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Learning to plan healthier cities with precise data

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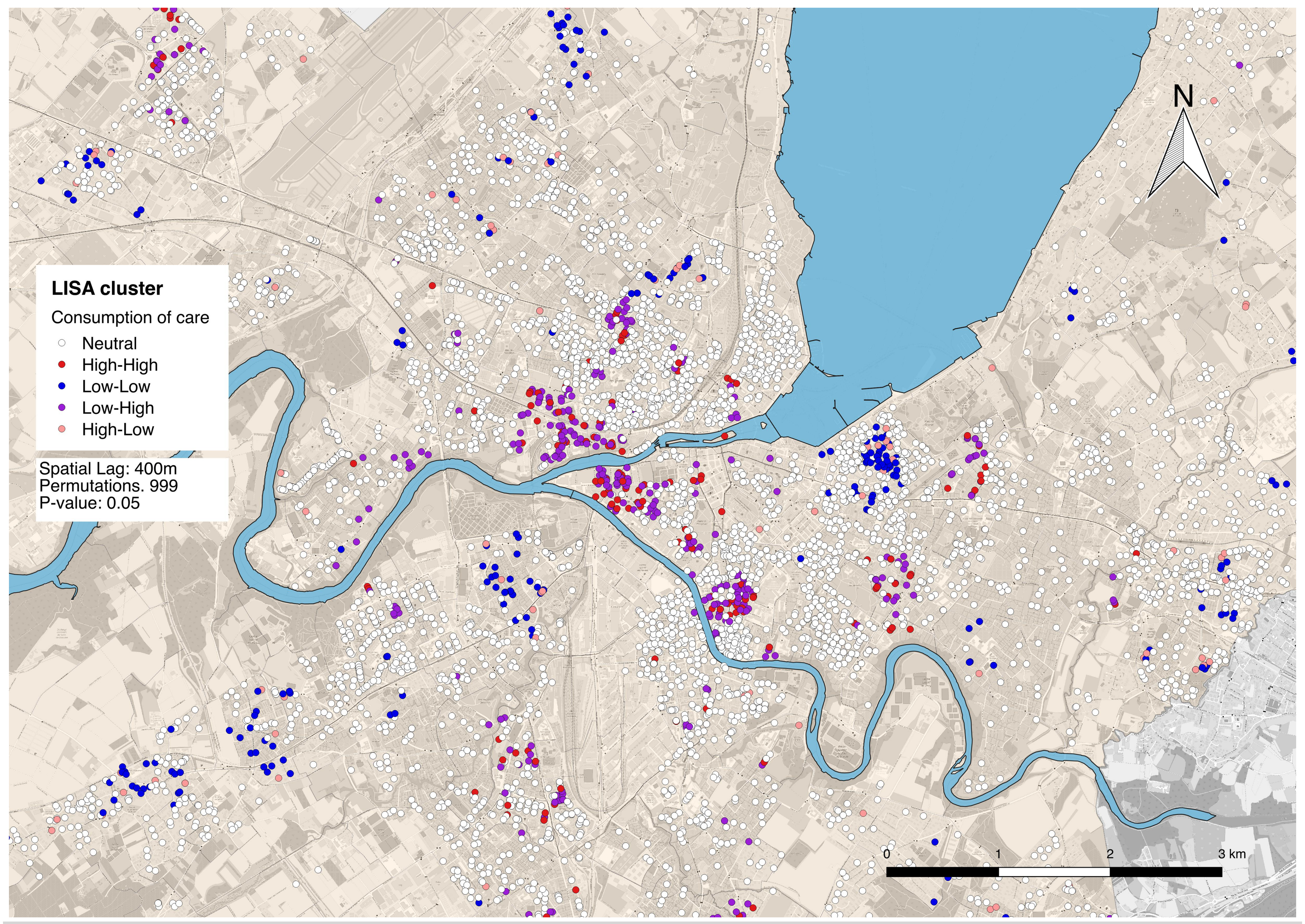
The intricate patterns of the precise data available in the town center of Geneva. Dataset includes land use attributes from roads to single tree canopies.



LISA clusters of consumption of care (as number of visits to health-care services).

INTRODUCTION

Prevention in public health should not be confined to the healthcare system alone: the cities where the majority of the world population lives may have an impact either positive or negative. Despite the knowledge which link health outcomes and built environment is well understood, it is still not clear how to optimise the delivery of health benefits to whole city with equity[1].

The governance of the territory which ameliorates health through urban planning, is called Healthy Urban Planning (HUP). In the context of the urban health, researches seek for standard quantitative and integrated approaches: assessments are often qualitative, or either focussed on a single public health burden.

In this poster, a novel methodology is shown, elaborated to assess how the different urban forms of cities are associated with health and wellbeing, through precise data on the built environment validated by health outcomes. The following methodology will be tested on the urban areas of Geneva as case study and is part of the **Health and Land-Use Planning project (HeLP).**

DATASET

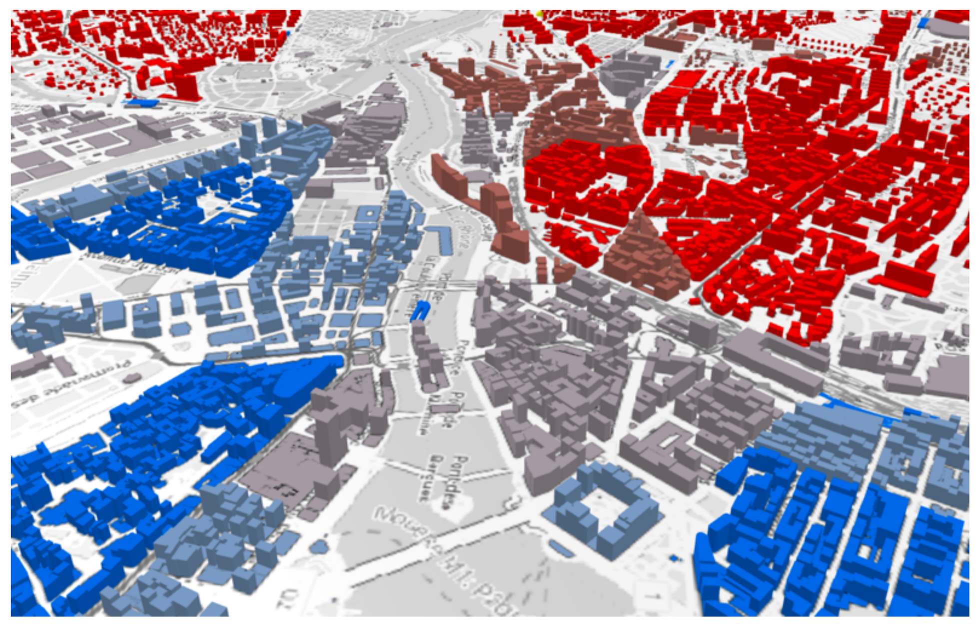
The cross-sectional study *Bus Santé*[2], collects geo-referenced health data of the 3% of the population of the canton of Geneva (Switzerland, 489,524 in December 2016). The health data can be divided into 3 categories: major health outcomes, mortality census and consumption of care. Multiple characteristics of the built environment, describe 4 different aspects[3]: the indoor and outdoor environment, the mobility and the social environment.

METHODOLOGY

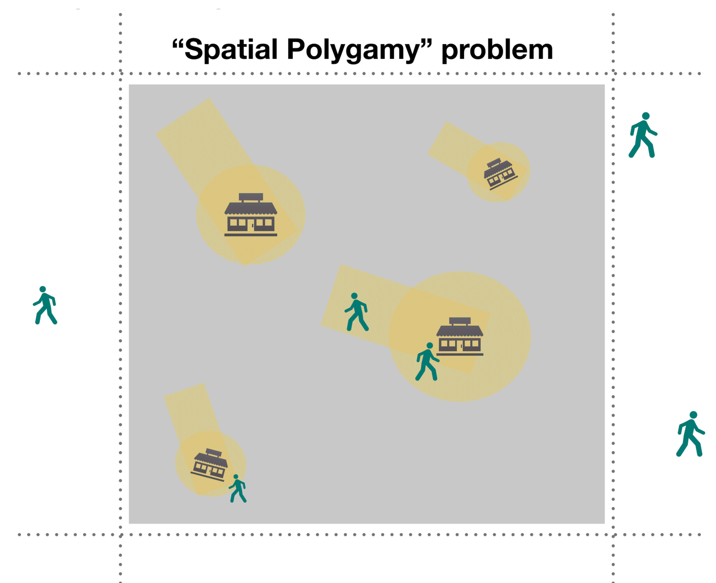
From the health datasets, spatial dependent cases are extracted using Local Indicators of Spatial Association per each of the health outcomes (using GeoDa©).

The study of such wide datasets and complex system, can be performed adopting machine learning methods[4], which fit with prediction and hypothesis generation. The health data allow the learning and validation itself, 90% to create the model and a 10% rotating to verify the robustness of the model. Unsupervised machine learning (using Scikit-Learn on Python©) is performed after principal component analysis within each of the 4 groups. Secondly, supervised learning is used, summing up the built environment characteristics with existing indexes able to describe single features, e.g. walkability. Changes introduced by plans and projects can be introduced modifying the input to predict the impact on health.

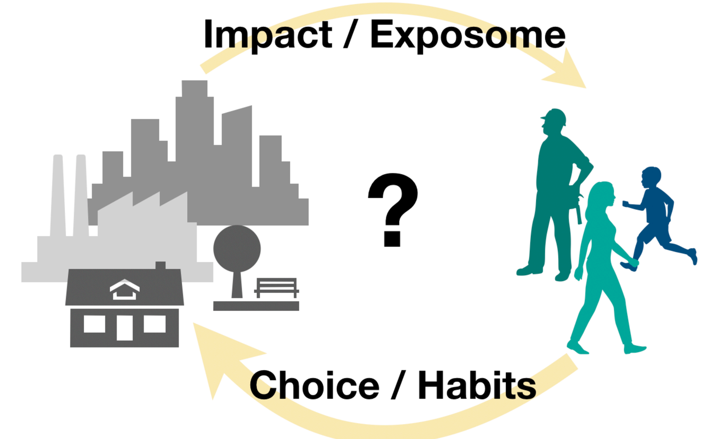
To take into advocacy health in the urban planning, results will be spread and compared with the evaluation produced by Multi Criteria Decision Analysis (MCDA) (using MACHBETH©). Weights will be assigned to evaluate the built environment attributes. Professionals coming from urban planning, public health and healthy urban planning will compare different choices allowing a modelling of the practice decision. In end, the approach based on machine learning and the one based on practice, will be compared.



Bivariate LISA clusters of obesity (body mass index) and building hight in a 3D model. The building hight may be used (in the urban area of Geneva) as predictor of quality of housing.



F.1

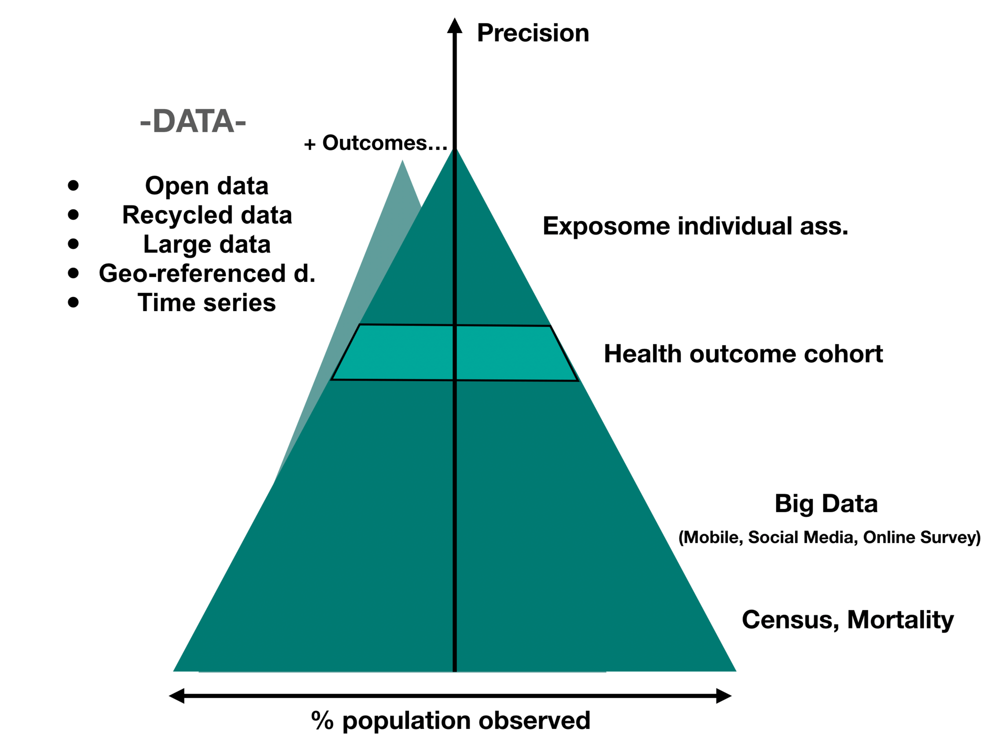


F.2

Following a parallel path, this study faces 4 fundamental points:

- Resistance to change/policy: time-dependent data can show when and changes in urban structure affected heath and wellbeing.
- "Spacial Polygamy" problem (F.1): the exposure or the impact of the built environment depend on multiple factors; areas of exposure/ impact has different shapes and sizes and depend on the mobility behaviour of individuals.
- "Is the neighbourhood having an impact on my health or I chose to live in a place that fits with my needs and habits?" (F.2) This theoretical question investigate the relocation behaviour and the perception of the environment.
- Do I have representative data? (F.3) Additional layers of data should be added, following multiple criteria. Layers will describe at multiple precisions, representative of different percentages of the population.

F.3



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