fully explored in the future.

## This presentation proposes :

- a synthetic data generator for Matching algorithm for geospatial vector data
- a method to obtain a matching algorithm optimized

Source code and data are available on an open git repository at :  
<https://github.com/paulguardiola/projetAppariement>.