Thèse n° 8483

Spatial analysis of the Healthy Built Environment: an application on Cardiovascular Risk Factors in the canton of Geneva

Présentée le 19 mars 2021

Faculté de l'environnement naturel, architectural et construit
Communauté d'études pour l'aménagement du territoire
Programme doctoral en génie civil et environnement

pour l'obtention du grade de Docteur ès Sciences

par

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École
polytechnique
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de Lausanne

2022

Acknowlegments

This thesis would not have been feasible without the support of a wide range of people, including colleagues and friends, my family, and everyone else who supported me during these years.

Following the sequence of events, I'd like to express my gratitude to Prof. Grazia Ghermandi, Prof. Alessandro Corsini, Prof. Alessandro Capra and Prof. Alessio Ferrari for making it possible for me to join the EPFL.

In particular, my sincere gratitude goes to the thesis director, Dr Jérôme Chenal, for allowing me to work on this PhD thesis. I want to thank you for the advice you provided throughout the years and for your patience and freedom in developing this study project. I would like to thank Prof. Idriss Guessous, Dr Stéphane Joost, and the GIRAPH team, who provided guidance, feedbacks and granted access to data.

Besides my director, I would like to thank the rest of my thesis jury: Prof. Corentin Fivet, Prof. Gina Lovasi, Dr Thiago Herick de Sa, and Dr Marc Soutter for their insightful comments and the encouragements, but also for reviewing the manuscript providing valuable perspectives. I am also very grateful to Prof. Michel Bierlaire as the external expert of my candidacy exam. I would also like to offer my special thanks to Marcus Grant and Carlos Dora for the precious feedback and comments.

I would want to thank the entire CEAT team for creating a beautiful workplace environment during these years and sharing priceless experiences outside of EPFL. I am grateful to Gladys for helping throughout these years; the CEAT would not be the same without you. To old and new collegues; Armel, Alexandre, Martí, Kamil, Stéphanie, Remí, Rolande, and Vitor for the stimulating debate, support, and fun both inside and outside of EPFL. Similarly, my gratitude extends to the many friends I've made within the gates of EPFL, particularly in the BP and GC buildings. I also want to thank all the friends who have supported me over these years, both in Italy, Switzerland and in different corners of the world. We have shared priceless moments that I will never forget.

Avant tout, je tiens à exprimer ma profonde gratitude à Julie, qui, grâce à sa gentillesse et son affection, m'a beaucoup aidé à mener à bien ma thèse, mais a aussi rendu ces années fantastiques et inoubliables.

Vorrei ringraziare tutti i membri della mia famiglia per esserci sempre stati per me. Ringrazio infinitamente i mie genitori, Angela e Claudio, per il vostro appoggio, la vostra gentilezza e per essermi stati da esempio.

Summary

More than half of the world's population lives in cities, and this proportion is expected to rise in the following decades. The complexity of different land uses and services in urban areas, which composes the built environment, influences human health and wellbeing. Concerning urban areas, to a large extent, spatial planning has the potential to shape the built environment to become healthier. The necessity of addressing the built environment is coherent with the crucial need for human health to effectively act in all policies outside healthcare to prevent adverse impacts and promote positive impacts across multiple sectors. Research and practice already addressed diverse health challenges related to the built environment, grouped under the large umbrella of "urban health". Policies, tools, projects, and programs have already been created in separate sectors to integrate health in governance. Despite these efforts, health is frequently viewed as a barrier to development in spatial planning, experiencing opposition at each stage. In this research, we focused on diagnosing the built environment, consequently studying its relationship with health through data and spatial analysis. The call for a built environment diagnosis aims to jointly address the most relevant health issues linked to the built environment and within urban areas. We addressed four concepts to understand the healthiness of the built environment: (i) the development of a structured framework to understand the stratification of multiple health determinants (ii) the analysis of the spatial distribution of those determinants to understand inequalities within an urban area, (iii) the integration of the stakeholders' perspectives in addressing urban health and its multiple issues, (iv) the understanding of the geospatial links between the built environment and the spatial distribution of health data.

The thesis aims to understand how the healthy built environment is spatially distributed in the state of Geneva (Switzerland). This work employs a holistic approach to explore how inequalities in the health-related built environment are distributed in space and compare it with geospatial health data adopting global and local geospatial approaches. Using multiple spatial analysis methods for both built environment and health data and building a framework for a broad assessment of urban health, three hypotheses are tested in three sections.

Before addressing the first hypothesis, we develop a framework for analysing the healthiness of the built environment. The framework is thought to reduce the overlap between its composing parts and collect a broad range of relevant urban health issues for a generic case study. In the first section (1), the framework is adapted to the case study to describe the heterogeneity of health-related built environments at a small geographic scale through a set of indicators corresponding to urban health issues. Statistical spatial and aspatial methods are applied to generate indicators to perform an explorative diagnosis that identifies inequities in the health-related built environment and its heterogeneity. This section contributes to visualising how a broad range of urban health issues are stratified within the study area and which geographic patterns they display. The second section (2) studies the differences between three stakeholders (urban health experts, local planning practitioners and residents in the canton) in rating urban health among planning objectives and urban health issues. This section also provides a weighting of the urban health issues indicators developed in the first section of the thesis, and it studies the spatial association of residents' responses with those indicators. This section shows how integrating viewpoints in addressing urban health issues could influence planning for urban health. The third section (3) studies the relation between geospatial health data and the built environment, using a cross-sectional spatial dataset of cardiovascular risk factors georeferenced by postal address in the study area. This section first describes the health dataset of six cardiovascular risk factors and identifies its spatial clusters. Afterwards, we assess the estimation power of the built environment characteristics and its indicators employing both spatial and aspatial approaches for the regression analysis with the health dataset. The regression analysis tests different neighbourhood sizes to sample built environment attributes and the sub-set of cluster health data. This section shows the limited power of prediction from built environment data, which cannot predict the totality of the health dataset but deliver a reliable prediction of health data belonging to clusters. By studying the contributes of built environment characteristics in the regression analysis, we demonstrate the non-stationarity in the geographic space of the relationship between cardiovascular risk factors and the built environment. In the end, we display how the spatial regression approach can recreate the clusters of cardiovascular risk factors using the built environment.

In general, the thesis shows that the built environment potentially deliver health benefits and impacts within the study area heterogeneously in the geographic space and depending on multiple urban health issues. Second, it demonstrates that the built environment is a limited predictor of individual cardiovascular risk factors by the residence's surroundings. Finally, we highlight the study's limitations by discussing the measures that should be taken to frame urban health in terms of the built environment and health input data and the methodology limitations for urban health spatial analysis. Afterwards, we discuss the potential role of this work in positively supporting urban health integration in spatial planning and its synergic role with other tools, policies, programs, and policies. The thesis suggests improving the understanding of the healthiness of urban environments by six points:

- Existing geospatial data can be used to assess and monitor the status of the built environment to understand the potential impacts on health within the whole city area so that priorities and inequities are identified.
- The development of a framework that addresses multiple urban health issues can ensure any issue is neglected at the strategic level, while interactions and the stratification of built environment impact human health are not missed.
- The combined use of global and local methodologies to examine inequality allows respectevely to get a broad view of urban health challenges, and to understand the spatial heterogeneity and incorporate accessibility considerations.
- The study of the association between the built environment and health take advantage of considering the non-stationarity of their relationship in the geographic space so that interventions are optimised and tailored to local exigencies.
- The complexity of the relationship of health with the built environment at the individual level requires a broad collection of data encompassing the temporal evolution of health data, built environment data and its contextual exposition.
- Only a part of urban health issues are handled by regulations, which mainly focuses on health prevention rather than health promotion. As a result of the absence of institutional implementation, most interventions rely on stakeholder initiative, while assessment and monitoring procedures are uncommon, preventing the implementation and diffusion of regulations for urban health.

This research uses a variety of spatial and aspatial methodologies to diagnose the healthiness of different elements of the built environment to advocate for health integration in spatial design in its entirety to address disparities. The thesis, in general, identifies inequities in the characteristics of the health-related built environment and the spatial clustering of health issues among the resident population within the study area. Also, the thesis contributes to understanding the association of health data with the built environment depending on the residence location, at multiple spatial scales, and at global and local level in the canton of Geneva.

Keywords:

spatial analysis, urban health, built environment, health inequities, , cardiovascular risk factors, Geneva, Switzerland.

Résumé

Plus de la moitié de la population mondiale vit dans les villes et cette proportion devrait augmenter au cours des prochaines décennies. Les différentes utilisations du sol et des services dans les zones urbaines, qui composent l'environnement bâti, influencent la santé et le bien-être. En ce qui concerne les zones urbaines, l'aménagement du territoire a le potentiel de façonner l'environnement bâti pour qu'il devienne plus sain. La nécessité de s'interesser à l'environnement bâti pour la santé est cohérente avec le besoin d'agir efficacement sur toutes les politiques, aussi en dehors des soins de la santé, pour prévenir les impacts négatifs et promouvoir les impacts positifs dans des multiples secteurs. La recherche et la pratique abordaient déjà divers problèmes de santé liés à l'environnement bâti, regroupés sous le terme de la «santé urbaine». Plusieurs politiques, outils, projets et programmes ont été créés dans des secteurs distincts pour intégrer la santé dans la gouvernance. Malgré ces efforts, la santé est fréquemment perçue comme un frein au développement de l'aménagement du territoire, rencontrant des oppositions à chaque étape. Dans cette recherche, nous nous sommes concentrés sur le diagnostic de l'environnement bâti, étudiant par conséquent sa relation avec la santé au travers des données et des analyses géographiques.

Nous avons traité quatre concepts pour comprendre la salubrité de l'environnement bâti: (i) le développement d'un schéma structuré pour comprendre la stratification des multiples déterminants de la santé (ii) l'analyse de la distribution spatiale de ces déterminants pour comprendre les inégalités au sein d'une zone urbaine, (iii) l'intégration des perspectives des stakeholders de la santé urbaine et de ses multiples enjeux, (iv) la compréhension des liens géospatiaux entre l'environnement bâti et la distribution spatiale des données de la santé.

La présente thèse vise à comprendre comment l'environnement bâti, lié à la santé, est spatialement distribué dans le canton de Genève (Suisse). Cette étude utilise une approche holistique pour explorer comment les inégalités dans l'environnement bâti lié à la santé, sont distribuées dans l'espace. Ces inégalités sont comparées avec les données géospatiales sur la santé en adoptant des approches géospatiales globales et locales. Trois hypothèses sont testées dans trois sections en utilisant plusieurs méthodes d'analyse spatiale et en créant un cadre pour une évaluation multisectorielle de la santé urbaine.

Avant de vérifier la première hypothèse, nous avons développé un shéma structuré de la salubrité de l'environnement bâti. On a établi un shéma pour réduire le chevauchement entre ses éléments constitutifs et pour regrouper la majorité des problèmes de santé urbaine pertinent pour une étude de cas générique. Dans la première section (1), le shéma est adapté à l'étude de cas pour décrire l'hétérogénéité des environnements bâtis liés à la santé à une petite échelle géographique à travers un ensemble d'indicateurs correspondant aux enjeux de la santé urbaine. Des méthodes statistiques spatiales et aspatiales sont appliquées pour générer des indicateurs afin d'effectuer un diagnostic exploratoire qui identifie les inégalités dans l'environnement bâti lié à la santé et à son hétérogénéité. Cette section contribue à visualiser comment les multiples problèmes de santé urbaine sont stratifiés dans la zone d'étude et comment ils sont répartis dans l'espace géographique.La deuxième partie (2) étudie les différences entre trois stakeholders (experts en santé urbaine, urbanistes de la Suisse romande et habitants du canton) dans l'évaluation de la santé urbaine parmi les objectifs d'aménagement et les enjeux de santé urbaine. Cette section fournit également une pondération des indicateurs des problèmes de santé urbaine développés dans la première section de la thèse. Elle étudie également le lien spatial des réponses des résidents avec ces indicateurs. Cette section montre comment l'intégration des points de vue des différents stakeholders pourrait influencer la planification de la santé urbaine.La troisième section (3) étudie la relation entre les données géospatiales de l'environnement bâti et de la santé. Les données sur la santé proviennent d'une étude sur les facteurs de risque cardiovasculaire et sont géoréférencés par le biais de l'adresse postale dans la zone d'étude. Cette section décrit d'abord l'ensemble de données sur la santé de six facteurs de risque cardiovasculaire et identifie ses clusters spatiaux. Ensuite, nous évaluons le pouvoir d'estimation des caractéristiques de l'environnement bâti et de ses indicateurs en utilisant des approches spatiales et aspatiales pour l'analyse de régression avec l'ensemble de données sur la santé. L'analyse de régression teste différentes tailles de quartiers pour échantillonner les attributs de l'environnement bâti ainsi que le sous-ensemble des clusters de la santé. Cette section montre le pouvoir limité de prédiction de l'environnement bâti qui ne peut pas prédire la totalité de l'ensemble de données de santé mais fournit une prédiction fiable des données de santé appartenant aux clusters.En étudiant les contributions des caractéristiques de l'environnement bâti dans l'analyse de régression, nous démontrons la non-stationnarité dans l'espace géographique de la relation entre les facteurs de risque cardiovasculaire et l'environnement bâti. Enfin, nous montrons comment l'approche de régression spatiale peut recréer les clusters de facteurs de risque cardiovasculaire en utilisant l'environnement bâti.

En général, la thèse montre que l'environnement bâti engendre potentiellement des bénéfices et des impacts sur la santé qui sont distribués de manière hétérogène dans l'espace géographique et pour les multiples problèmes de santé urbaine. Ensuite, il démontre que l'environnement bâti n'est pas un prédicteur fiable des facteurs de risque cardiovasculaire à l'échelle individuelle selon l'adresse de résidence. De plus, nous soulignons les limites de l'étude au regard des données sur l'environnement bâti et de la santé, ainsi que de la méthodologie pour l'analyse spatiale de la santé urbaine. Pour terminer, nous mettons en évidence le rôle potentiel de ce travail dans le soutien de l'intégration de la santé urbaine dans l'aménagement du territoire et de son rôle synergique avec d'autres outils de la planification. La thèse propose d'améliorer la compréhension de la salubrité des milieux urbains en six points:

- Les données géospatiales existantes peuvent être utilisées pour évaluer et surveiller l'état de l'environnement bâti afin de comprendre les impacts potentiels sur la santé dans l'ensemble de la zone urbaine afin d'identifier les priorités et les inégalités.

- L'élaboration d'un schéma structuré, qui traite des multiples problèmes de la santé urbaine, peut garantir qu'aucun problème ne soit omis au niveau stratégique, tandis que les interactions et la stratification des impacts potentiels sont prises en compte.

- L'utilisation combinée de méthodologies globales et locales pour examiner les inégalités permet respectivement d'avoir une vision large des défis de santé urbaine et de comprendre l'hétérogénéité spatiale et également d'intégrer des critères d'accessibilité.

- L'étude des liens entre l'environnement bâti et la santé est avantagé par la prise en compte de la non-stationnarité de leur relation dans l'espace géographique afin que les interventions soient optimisées et adaptées aux exigences locales.

- La complexité de la relation entre la santé et l'environnement bâti au niveau individuel nécessite une large collecte de données englobant l'évolution temporelle des données sur la santé, les données sur l'environnement bâti et leur exposition contextuelle.

- Seule une partie des problèmes de santé urbaine est traitée par les réglementations, qui se concentrent principalement sur la prévention plutôt que sur la promotion de la santé. En raison de l'absence de mise en œuvre institutionnelle, la plupart des interventions repose sur l'initiative des stakeholders, tandis que les procédures d'évaluation et de suivis sont rares, empêchant la mise en œuvre et la diffusion des réglementations pour la santé urbaine.

Cette recherche utilise une variété de méthodologies spatiales et aspatiales pour diagnostiquer la salubrité de différents éléments de l'environnement bâti. Une meilleure compréhension de l'environnement bâti peut plaider en faveur de l'intégration de la santé dans la planification urbaine afin de remédier aux disparités. La thèse identifie les inégalités dans les caractéristiques de l'environnement bâti lié à la santé et le clustering spatial des problèmes de santé parmi la population résidente dans la zone d'étude. De plus, la thèse contribue à comprendre le lien entre les données de la santé et l'environnement bâti en fonction du lieu de résidence, des multiples échelles spatiales, ainsi qu'au niveau global et local dans le canton de Genève.

Mots clées:

analyse spatiale, santé urbaine, environnement bâti, inégalités de santé, facteurs de risque cardiovasculaire, Genève, Suisse.

Riassunto

Più della metà della popolazione mondiale vive nelle città e si prevede che questa percentuale aumenterà nei prossimi decenni. La complessità dei diversi usi des suolo e relativi servizi nelle aree urbane, che compongono l'ambiente costruito, influenza la salute e il benessere dell'uomo. Per quanto riguarda le aree urbane, in larga misura, la pianificazione territoriale ha il potenziale per modellare l'ambiente costruito per diventare più salubre. La necessità di considerare l'ambiente costruito in relazione alla salute umana è coerente con la necessità di agire efficacemente in tutte le politiche e al di fuori dell'assistenza sanitaria per prevenire impatti negativi e promuovere impatti positivi in più settori. La ricerca e la pratica hanno già affrontato diverse sfide sanitarie legate all'ambiente costruito, raggruppate sotto l'ampio ombrello della "salute urbana". Politiche, strumenti, progetti e programmi sono già stati creati in settori separati per integrare la salute nella governance. Nonostante ció, la salute è spesso vista come una barriera allo sviluppo nella pianificazione territoriale, incontrando opposizione in ogni fase. In questa ricerca, ci siamo concentrati sulla diagnosi dell'ambiente costruito come fattore critico per comprendere la sua relazione con la salute attraverso dati e analisi geostatistiche. L'obbiettivo di fare una diagnosi dell'ambiente costruito mira ad affrontare contemporaneamente molteplici problemi di salute urbana all'interno delle stesse aree urbane. Abbiamo affrontato quattro concetti per occuparci della diagnosi della salubrità dell'ambiente costruito: (i) lo sviluppo di uno schema strutturato per comprendere la stratificazione di molteplici determinanti della salute (ii) l'analisi della distribuzione spaziale di tali determinanti per comprendere le disuguaglianze all'interno di un area urbana, (iii) l'integrazione delle prospettive delle parti interessate nell'affrontare la salute urbana e le sue molteplici problematiche, (iv) la comprensione delle associazioni geospaziali tra l'ambiente costruito e la distribuzione spaziale dei dati individuali sulla salute.

La tesi mira a comprendere come l'ambiente costruito in relazione alla salute umana sia distribuito nello spazio nello stato di Ginevra (Svizzera). Questa ricerca utilizza un approccio olistico per esplorare come le disuguaglianze nell'ambiente costruito legato alla salute, sono distribuite nello spazio e le confronta con i dati sanitari geospaziali adottando approcci geospaziali globali e locali. Utilizzando più metodi di analisi spaziale sia per l'ambiente costruito che per i dati sanitari e costruendo un quadro per un'ampia valutazione della salute urbana, vengono testate tre ipotesi in tre sezioni.

Prima della la prima ipotesi, é stato sviluppato uno schema per l'analisi della salubrità dell'ambiente costruito. Lo schema é pensato per ridurre la sovrapposizione fra le parti che lo compongono e raccolglie un'ampia gamma di problemi di salute urbana rilevanti per un caso di studio generico. Nella prima sezione (1), lo schema è adattato al caso di studio per descrivere l'eterogeneità degli ambienti costruiti legati alla salute su piccola scala geografica, attraverso una serie di indicatori che corrispondono ai problemi di salute urbana. I metodi statistici locali e globali vengono applicati per generare indicatori in modo da eseguire una diagnosi esplorativa che identifichi le disuguaglianze nell'ambiente edificato associato alla salute e la sua eterogeneità. Questa sezione contribuisce a visualizzare come un'ampia gamma di problemi di salute urbana, sono stratificati all'interno dell'area di studio, e come sono disposti geograficamente. La seconda sezione (2) studia le differenze tra tre parti interessate al processo di pianificazione (esperti di salute urbana, professionisti della pianificazione locale e residenti nel cantone) nel valutare la salute urbana rispetto ad altri obiettivi di pianificazione, e nel valutare i problemi di salute urbana. Questa sezione utilizza le valutazioni per ponderare gli indicatori dei problemi di salute urbana sviluppati nella prima sezione della tesi e studia l'associazione spaziale delle risposte dei residenti con tali indicatori. Questa sezione mostra come l'integrazione dei punti di vista nell'affrontare i problemi di salute urbana possa influenzare la pianificazione per la salute urbana aseconda del gruppo di appartenenza. La terza sezione (3) studia la relazione tra i dati sanitari geospaziali e l'ambiente costruito, utilizzando un set di dati spaziali trasversali di fattori di rischio cardiovascolare, georeferenziati per indirizzo postale nell'area di studio. Questa sezione descrive innanzitutto il set di dati sanitari di sei fattori di rischio cardiovascolare e ne identifica i cluster spaziali. Successivamente, valutiamo come le caratteristiche dell'ambiente e i suoi indicatori costruito sono in grado di stimare il rischio cardiovascolare utilizzando approcci statistici locali e globali per l'analisi della regressione. L'analisi della regressione testa diverse distanze per definire il raggio di campionamento degli attributi dell'ambiente costruito oltre a testre le regressioni sul sottoinsieme di dati appartenenti ai cluster. Questa sezione mostra il potere limitato dati dell'ambiente costruito, che non possono prevedere la totalità del set di dati sanitari ma forniscono una previsione affidabile dei dati sanitari appartenenti ai cluster spaziali. Studiando i contributi delle caratteristiche dell'ambiente costruito nell'analisi di regressione, dimostriamo la non-stazionarietà nello spazio geografico della relazione tra i fattori di rischio cardiovascolare e l'ambiente edificato. Alla fine, mostriamo come l'approccio della regressione spaziale può ricreare i gruppi di fattori di rischio cardiovascolare utilizzando l'ambiente costruito.

In generale, la tesi mostra che l'ambiente costruito potenzialmente offre benefici e impatti per la salute all'interno dell'area di studio in modo eterogeneo nello spazio geografico, e riguardo a molteplici problemi di salute urbana. In secondo luogo, dimostra che l'ambiente edificato stima limitatamente i fattori di rischio cardiovascolare a livello individuale utilizzando l'ambiente circostante la l'indirizzo di residenza. Infine, sottolineiamo i limiti dello studio mettendo in discussione le misure che dovrebbero essere adottate per inquadrare la salute urbana in termini di ambiente costruito, i dati di input sulla salute e i limiti della metodologia per l'analisi spaziale della salute urbana. Successivamente, discutiamo il ruolo potenziale di questo lavoro nel sostenere positivamente l'integrazione della salute urbana nella pianificazione territoriale e il suo ruolo sinergico con altri strumenti, quali programmi e strategie. La tesi suggerisce di migliorare la comprensione della salubrità degli ambienti urbani di sei punti:

- I dati geospaziali esistenti possono essere utilizzati per valutare e monitorare lo stato dell'ambiente edificato e comprendere i potenziali impatti sulla salute all'interno dell'intera area cittadina in modo da identificare priorità e disuguaglianze.

- Lo sviluppo di un o schema che affronti molteplici problemi di salute urbana, può garantire che qualsiasi problema ad essa connesso non venga trascurato a livello strategico, in modo che le interazioni e la stratificazione degli impatti dell'ambiente costruito sulla salute umana non siano trascurati.

- L'uso combinato di un metodo statistico globale e locale per esaminare la disuguaglianza consente tramite il primo, di avere una visione ampia delle sfide della salute urbana nell'area di studio, tramite il secondo, di comprendere l'eterogeneità e di incorporare considerazioni sull'accessibilità.

- Lo studio dell'associazione tra ambiente costruito e salute sfrutta la non-stazionarietà del loro rapporto nello spazio geografico in modo che gli interventi siano ottimizzati e adattati alle esigenze locali.

- La complessità del rapporto tra salute e ambiente costruito a livello individuale richiede un'ampia raccolta di dati che comprenda l'evoluzione temporale dei dati sanitari, i dati dell'ambiente costruito e la loro coesistenza contestuale.

- Solo una parte delle questioni di salute urbana sono gestite da normative, che si concentrano principalmente sulla prevenzione della salute piuttosto che sulla promozione della salute tramite la pianificazione territoriale. A causa dell'assenza di norme, la maggior parte degli interventi si basa sull'iniziativa degli stakeholders, mentre le procedure di valutazione e monitoraggio sono rare, impedendo l'attuazione e la diffusione delle normative per la salute urbana.

Questa ricerca utilizza una varietà di metodologie locali e globali per diagnosticare la salubrità di diversi elementi dell'ambiente costruito per sostenere l'integrazione della salute nella progettazione territoriale nella sua interezza per affrontare le disuguaglianze. La tesi identifica le disuguaglianze nelle caratteristiche dell'ambiente costruito legato alla salute e la loro disposizione nello spazio, i cluster di rischio cardiovascolare della popolazione residente. Inoltre, la tesi contribuisce a comprendere l'associazione dei dati sanitari con l'ambiente costruito a seconda del luogo di residenza a più scale geografiche nel cantone di Ginevra.

Parole chiave:

analisi spaziale, salute urbana, ambiente costruito, disuguaglianze sanitarie, fattori di rischio cardiovascolare, Ginevra, Svizzera.

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Chapter 1 Introduction

1.1 Motivation

The disciplines of spatial planning are facing and will face new challenges to address urban population growth and improve the quality of urban environments (UN-Habitat, 2020). Spatial planning is fundamental to address the development of human settlements to build and manage the environment most suitable for human life UN, 2010). On the one hand, urban environments have the potential to influence both positively and negatively human health (Barton and Grant, 2006). On the other hand, spatial planning has the potential of shaping urban environments to become healthier (WHO, 2020). The opportunity for spatial planning of making cities healthier is of primary importance. For example, 7 million deaths in 2016 occured as result of air pollution only, while only one city in ten has air quality standards under the limit (WHO, 2020). Overall, approximately 25% of global deaths can be traced back to unhealthy living and working environments (WHO, 2020), while in urban environments, planning is a leading factor in regulating population health (RPA, 2012). According to Mueller et al., implementing planning measures that adhere to international guidelines for physical activity, air pollution, noise pollution, and ambient heat could prevent 20% of the city of Barcelona's annual mortality (Mueller et al., 2017). Framing population health is challenging without including the characteristics of the place where we live. For example, the epidemiologic transition postulates that urban development makes chronic diseases supersede infective diseases (Omran, 2005). This transition can cease when quick and uncontrolled urban growth is not managed, instead of imposing a triple burden on the health of the population. Indeed, cities can become centres of diffusion of epidemics; places where people are exposed to harmful environments or where healthy behaviours are hampered, leading to chronic diseases; and place where accidental injuries can take place systematically (Mberu et al., 2016; Rydin, Bleahu, Davies, Dávila, Friel, De Grandis, Groce, Hallal, Hamilton, Howden-Chapman, Lai, CJ Lim, et al., 2012). On the contrary, urban environments can impact health by preventing dangers and promoting healthy behaviour as a result of planning, addressing both communicable and non-communicable diseases. (Corburn, 2004; Rydin, Bleahu, Davies, Dávila, Friel, De Grandis, Groce, Hallal, Hamilton, Howden-Chapman, Lai, CJ Lim, et al., 2012; WHO, 2020). For example, a broad and exhaustive representation of the multiple levels according to which places shape human health has been proposed by the health map of Barton and Grant (Barton and Grant, 2006) and schematised in the adapted system represented in Figure 1.

Generally, human health itself is defined as "a state of complete physical, mental and social wellbeing and not merely the absence of disease or infirmity" (WHO, 2006). The challenge and the opportunity of spatial planning are to shift urban environments from adverse to beneficial to human health, going beyond the concept of "neutrality", but conceive health as a continuum, leading to pathogenesis or salutogenesis, rather than a dichotomy between illness and absence of illness (Franz W. Gatzweiler, ; Maass et al., 2017). The representation of health through data can encompass multiple dimensions, and includes objective measures, perceptions, behaviours and care information (Künn-Nelen, 2016). The inclusion of health as a human right has highlighted the significance of health. WHO declared health an international human right in 1946, and since then, 36% of countries worldwide integrated the right to health in their constitution before 2011 (*Bulletin of the World Health Organization*, 2002; Heymann et al., 2013). Research and practice belonging to the large umbrella of "urban health" have contributed to produce evidence about the relationship between various urban characteristics and human health, driving the creation of healthier policies, projects, and programs. The latter follows the general concept of integrating Health in All Policies (HiAP), according to which it is crucial to address human health from all sectors, therefore also outside the healthcare system (PAHO, 2014). The healthcare system alone has an essential but limited power in shaping health since it is based on the idea that if a determinant fails, it must intervene. Prevention is not excluded in the healthcare system, although only a tiny share of the total spending is used for prevention, i.e. 12% health worldwide in 2016 (WHO, 2019), where percentages in high-income countries are below 5% (de Bekker-Grob et al., 2007; WHO, 2018, 2019) despite some underestimations of prevention spending (de Bekker-Grob et al., 2007).

While the healthcare system cannot manage all health determinants, planning sectors cannot be subordinated hierarchically to the healthcare system. The experience of the fifth phase of the network of Healthy Cities showed how health integration is counterproductive when forced (Grant, 2015; Leeuw and Simos, 2017a). Because spatial planning is a transdisciplinary process that spatially develops and designs human settlements by resolving conflicts among various purposes and harnessing synergies among them, a forced prioritising of a new concept goal is likely to encounter resistance (Levy, 2016; Sallis et al., 2016). Nonetheless, the need to improve people's lives can be traced back to the disciplines of spatial planning as the guiding premise underpinning the multiple purposes of spatial planning. This underlying concept has been summarised by Dr Maria Neira of WHO: “If the purpose of urban planning is not for human health, then what is it for? Ideally, cities are planned for adequate standards of living and working, sustained economic growth, social development, environmental sustainability, better connectivity… but the 'why' at the core of all these things comes down to physical and mental health and wellbeing." (WHO, 2020). This principle is embraced by the concept of "Healthy Urban Planning" (HUP), which consists in "planning for people". Health integration is critical for future development since it is directly addressed by the Sustainable Development Goals (SDGs) 3 and 11, respectively, "excellent health and wellbeing" and "sustainable cities and communities" (WHO, 2016), as well as being interconnected with all other SDGs (WHO, 2020). More precisely, when planning drives interventions "to change the physical form or physical management of the city or part of it, with the intention of a positive health outcome; and an increase in health equity is considered a positive health outcome", it is termed Healthy Urban Planning (HUP) (page i57) (Grant, 2015). Alternatively HUP is named City Health Development Planning (Green et al., 2009) or Healthy Urban Environment and Design (Grant, 2015).

The intrinsic objective of HUP is to target all inhabitants, with no inequities in delivering health benefits as well as in preventing hazards through urban planning (Corburn, 2017), coherently with recognition of health as a human right (WHO, 2010). According to the founding principles of the 2030 Agenda for Sustainable Development and the Healthy People 2030 initiative, equity in health should be attained for everyone with equity through sustainable development of cities and communities (United Nations, 2015) (Healthy People 2020,). In essence, considerable and persistent differences can be observed between countries, within countries and even within cities (FOPH, 2019; Mattig et al., 2017; OBSAN and Canton de Genève, 2020)(Elsey et al., 2016; WHO, 2016). To target inequity in health, WHO launched the Urban Health Equity Assessment and Response Tool to help countries achieve equity in health in all sectors, including urban planning (WHO Centre for Health Development of Kobe, Japan, 2010). Also, equity is a founding principle employed by the Healthy Cities Network, which at the current state of Phase VII, still highlight its essential importance (Implementation framework for Phase VII (2019–2024) of the WHO European Healthy Cities Network: goals, requirements and strategic approaches (2019),). After selecting a group of health indicators to compare 57 cities, Stauber et al. concluded that environmental improvements significantly influence population health and its disparities (Stauber et al., 2018).

The subject of HUP is the living environment, which can include both human-made rural and urban environments. The inclusive term used to identify places where human life takes place is Built Environment, a term commonly used in fields of urban health. The built environment (BE) is defined by Roof and Oleru as "the human-made space where people live, work, and recreate on a day-to-day basis"(Roof and Oleru, 2008). Multiple conceptualisations of the built environment can be found depending on the discipline which studies it (Moffatt and Kohler, 2008) since the built environment includes many features besides a geographic setting, not detangled by nature, culture and society (Lang and Rayner, 2012). The context of the relationship between the built environment and health encompasses the urban physical space and measures of built and natural environment, transport networks, or the social environment (Leeuw and Simos, 2017a). Furthermore, to refer to BE characteristics related to health, the term Health Built Environment (HBE), coined after the "Healthy Built Environment program" of the University of New South Wales (Thompson et al., 2010); has been used in general contexts of urban health (Callway et al., 2020; Harris et al., 2018; Loftness and Snyder, 2020).

The HUP can be guided by multiple strategies, mainly summarised by three actions (Sallis et al., 2016):

- the study of the relationship between urban environments on population health,
- the adaption of planning procedures to promote and protect health,
- the spread of findings to policymakers and stakeholders to raise awareness and provide urban health formation.

Only the joint application of these three actions allows for a positive outcome of an intervention, due to the crucial role they play in delivering better health through spatial planning (Sallis et al., 2016). However, comprehending the relationship between the urban environment and health is a prerogative activity to the following two, which is why it is more addressed subject in dealing with urban health issues (Friel, Vlahov, et al., 2011; Pineo, Zimmermann, et al., 2020; Sallis et al., 2016). This thesis begins by examining the impact of HBE on spatial planning for the case study of the state (canton) of Geneva (Switzerland).

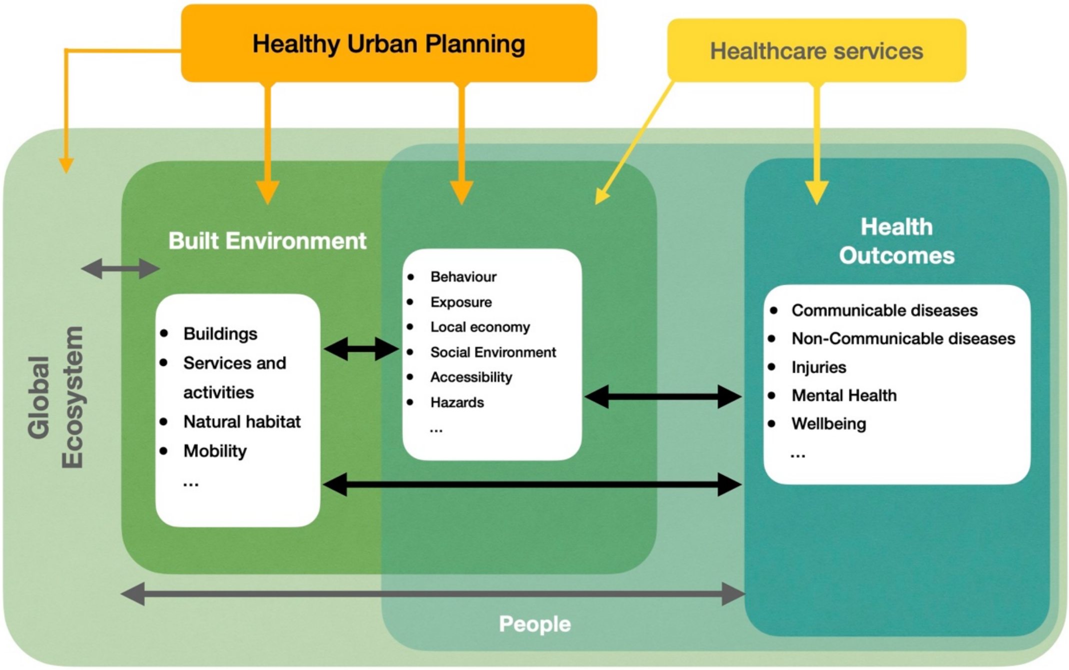

Figure 1: An adaptation of the health map by Burton and Grant (Barton and Grant, 2006).

Switzerland is the third country globally for life expectancy (WHO, 2019) while also the second in terms of health spending per capita (WHO,). The Health Strategy for 2030 of the Swiss Federal Council, include spatial planning as an opportunity to attain better health prevention and promotion (FOPH; Mattig et al., 2017; OBSAN and Canton de Genève, 2020). Spatial planning in Switzerland is coherent with the HiAP and SDGs regarding the Federal Office for Spatial Development's strategies (ARE). Indeed, the latter's implementation relies upon spatial planning instruments at the cantonal level, leading differently to the strategies of ARE (ARE; Promotion Santé Suisse, 2015). Consequently, the planning autonomy, the canton of Geneva, started first by adopting and institutionalising the Health Impact Assessment (HIA) procedure, which implementation at the federal level failed in 2012 (Mattig et al., 2017; Promotion Santé Suisse, 2015). However, despite the initial implementation of HIA and most number of procedures, regulations have not been adopted, nor HIA got spread efficiently among cantons (Promotion Santé Suisse, 2015). Overall, the integration of health is not missed by spatial planning in the canton of Geneva, but scattered interventions address it with little or no explicit reference to its relation with population health (Ville de Genève, 2009).

In parallel, the cantonal health report of 2017 coherently addresses HBE as a determinant of health, identifying common priorities, such as noise pollution and obesity prevention (OBSAN and Canton de Genève, 2020). However, official health reports are contextualised at the geographic scale of cantons, While geospatial approaches to population health below the cantonal geographic scale are limited to scientific literature, which has rarely examined its relationship with the HBE, (Paragraph 1.1.3.1). The promotion of health data study is also set as goal of the Health Strategy for 2030 for Switzerland (FOPH, 2019). The federal health report of Switzerland and environmental reports, and other cantonal reports explicitly identify BE characteristics as a relevant determinant of health (FOEN, 2018; OBSAN and Canton de Genève, 2020). Despite this widespread acknowledgement, approaches are moderately fragmented across planning disciplines and are addressed differently by Swiss cantons, lacking a comprehensive and interdisciplinary approach capable of framing and subsequently implementing urban health in Switzerland. (Chastonay et al., 2017; Mattig et al., 2017; Promotion Santé Suisse, 2015). Lack of understanding, backed up by evidence, about the relationship between HBE and health issues may contribute to inaction and unsystematic HUP in Switzerland, whose strategic agenda call for intervention through spatial planning and employment of health data (FOPH, 2019).

1.1.1 Research hypotheses

Urban health research calls for an approach that jointly address multiple disciplines and tackle inequities to integrate health in spatial planning. By addressing a broad variety of disciplines, planning can ensure that no issue is omitted from consideration a priori. By addressing equity, spatial planning may help ensure that no one is exposed to harmful conditions or is unable to live a healthy lifestyle. The prerogative of this task is to assess the healthiness of the BE to inform decision-makers and advocate for healthier cities for all. We discuss how an adequate spatial analysis is crucial in delivering the representation of the HBE among urban health issues and within the study area. **The thesis aims to understand how the healthy built environment is spatially distributed in the state of Geneva (Switzerland)**.

Three research hypotheses, each corresponding to a chapter of the thesis, address the four research gaps identified in paragraph 1.1.2 and displayed in the summary workflow (Figure 5, page 37). Each chapter's purpose defines its order in addressing the thesis's aim: the third chapter's findings are incorporated into and form part of the subsequent chapters.

The research hypotheses are:

- **The characteristics of a healthy built environment are heterogeneously distributed in space within the canton of Geneva for multiple urban health issues.**
- **The integration of experts' perspective provides a diverse outcome in appraising multiple urban health issues.**
- **The healthy built environment characteristics are associated to cardiovascular risk factors measures in their geographic context.**

The motivation and design of this study extend beyond the selection of the case study. The data availability is the main driver behind the choice of the study area, which allowed the design of a challenging subject of study. The choice of this case was necessary to deal with multiple urban health issues by focusing on data analysis reducing data collection; however, while introducing the case study, we outline the study area is characterised in the previous literature, introducing assumptions under which it constitutes that is worth to be studied.

1.1.2 Research gaps

Health is a critical component of human development, which cannot be accomplished alone through healthcare services, but call for promotion and protection of health through spatial planning (Barton and Grant, 2013; Rydin, Bleahu, Davies, Dávila, Friel, De Grandis, Groce, Hallal, Hamilton, Howden-Chapman, Lai, CJ Lim, et al., 2012; United Nations, 2015). Thanks to many disciplines contributing to urban health research, such as spatial epidemiology, geographic medicine, or public health; it is widely recognised the role of BE in shaping human health, so that findings have been traduced into successful interventions in separate sectors of spatial planning, such as housing, transportation, land-use and environmental protection (Rydin, Bleahu, Davies, Dávila, Friel, De Grandis, Groce, Hallal, Hamilton, Howden-Chapman, Lai, CJ Lim, et al., 2012). However, integration of health in spatial planning is not the norm among the multitude of urban issues, as well as between different places; thus, between countries, between cities, and within cities (Elsey et al., 2016; WHO Europe, 2018). A precursor and crucial factor for health integration are understanding the healthiness of the BE where people live. Consequently, the implementation of methods and production of sound evidence by separate silos of urban health, HUP calls for further efforts in representing the multidisciplinary nature of urban health issues and in targeting inequalities in the latter (D'Alessandro, 2020; Glanz et al., 2016; Lawrence and Gatzweiler, 2017; Pineo, Zimmermann, et al., 2020).

This study responds to the call for a methodology to evaluate the healthiness of the HBE that implement all relevant urban health issues and identifies inequities in their spatial distribution. Hence, the novelty and the challenge of this work address simultaneously four research gaps, rather than providing innovative methodologies. In summary, the thesis addresses the need to comprehend a broad range of built environment characteristics associated with multiple health impacts, the importance of employing small spatial scales and precise spatial methods to comprehend the distribution of inequities, the importance of integrating stakeholders' perspectives, and, finally, the importance of studying the built environment's association with geospatial health data. The coordination and joint application of multiple requirements and potentials found in urban health is the research's originality. HUP calls for studies able to deal with to address multidisciplinary and equity in delivering an approach to diagnose HBE (Giles-Corti et al., 2016). Challenges include the joint diagnosis of multiple relevant urban health issues by studying HBEs, the spatial analysis of those issues so that inequalities related to different HBEs are identified, the understanding and integration of expert knowledge in HUP, and the joint study of the relation between health and HBE spatial data. Understanding the healthiness of the BE is necessary to inform governance and deliver healthier interventions in spatial planning.

INTEGRATION OF MULTIPLE DISCIPLINES IN URBAN HEALTH

The importance of spatial planning in shaping health is not a new concept, and it is widely recognised and supported by a large body of evidence by urban health research (D'Alessandro, 2020). The latter collects disciplines, such as spatial epidemiology and geographic medicine, public health, behavioural sciences, urban design, and spatial analysis, et cetera, which have addressed a broad range of urban health issues from different viewpoints among planning sectors (Rydin et al., 2012). In spatial planning, urban health is entangled with its composing sectors, such as transportation, housing, land use and environmental protection, which in turn have the potential to deal the triple burden of injuries, communicable and non-communicable diseases (Rydin, Bleahu, Davies, Dávila, Friel, De Grandis, Groce, Hallal, Hamilton, Howden-Chapman, Lai, CJ Lim, et al., 2012). In contrast to the multidisciplinary nature of urban health, the practice has gradually addressed separately urban health through monodisciplinary approaches, adopting biomedical models based upon symptom and treatment (Diez Roux, 2007; Reis et al., 2015). In this way, successful applications have seen the light, particularly in treating part of communicable diseases or injuries, in cases where disease determinants were in small numbers and time and spatial lags between adverse events and illness are short (Rothman et al., 2008). These characteristics allow easier identification of a "dose-effect", and therefore governance endorsed effective direct interventions investing more in preventive measures (WHO, 2015). Instead, when the aetiology is more complex, successful urban health application is more scarce, such as non-communicable diseases (Kelly and Russo, 2018; Walls et al., 2016). From the research viewpoint, inference between HBE and health may be hidden by the complexity of the phenomena (Rydin, Bleahu, Davies, Dávila, Friel, De Grandis, Groce, Hallal, Hamilton, Howden-Chapman, Lai, CJ Lim, et al., 2012). From the practical viewpoint, responsibility can be easily dodged and discharged on outsider determinants, such as individual behaviour (Friel et al., 2011; Leeuw and Simos, 2017; Rydin et al., 2012; Sallis et al., 2016). However, successful interventions are many in different planning sectors, including when dealing with non-communicable diseases, although they are not the norm yet (Franz W. Gatzweiler, ; Grant, 2015; Leeuw and Simos, 2017a). Spatial planning is far from adopting a systematic approach to integrate the vast range of urban health issues (D'Alessandro, 2020). Indeed, in literature, theoretical studies illustrate the interdisciplinary nature of urban health, although comprehensive approaches to assessing HBE, in terms of the comprehensiveness of urban health, remain scarce (Barton and Grant, 2006; Capolongo et al., 2020; Galea and Vlahov, 2005; Northridge and Sclar, 2003). Many approaches have been used to broadly inform, guide and support practice in addressing the multidisciplinary nature of urban health (Leeuw and Simos, 2017a; LHUDU, 2017; Reis et al., 2015; WHO, 2020). The danger of sectoral approaches is that they provide insufficient information to the government, failing to capture synergies and tensions, as well as stratification of urban health issues (Damen et al., 2019; Glanz et al., 2016; Rothenberg et al., 2015; Stauber et al., 2018; Verma et al., 2017). The diagnosis of a broad range of urban health issues is already composing part of institutionalised tools, such as the HIA, which assess the impact of policies, projects and programs depending on the application target. Hence, the starting point of such tools and procedures can detect multiple urban health issues and equity only depending on the chosen target (in terms of health impacts and terms of geographic area). Otherwise, little has been done to provide a standard structure for the multidisciplinary understanding of the many urban health issues (Callway et al., 2020; Glanz et al., 2016; Phoenix et al., 2013). The recent study of Pineo et al. shows the importance of rethink to standard and the structure able to clearly and efficiently inform planning about the use of urban health indicators (Pineo, Zimmermann, et al., 2020). Furthermore, the variety of knowledge requires approaches that summarise the information in their intrinsic complexity without impeding the decision-making process but instead boosting the translation into practice (Sallis et al., 2016)(Callway et al., 2020). In urban health, utilising indicators to provide information to stakeholders has been shown to be effective (Lowe et al., 2015; Pineo, Zimmermann, et al., 2020; Rothenberg et al., 2015; WHO et al., 2014).

EXPLICIT SPATIAL CONTEXT AND SMALL GEOGRAPHIC SCALES

In general, HUP does not universally rely on data. The data availability and quality of data influence the integration of health in spatial planning (Elsey et al., 2016; Friel, Vlahov, et al., 2011; Hersperger et al., 2018). HUP is moving toward improving data collection by quantity, diversity and quality of data (Patel and Sharma, 2014; Rathore et al., 2016). However, the example of the Healthy Cities Network showed how data collection is not paid by the following data analysis able to take advantage of the complexity of data (de Leeuw et al., 2015; Implementation framework for Phase VII (2019–2024) of the WHO European Healthy Cities Network: goals, requirements and strategic approaches (2019), ; Phase VI (2014-2018) of the WHO European Healthy Cities Network goals and requirements,). HUP practice cannot rely on examples only, leading to a missed opportunity to understand local peculiarities and address urban health issues. The crucial role of spatial planning is played spatial contextualisation, which allows the study of population health under the lens of place (Elsey et al., 2016; Kanaroglou and Delmelle, 2016; Lu and Delmelle, 2019). The lack of spatial data on the built environment and health mainly affects the urban most deprived areas as it leads to a strong bias in the analysis of health inequities within cities and comparative studies between rural and urban health (Verma et al., 2017; WHO Centre for Health Development of Kobe, Japan, 2010). Afterwards, spatial contextualisation requires adequate scales to identify differences within cities, and finally, optimise health benefits delivery through targeted interventions (Verma et al., 2017). Indeed HUP needs to be spatially explicit at finer geographic scales to tackle urban health issues with equity (Elsey et al., 2016; Verma et al., 2017). Rothenberg et al. reviewing urban health indices, highlight the lack and need for local data on small areas (Rothenberg et al., 2015), although HUP has seen an increase in small scale approaches in Europe in the last decades (Grant, 2015).

As a result, knowing the beginning condition, namely the HBE status, can drive the intervention proposal in urban planning, allowing urban health to actively participate in spatial planning. When regulations demand project planning to prevent and promote better health in order to achieve various goals, the application is confined to those changes (de Leeuw et al., 2015). Examples of intervention for urban health as primary goal are still limited and rely on external advocacy of HBEs, rather than being implemented or even institutionalised so that health is constantly integrated as a primary goal. Pursuing the knowledge of the BE status is coherent with the concept of urban renewal and the concept of equity in urban health. Urban renewal is tangled with urban health by preventing urban sprawl and land consumption and consequently addressing the global issue of climate change (Battisti et al., 2020; Mehdipanah et al., 2013). Also, equity in urban health requires the understanding of HBE in the whole study area so that the most vulnerable people and most adverse BE are not missed since they are the most likely to be underrepresented by data (Costa et al., 2019; Elsey et al., 2016; WHO Centre for Health Development of Kobe, Japan, 2010).

STAKEHOLDERS VIEWPOINTS OF HEALTHY URBAN PLANNING

Data and analysis methods have limitations in addressing the multiple urban health issues, which are daily addressed by the know-how of experts in spatial planning (WHO et al., 2014). Health integration in spatial planning is a task that is not linearly influenced by the understanding of HBE but rather involves perspectives of actors of the decision-making process. Understanding the role of urban health among those actors is helpful to understand how the diagnosis of HBE could be processed and deliver the intervention in planning. Knowledge about the direction of the perspective can be integrated into the diagnosis process itself, potentially making the advocacy of findings more sound (Sallis et al., 2016; WHO, 2020). However, the participation of stakeholders in designing the approach of evaluation of HBE raised concern about excessive compromises with other planning goals (Leeuw and Simos, 2017a).

The integrative process is shown successful strategies to drive towards HUP (de Leeuw et al., 2015; Pineo, Zimmermann, et al., 2020; Sallis et al., 2016). Furthermore, the integration of stakeholders viewpoint is suggested to contribute positively to the integration of health in planning, as stakeholders become a composing part of the approach of diagnosis of HBE and can get formed during the process (Sallis et al., 2016). Also, understanding experts' viewpoint is an outcome for HUP by itself, displaying how and where governance may expect to find resistance or cooperation to health integration (Sallis et al., 2016).

THE SPATIAL RELATION BETWEEN HBE AND HEALTH

Currently, the diagnosis of the HBEs can be based on existing evidence in similar contexts, thus assuming that similar urban environments lead to similar health outcomes. However, this concept assumes that similar HBEs leads to similar population health. Instead, the study of the relation between HBE and health can be achieved by using health data so that their joint spatial analysis allows the contextualisation of health condition in places, optimising the delivery of HUP interventions. Even if the concept is not new in urban health, lack of collaboration between healthcare and spatial planning has historically interfered in this task: health studies lack spatial approaches, while studies on the urban environments lack health data use (Frank and Kavage, 2008; Leeuw and Simos, 2017a; Yang et al., 2013a). Health measurements are frequently spatially un-explicit, or idependent form the spatial context, during the planning process and planning interventions (Grant, 2015; Matthews and Yang, 2013; Rydin, Bleahu, Davies, Dávila, Friel, De Grandis, Groce, Hallal, Hamilton, Howden-Chapman, Lai, CJ Lim, et al., 2012; WHO, 2010). Moreover, the health data can be used as input for HBEs diagnosis, being an active contributor in HUP, rather than only an outcome to monitor (WHO, 2020).

1.1.3 Study Area

The study area is the canton (state) of Geneva, located in Switzerland's southwest region (Figure 2). The canton of Geneva is settled on the flat area at the eastern point of the homonymous lake, confining with France and canton Vaud. The canton of Geneva population was approximately 500'000 in 2018, characterised by a density of 1442 inhabitants per square kilometres, the second among the other swiss cantons (OFS, 2021d). The canton includes both the urban area of the city of Geneva and the surrounding towns in a mixture of urban and rural areas. The population is mainly resident in the central and periurban municipalities in multiple directions: along the lakeshores toward canton Vaud and France and towards the France border in the south and southwest directions (Figure 2). We excluded the enclave territory of Geneva of the municipality of Celigny, located in the north of Geneva since a continuous geographic was required for the spatial analysis.

The "functional" Geneva is a transborder urban agglomeration with an important part of its population living beyond the border in France and in canton Vaud. Namely, the whole area is called "Gran Genève" in spatial planning (Grand Genève, 2021). The geographical areas outside the administrative borders of the canton of Geneva are not included in this study.

Residential population experienced a yearly average increase of 0.9% between 2010 and 2020, with one event of decrease (2014) of -0.4% followed a maximum increase (2015) of 1.8% in the same time lag (OFS, 2021a). Due to its geographic position and the work market, the canton of Geneva host a larger number of cross-border commuter compared its resident population, which is tin average the 16% of the resident population. Also, the ratio of cross border commuters over resident population increased in average 0.5% each year (OFS, 2021a, 2021b).

The canton of Geneva has been chosen to employ advanced methods requiring spatial dataset of BE and health at small spatial resolution. Whether the excellent data availability eases the task of data collection, the canton of Geneva is a challenging case since it is generally deemed one of the healthiest and more liveable cities in Switzerland and the world and in Switzerland too (Mercer, 2019; Monocle, 2019; OFS, 2017; The Economist, 2021).

The three hypotheses are tested in the study area. The first hypothesis, which performs a spatial analysis of HBE, uses spatial data at a predetermined geographic scale within the study area, while the third hypothesis also integrates spatial health data in the study area. Instead, the second hypothesis is not directly contextual to the study area but integrate survey findings in the diagnosis provided by the first chapter (Paragraph 1.1.1).

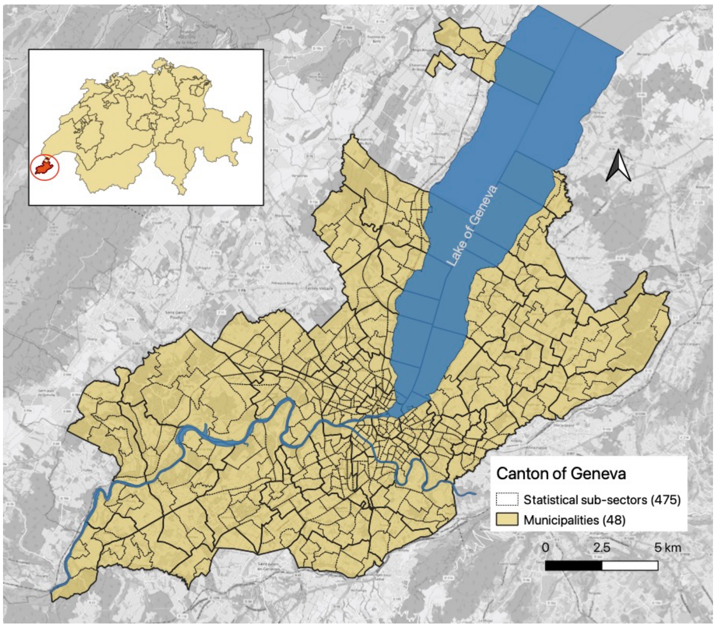

Figure 2: The territory of the canton of Geneva.

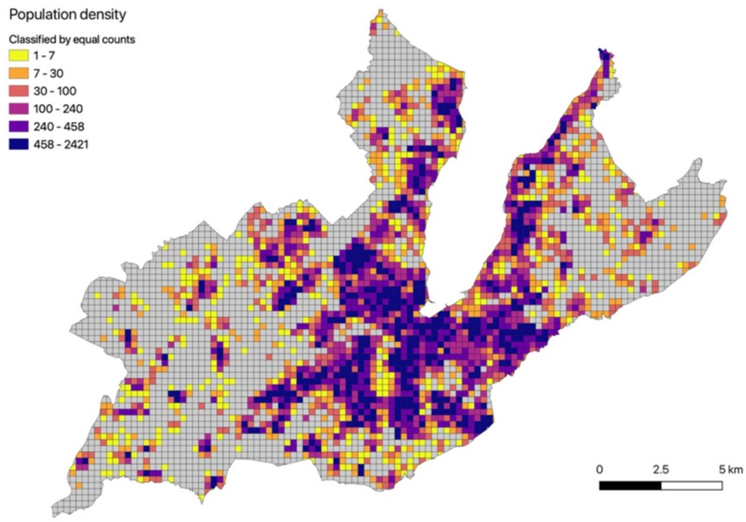

Figure 3: Population density in the study area represented a unit area of data aggregation (SITG | Le territoire genevois à la carte,).

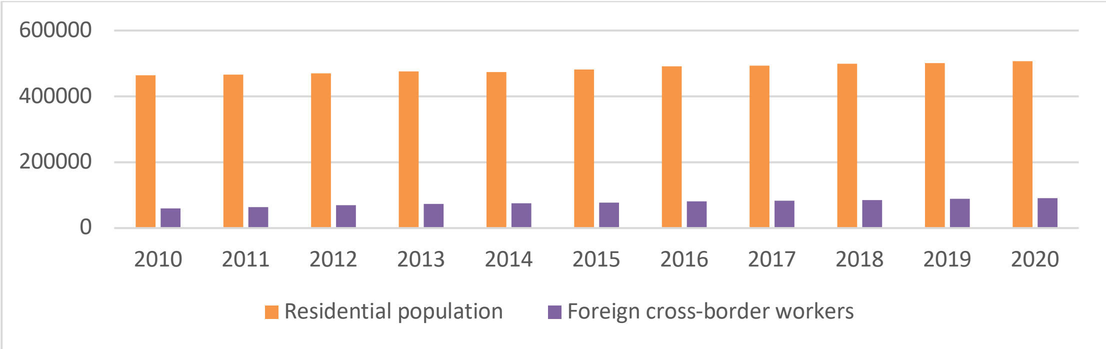

Figure 4: Residential population and cross-border workers in the canton of Geneva between 2010 and 2020 (OFS OFS, 2021b).

1.1.3.1 Health and places in the context of the canton Geneva

Switzerland is considered a healthy population and one of the best health care systems globally (OECD, 2018). Life expectancy at birth in 2019 in Switzerland was the second in the world, with 83.4 years, and healthy average life expectancy was the fourth highest, with 72.5 years (WHO, 2020). Among the OECD countries, Switzerland ranks among the best countries for overall health indicators, except for health expenditure per capita, which is the second-highest, counting for the 12.2% of GDP in 2018 (OECD, 2018).

The swiss confederation periodically surveys the health of inhabitants by collecting information on health conditions, behaviour, life and work condition, healthcare service use, and health insurance spending (OBSAN and Canton de Genève, 2020). According to the last report (2017), namely the OBSAN report, 83% of the residential population reports a good health status, with a similar percentage (71%) in the subset of the aged population. The primary health burdens are overweight, hypertension, diabetes, physical problem and mental health, or risk factors linked with diet, physical activity, alcohol, and tobacco consumption (OBSAN and Canton de Genève, 2020). The primary cause of death in the canton of Geneva is Cardiovascular diseases and cancer, and mortality rates are lower compared to the swiss average, except for colon and breast cancers and respiratory diseases (Table 2) (FSO OFS, 2021c) (OFS, 2020) (OFS, 2021a) (OFS, 2017). Non-communicable diseases predominately dominate the health landscape, a share which is expected to increase (WHO, 2013; Zellweger et al., 2014).

	Switzerland		*Canton geneva*		*Difference [%]*	
Life expectancy at age (x):	0	65	0	65*	0	65
Men	81.7	19.9	81.4	20.1	-0.4	-1.0
Women	85.4	22.7	85.7	23.15	+0.4	+2.0
Average	83.6	21.3	83.6	21.6	0.0	+1.5

Table 1: life expectancy in the canton of Geneva and in Switzerland.

	Switzerland				***Canton of Geneva***				
	Men	Women	Total	mortality* rates	Men	Women	Total	mortality* rates	difference in mortality [%]
All causes of death	32398	34690	67088	785.1	-	-	3389	678.5	-13.6
Infectious diseases	374	432	806	9.4	21	20	41	8.2	-13.0
Total malignant tumours	9545	7815	17360	203.2	494	478	972	194.6	-4.2
*Colon tumors***	617	496	1113	13.0	47	38	85	17.0	+30.6
Lung tumors	1988	1330	3318	38.8	112	75	187	37.4	-3.6
Breast turmor	10	1409	1419	16.6	0	101	101	20.2	+21.8
Diabetes mellitus	574	578	1152	13.5	24	24	48	9.6	-28.7
Dementia	2004	4450	6454	75.5	67	47	114	22.8	-69.8
Cardiovascular diseases	9418	11178	20596	241.0	391	421	812	162.6	-32.5
Total heart disease	7438	8627	16065	188.0	241	234	475	95.1	-49.4
Ischemic heart disease	3793	3054	6847	80.1	115	73	188	37.6	-53.0
Cerebral vascular disease	1444	2028	3472	40.6	79	100	179	35.8	-11.8
Total respiratory diseases	2395	2228	4623	54.1	128	152	280	56.0	+3.6
Accidents and violent deaths	2233	1687	3920	45.9	82	73	155	31.0	-32.4

Table 2: Health perspectives in Switzerland and canton Geneva. Deaths and Mortality of significant causes of death. *Mortality per 100 000 residents. Data updated 2018. (FSO OFS, 2021c) (OFS, 2020), (OFS, 2017).

In terms of morbidity, it is estimated that the residents of the canton of Geneva are less affected by chronic diseases than the national average (28,8% versus 32.7%) (OBSAN and Canton de Genève, 2020). Among the risk factors, overweight and obesity showed a constant increase, increasing from 26% to 42% from 1992 to 2017. The observation parallels an increase in physical activity and a significant lack of attention for healthy nutrition. The canton also indicates mental diseases as a priority for health intervention since its observed occurrence is twice the one observed in Switzerland for females only (Canton de Genève, 2020). Furthermore, the OBSAN report and the Environmental reports, and other cantonal reports explicitly identify BE characteristics as a relevant determinant of health (FOEN; OBSAN and Canton de Genève, 2020). Despite this widespread recognition, the health information periodically reported is only characterised in space at the cantonal level.

Spatial differences in health conditions have been observed between the rural and urban area in Switzerland. The "urban advantage" of living in cities compared to the rural area observed in the last century (Fei et al., 1998) gradually flattened while lower mortality risks were reported to be lower in peri-urban areas (Lerch et al., 2017). According to Lerch et al., those differences were explained by healthier behaviour and lifestyle (Lerch et al., 2017). Also, Zuffrey and Oris report that health differences are why populations with different socioeconomic statuses (SES) live respectively in urban, peri-urban, and rural areas (Zufferey and Oris, 2018).

While it is not understood yet if those differences are related to the contextual BE, the difference in BE determinants of health are indicated as a contributor of health and wellbeing in Switzerland and the canton of Geneva (FOEN ; OBSAN and Canton de Genève, 2020; Ville de Genève, 2009). The OBSAN report highlights for the canton of Geneva, among the relevant determinants of health, the burden of exposure to excessive noise levels. Approximately 40% of the Swiss population is daily exposed to the noise level above the threshold of acceptance set by the swiss confederation (which is 22% higher than the WHO suggested threshold). The federal office of the environment concluded that adopted measures to contrast noise pollution were not sufficient to balance the increase of overexposed population driven by urbanisation and demographic growth (OFEV). In the canton of Geneva, 60% of the population reports that at least on environmental issue in the place of residence compared to the 44.3% in Switzerland. Among the environmental determinants, 28,1% reports annoyance from road traffic, 24.6% from social sources, 14.7% from air traffic(Canton de

Genève, 2020). The residents of the centres of urban agglomeration report higher annoyance by noise (60.1 and 64.6%), while residential areas report slightly lower annoyance (52.5%). Also, reported annoyance from environmental determinants is associated with a higher occurrence of two health conditions when more sources of environmental annoyance are reported: depressive symptoms and sleep trouble. The latter is widespread, with 34.7% of the population reporting it.

Otherwise, BE determinants of health are addressed by the master plan (Plan Directeur) of the canton Geneva for 2019-2030 about a large set of urban health issues (Canton de Genève, 2019). The intention of the master plan is explicitly declared to be coherent with HiAP and SDS strategies. Also, the master plan reports the estimates of Spectra about the role of core determinants of health, according to which the environment and ecosystem contribute at 20% in shaping human health (Spectra, 2018). The master plan points up the need to take action out of the healthcare system on the whole system by a multidisciplinary strategy that addresses the totality of health and well-being determinants. This necessity is also justified by the increasing economic cost of health, estimated to be 11% of the internal product, while health prevention costs only 2%. Also, the master plan aims to address all possible health determinants not without equality, mainly focusing on vulnerable people such as children and the aged population. It is reported that health and wellbeing are improving overall, but inequities are stable, and they are likely to be determined by multiple determinants rather than an isolated factor.

Among five strategic axes, the first call for "an auspicious environment physique to a way of living healthy and free of risks for health". This strategic axe explicitly identifies spatial planning as the decisive factor in shaping environmental exposures and leading to healthy behaviour and lifestyles. More precisely, this strategic axe call for intervention in physical activity and active mobility promotion; better public spaces; green spaces, leisure spaces, a food environment directed towards healthier nutrition, reduction of air pollution (ambient and indoor), protection from contaminated land and radiations; and healthier housing in terms of biologic hazards, unsafe chemicals, noise pollution, and unsafe design for domestic injuries. While the many themes of the master plan and their strategies have an intrinsic relation with health conditions, this relation is not explicit, except for contaminated land, noise pollution and active mobility and physical activity promotion. For example, air pollution is addressed for its contribution to climate change and the energy efficiency of buildings. The master plan includes general and local plans of intervention that target HBEs concerning waste disposal, green areas, water management, contaminated sites, noise pollution, active mobility (cycling and walking separately), community places and risk management of transportation and storage of hazardous compounds.

Priorities of intervention for health in French-speaking cantons were summarised by the study of Chastoney et al., which point out heterogeneous contents and similar approach in the region (Chastonay et al., 2017). Despite addressing the principle of inequity, cantons disposed of mainly regional and national level health data. Similarly, the principle of implementing a multidisciplinary approach for HUP was embraced in theory but was not adopted (Chastonay et al., 2017). In the early 2000s, Schopper et al. conducted a Delphi survey among stakeholders in the canton of Geneva, reporting the need for quantitative and qualitative approaches to address a broad range of health priorities (Schopper et al., 2000).

Health Impact Assessment in Switzerland and in the canton of Geneva

Among the methods for determining the BE's health consequences, the Health Impact Assessment method takes the lead (Buse et al., 2019; European Center for Healthy Policy, 1999; Leeuw and Simos, 2017a). Health spending in Switzerland focuses mainly on fostering the healthcare sector despite cost-benefit approaches suggest that it would be more efficient to integrate health in policies. In 2005, the government published guidelines to address HiAP (despite its not directly cited), including HIA, leading to successful application in few cantons (Mattig et al., 2017). The guidelines identified broad policy areas to be implemented to target population health. Therefore, five in seven sectors were detached from the healthcare sector. However, guidelines did not involve cantons in turning them into policies, and later, HIA was institutionalised at the federal level as an example of good practice but still optional (Mattig et al., 2017). Since cantons (states of the swiss confederation) are independent of formulating health policies by the Swiss Confederation, the first application of HIA in Switzerland has been introduced and tested by three cantons: Ticino, Geneva, and Jura. (Cantoreggi et al., 2007). These early examples of the application of HIA experienced resistance at three levels. Firstly, the HIA is perceived as penalising in terms of time and costs and not supportive, probably due to the association with the constraining negative experience of EIA. Secondly, the HIA embrace concepts shared by EIA, resulting in competition between tools. Thirdly, the HIA could take advantage of a more shared basis (knowledge, definitions, and practice) to model the transfer of skills among the institution to address the holistic nature of health. Cantoreggi et al. also concluded that the interaction of HIA took advantage of soft" versions of HIA (rapid and desktop HIA) due to the lack of participation and reduced time and financial resource to apply it (Cantoreggi et al., 2007). The Promotion Santé Suisse reports that 13 on 22 HIA adopted a rapid HIA between 2001 and 2014. The examples lead by these three cantons allowed the creation of the Swiss HIA platform created by Health Promotion Switzerland to bolster the exchange and transfer inter-cantons, to raise the priority of HIA and HiAP and to manage the synergies with other tools (Cantoreggi et al., 2007; Mattig et al., 2017). The Health Promotion Switzerland reported the number of HIA undertaken by each canton, showing the Latin speaking regions leading over the German-speaking region (Mattig et al., 2017; Promotion Santé Suisse, 2015). Besides the number of HIA, we are aware that we have to detangle the HIA number by its effectiveness. In 2012, federal law on health prevention was rejected due to objections to HIA and resistance made by the pro-business lobby. Similarly to early applications of HIA, oppositions to the law argued the necessity of another bureaucratic burden, often reducing HIA as a copy of EIA in force since 1988 (Mattig et al., 2017). A bottom-up implementation is now more likely to implement HiAP at the cantonal level or transfer horizontally between canton (Mattig et al., 2017).

The canton of Geneva approached urban health since the 90's following the strategy of HiAP (Health in all policies), leading to the participation in the Healthy Cities network in 1994 (Cantoreggi et al., 2007; Mattig et al., 2017; Promotion Santé Suisse, 2015). Concerning HIA, in 2007, the canton of Geneva already tested and implemented HIA, resulting in 5 uses of HIA. Moreover, since 2006, developed a law according to which governance can make legislative projects undertake HIA (Cantoreggi et al., 2007). However, the implementing regulations have yet to be adopted (Promotion Santé Suisse, 2015). The early experience of the canton Geneva did not present a specific conclusion besides the understanding of the importance of the transfer of competencies and the importance of the legal basis to support HIA (Cantoreggi et al., 2007). In 2014, The canton of Geneva was the canton that adopted HIA 8 times, more than other cantons, even if all application in the canton took place between 2001 and 2008.

Urban health and spatial health research in the canton of Geneva and Switzerland

Overall, a consistent body of literature addressed the spatial analysis of health data in Switzerland, studying differences in spatial distribution at regional a cantonal level and in few cases al local geographic scale (Joost et al., 2016, 2018; Konstantinoudis et al., 2020; Vallarta-Robledo et al., 2021; Wennberg International Collaborative, ; Wertli et al., 2020). For example, the Wennberg international collaboration counts 23 spatial studies of health data on the swiss territory, with more than half studies dedicated to healthcare services use, and one article on four addressing cancer (Wennberg International Collaborative,). However, literature is scarce upon the joint spatial study of BE and health data. For example, the study of Moser reports a strong association between mortality rates and SES at the neighbourhood spatial scale (Moser et al., 2014). The study of Joost et al. links daytime sleepiness and nighttime noise level in the city of Lausanne by residential postal address (Joost et al., 2018). Concerning the canton of Geneva, spatial studies of health data explored the distribution of different health conditions, such as Parkinson disease, body mass index, Sars-Cov-2, sodium intake, mammography adherence (De Ridder, Belle, et al., 2021; De Ridder, Sandoval, et al., 2021; Fleury et al., 2021; Guessous et al., 2014a; Joost et al., 2019). Among the latter, one study explored the association with BE characteristics. The study of Fleury et al. showed how clusters of cases of Parkinson disease were spatially associated with higher levels of air pollution of nitrogen dioxide and particular matter by the place of residence (Fleury et al., 2021). In general, spatial analysis of health data is not a novel application within the swiss territory and the canton of Geneva, but spatial studies of both health and BE data are still scarce.

Comparing Geneva with other cities

In general, the city of Geneva is frequently considered among the healthiest cities in the world, with better quality of life or liveability (Mercer, 2019; Monocle, 2018; *The Economist*, 2021). Furthermore, the OFS yearly uses a set of indicators adapted from the list of OCSE (OECD,) to assess the quality of life in Swiss cities (FSO OFS, 2021b). This audit assesses every year quality of life in the eight major urban areas of Switzerland (Zurich, Geneva, Basel, Lausanne, Bern, Lucern, Saint-Gall, Lugano). A set of 200 indicators is used to rank cities according to 13 domains of revenue and job, housing, health, formation, environmental quality, personal safety, civic engagement, work private life equilibrium, infrastructures and services, mobility, culture and recreational activity, economic context, and demographic context. Concerning BE and health indicators, the Geneva rank occupies both top and bottom places (Table 3). Geneva is reported to be the city with the lowest Mortality and higher service density, including public transports. Instead, it is the last in terms of noise, air quality, road injuries, housing crowding, cultural spaces and the second last for green areas.

Rank	*Domain*	*Measure in City of Geneva*
8	Overcrowding	15% of the population live in housing with more than 1 person per room. It is also the city with smallest housing surface per person. (and with less vacant houding ca. 0.5%
8	Noise	More than 40% of the population is exposed to nighttime noise (over 55 dBA).
8	Air quality	In terms of long-term exposure to PM10 NO_2 and O_3.
7	Green area	Less than 20% of the city
8	Road accidents	Over 8 serious injured person each 10 000 residents
5	Mobility	Over 35 minutes of commuting to work per day
1	Public transport	Concentration of publix transport stops ca. 10 per km^2. Utilization of both PT and active mobility, ca. 80%)
1	Service proximi-ty	Mean distance to multiple services below 600 m. Services: groceries, post office, schools, physicians cabinets, and pharmacies.
8	Cutural places	Less than 15 museums, cinemas and theaters per 100 000 residents
1	Mortality	Mortality (less than 65 yo) ca. 20 per 100000 residents
2	Demographic	Second largest city and agglomeration of Switzerland, with a 5 years variation of +5.7% and 6.6% respectively. First city in foreigner shares of residents (more than 40%).

Table 3: Rank of Geneva among swiss large cities. The rank among 8 cities, from best to worst.

1.2 Theoretical background

1.2.1 The historical relation between spatial planning and health

Human development profited from banding and then settling to address survival through the secure food supply and protection from human and environmental threats (Leeuw and Simos, 2017b). Farming, agriculture and sedentism allowed more efficient use of resources and energies, moving from survival to demographic growth (Bocquet-Appel and Bar-Yosef, 2008). Human settlements started growing up close to freshwaters or other natural resources, allowing the specialisation among community members and capital accumulation. Afterwards, settlements started trading, and more settlements started growing along trading routes, thus developing as society results rather than natural resources(J. M. Diamond, 1998).

The process of concentration and growing communities and settlements, also called urbanisation (ScienceDirect Topics, 2019), led to implicit or explicit institutionalisation to address the change in the etiological and pathological ecosystem responsible for shaping human health. Sedentism shifted health determinant from anthropoktony (human violence), zoonosis and parasites belonging to diverse ecosystems constantly in time to seasonal variations and more artificial determinants (Caldwell and Caldwell, 2003; McMichael, 2001). In response to these shifts and tackle the new determinants of health, city rulers developed the first solution to safely store water and food or dispose of wastewater, also at the collective level (Leeuw and Simos, 2017b). Consequently, the further advancements of humankind generated a more complex form of governance and society, early physicians, such as Hippocrates and his followers, introduced hypothesis according to which health is shaped. Their empiric observation of health determinants and places related location and dwelling architecture with classes of diseases. A better insight given by Marcus Vitruvius Pollio identified three qualities to build a structure: solidity, utility, beauty; already disserting the relation between the built environment and the population with instruction about the environmental risk of the location, thermos-hygrometry and orientation (ventilation, dampness, temperature), overcrowding and utility, cost-effective, durable materials, solid structure and basement (Leeuw and Simos, 2017b).

Instead, we have to wait approximately one thousand years to find the first organised health care provision by the governance in Baghdad, or later government arrangements and practice to isolate infected during the middle-age plague epidemics in central Europe (Leeuw and Simos, 2017b). Centuries later, during the Enlightenment, the implicit link between filthiness, overcrowding and infectious disease consolidated during the previous centuries, were debated but saw its first application only after one century, when health started to be a matter of public responsibility. During the 19th century, the unbearable living condition carried with the industrial revolution provided fertile ground for the so-called hygienist movement or the sanitary awakening, also followed by the first association and network of healthy cities (Health, 1988; Leeuw and Simos, 2017b).

Meanwhile, advances in the biomedical field deepened the understanding of the causal path to disease through spatial epidemiology, with the comprehension of cholera diffusion by John Snow; and in microbiology with Pasteur and Koch's germ theory(Health, 1988; Leeuw and Simos, 2017b). At the end of the 19th century, visionary sociocultural perspectives of urbanism theorised the integration of multiple concepts: sanitation and hygiene, but also concepts of public transport, healthcare, community occupational health, ecosystem services, occupational health and safety as well as substance consumption (Leeuw and Simos, 2017b). Despite these optimistic assumptions, during the 20th century, spatial planning and public health diverged: the first giving importance to the physical structure of building cities, the second advancing in a structural-biomedical approach (Davies et al., 2014; Leeuw and Simos, 2017b). After the world-wars, the debate upon the spatial association of social determinants of health determinants with deprivation and wealth concludes that "wealth bring health" rather than being one of the measures of inequality together with health (Pickett and Wilkinson, 2015). This exploitation by politics and many other sectors led to the reductive approximation of health as an individual responsibility, leading to inaction in public health prevention in all sectors.

Meanwhile, the work of L. Dulh and the other members of the Space Cadets on human behaviour and environmental determinants offered an interpretation of urban health as a complex ecological dynamic system (Leeuw and Simos, 2017b). Unfortunately, their work passed almost undisturbed until the end of the 20th century, when re-evaluated, creating a founding basis for Healthy Cities' network. Since then, many other healthy cities have been created to integrate public health in spatial planning (Leeuw and Simos, 2017b).

1.2.2 Health integration in planning

The model of Kingdon and Thurber identifies the conditions grouped in three streams that must converge before policy progress can be expected (Kingdon, 1984): the problem stream, the proposal stream, and the policy stream. Firstly decision-makers must recognise the issue as a problem. However, while epidemiological research demonstrates a plethora of health concerns, evidence indicating treatments is scarce. Secondly, the proposal identifies a feasible solution trading off between an adequate evaluation and time and monetary costs. Thirdly, the policy stream is concerned with politicians' willingness to act, tangled with the support for certain policies, such as public opinion and media coverage. By bringing together these three streams, the policy can be facilitated even if intervention is not granted. In HUP, for example, the four phases of the model of Giles-Corti aim to translate research in urban health into planning intervention in land-use and transportation planning (Giles-Corti et al., 2015). The four phases ask for:

- conduct studies in which research questions are also established in cooperation with policymakers.
- adopt methods that engage compelling concepts for policymakers, such as diagnostics and experiments on a broad range of outcomes, in terms of health, society, environment and economy.
- adopt communication approaches suitable to report findings to decision-makers.
- participate in advocacy as a means of effecting policy change, directly or through intermediates, such as non-profit institution.

For example, the study of Sallis et al. collects the experience of translation of urban health research in different contexts in terms of strategy and subject of health integration. Otherwise, health integration in planning can be partitioned into the following four phases, which reflect the operational steps undertaken for the implementation of health in settlements (Rydin, Bleahu, Davies, Dávila, Friel, De Grandis, Groce, Hallal, Hamilton, Howden-Chapman, Lai, CJ Lim, et al., 2012). These phases support the historical development (Paragraph 1.2.1), and moving forward, each stage requires more advanced technologies, resources and knowledge. Follow this phase can be suitable in case of lack of resource since it implements first less expensive interventions that have a quick and efficient effect on population health and where these opportunities were missed, particularly in the case of HBE inequities. Evaluation of the accomplishment of each of these phases allows a screening assessment of HUP intervention. The four phases are summarised, from sanitation to healthy behaviour promotion, and in the end to the health integration in the governance.

The first phase ensures that the essentials are provided: shelter, food, clean water, clean air and sewerage. It is implemented as soon as health is considered a public responsibility (Institute of Medicine (US), 1988). This phase mainly tackles communicable diseases. The first phase took place after the Industrial Revolution in the current high-income countries (Cutler et al., 2006; Rydin, Bleahu, Davies, Dávila, Friel, De Grandis, Groce, Hallal, Hamilton, Howden-Chapman, Lai, CJ Lim, et al., 2012). In contrast, the low-income countries started experiencing this transition in the second half of the 20th century (Galea et al., 2005). The first phase requires similar standards worldwide, and it can quickly improve population health (WHO,).

The second phase is based on the concept that the built environment may influence lifestyle to be healthier. The control of these variables encourages healthy behaviour, which might be ineffective due to individual choices and other factors. Availability of public transport, or public spaces, are examples of facilities implemented at this stage. The second phase tackles mainly non-communicable diseases (Goryakin et al., 2017).

The third phase requires an integrated understanding of the built environment and its relationship with health, including population health inquiry. The assessment of the healthiness of the built environment allows the identification of priorities, the inequities within the cities and the monitoring of interventions adopted during the previous phases. Moreover, the explorative nature of this phase allows generating a new hypothesis and identifying local requirements and phenomena. This phase is all about optimising the previous phases and ensuring that health is implemented with equity.

In the recent sourcebook for HUP of WHO, there is no privileged strategy to address the integration of health in spatial planning. However, it is recommended to begin at one of four entry points: by setting, by the outcome, by principle or by sector (WHO, 2020). The sourcebook provides examples of health integration and a tool to apply directly on local data, opening the possibility to build standard procedures in HUP. Otherwise, the network of Healthy Cities takes the lead in terms of practice and experience. The Healthy Cities Network was created more than 30 years ago, and it is now at its seventh phase to collaborate with local decision-makers to test and share HUP interventions and provide support to HUP transition. According to the book of F. W. Gatzweiler, acknowledging that human needs and difficulties, such as health and wellbeing, demand a transformational, transdisciplinary, and integrative systems approach is necessary for changing cities (Franz W. Gatzweiler,). This requirement was highlighted in Pineo et al. study on the integration of urban health indicators, emphasising the importance of engaging diverse health issues and approaching urban health from a transdisciplinary perspective (Pineo, Zimmermann, et al., 2020).

1.2.3 Health levels

HUP should be integrated employing health data too, not only as output but as a driving input to understand the relation of heath with places (Costa et al., 2019; Friel, Vlahov, et al., 2011; WHO, 2020). Health is mainly investigated and monitored through measures of health outcomes. However, health outcomes are not easily collected since they need to be validated by professionals, require expensive tests, and handle sensitive information. Otherwise, Health conditions can be represented by indirect measurements such as self-reported health data and health determinants such as behaviour. While the latter is usually outlined as an individual characteristic, it also shaped by the built environment, social environment, natural environment and the economy (Barton and Grant, 2006). Therefore, the investigation of health can be composed of additional levels to draw a picture of population health about the built environment or the related risk intake (Frank et al., 2019; Künn-Nelen, 2016). In particular, the study of the impact of commuting on health made by Künn-Nelen, can be extended to a general urban health investigation (Künn-Nelen, 2016). Health can be concurrently represented through four levels:

- the objective health, thus the actual health outcome, e.g., a measurement or a diagnosis that identify a health condition.
- the subjective health, e.g., the health perception or satisfaction of the personal state of health.
- the health behaviour, e.g., the lifestyle and the habits.
- and healthcare consumption, e.g., the utilisation of healthcare service.

The large body or urban health literature frequently investigates health using one or two levels. Between levels, health consumption investigation is scarce in the literature, and it is difficult to interpret. For example, a low rate of healthcare service uptake could indicate reduced accessibility (physically, economically, or socially) as well as an absence of illness. Health satisfaction is considered an indicator of the quality of life and not frequently discussed in urban health studies. The "embodiment" process of place in health (Krieger, 2001) should be based more on mixed methods (Amaratunga et al., 2002): studies that are mainly based on quantitative approaches which collect biometrics, without including perceptions and stories of participants (Brownson et al., 2009; Miller and Tolle, 2016; Petteway et al., 2019). For example, Paine et al. audited the living experience of residents and users in four developing residential areas in New South Wales, Australia, reporting the necessity of monitoring, guidance and promotion of the adequate use of built environment besides the physical intervention (Paine et al., 2018). The NHS Scotland created a participatory tool based on a broad framework to understand perception and use of the daily living places, collecting data about perception and stimulating urban health knowledge and population engagement (NHS, 2019). Understanding the association between place and health depends on all four levels, allowing the characterisation of heterogeneity in health conditions at the individual level.

1.2.4 Complexity in urban health inference

The study of health and built environment relations means researching pathways of illness or health promotion. Firstly, urban health research suggests that causality may fade away due to feedback loops or social selectivity (Duncan et al., 2014; Jokela, 2014), (Eid et al., 2008). An example of a feedback loop can be identified in the study of obesity. In essence, car use leads to air pollution, which discourages physical activity and increases the risk of being obese, which boosts car use (An et al., 2018). Generally, loops are either negative or positive, depending on the need for resources to be maintained. Negative feedback loops can be subsidised to maintain stability, e.g., public transport has good viability and low fares thanks to public funds, while positive loops are often self-nourished to unstable growth, as periphery expansion led by the construction of new motorways (CSDH, 2008).

Uncertainties carried by feedback loops do not easily allow the identification of frequencies of response in population health (i.e. a "dose-response" measure) which is a great challenge for HUP (Saarloos et al., 2009). The response to interventions in urban settings is not linear but exhibits adaptation and resistance to interventions at larger scales than individual ones (Saarloos et al., 2009; Tozan and Ompad, 2015). Likewise, urban systems can cope with breakdowns and dissipate overloads (Rydin, Bleahu, Davies, Dávila, Friel, De Grandis, Groce, Hallal, Hamilton, Howden-Chapman, Lai, CJ Lim, et al., 2012). In a socio-ecological system, a higher complexity is brought by human agency, namely "the ability of individuals and groups to act knowingly based on what they value in order to maintain or improve their wellbeing" (Lawrence and Gatzweiler, 2017). Individual behaviour is self-organising, non-linear, path-dependent, dynamic and influenced at different hierarchical levels by interrelated factors (Saarloos et al., 2009). In addition, individual behaviour is incorporated into the multi-causal web that is formed between health outcomes and urban environments (Tesh, 1994; Thomas, 2006).

However, following the concept that individuals are also active agents in shaping health, HUP research investigates impacts on population health, missing the opportunity to understand whether individuals likelihood to select unhealthy urban environments or choose unhealthy behaviours (Eid et al., 2008; Gomez et al., 2015). In theory, on the one hand, HUP should not let populations live in unhealthy urban environments (Kundi Michael, 2006); on the other HUP could better understand whether unhealthy life human agency copes with intervention for health promotion or protection to address any urban health issues at the local area and prevent adverse health outcomes (Franz W. Gatzweiler, ; Lawrence and Gatzweiler, 2017). Understanding both HBE and health data have the ability to reveal their mutual coexistence, allowing for the optimisation of HUP intervention.

Besides the complexity in defining the concept of causality in urban health research, in practice, studying impacts on overall health involves both exposures and experiences of hazards or health benefits, which have multiple spatial and temporal outreach. A broad assessment and adequate geographic contextualisation are required to identify inequities within the city and synergies and conflicts between interventions in space (WHO Centre for Health Development of Kobe, Japan, 2010). Understanding the stratification and spatial distribution of HBEs and health data is addressed in Chapter 3 and Chapter 1. Further challenges are discussed in the limitation of this study in Chapter 6.

1.2.5 Assessment Tools of HBE

Understanding the role of BE to attain a specific function or about determined phenomena; is a fluid concept that has not been formally defined and assumes different names, such as assessment, evaluation, diagnosis, or appraisal, among the many. In general, understanding the BE is attained by a procedure to identify the geographic location of specific characteristics of an urban setting and characterise the BE for its role in accomplishing a specific task, e.g., in delivering health benefits or hazards. The BE is often represented inadequately. A place of BE is a context where its composing features are summarised by three outlines: availability (as the existence of a built environment feature); accessibility (as the location or spatial organisation of an object); and the quality (conceived as the characteristics linked with their practical utility or impact). A large body of quantitative HUP studies does not consider the quality of urban features related to their practical use (Franz W. Gatzweiler,) and their effects on health, including their perception (An et al., 2018).

Evidence from urban health research, can serve as the foundation for the health assessment. Evidence about the relation between environment and illness is widely recognised for a large number of urban health issues (Barton et al., 2013; Grant, 2015; Northridge et al., 2003), such as air pollution, active mobility, thermic stress, road injuries, and sanitation among the many. However, other urban health issues are challenging to address, e.g. electromagnetic pollution, noise pollution, climate change, social cohesion, urban agriculture or the food environment (Bandara and Carpenter, 2018; Caspi et al., 2012; Halperin, 2014; Jennings and Bamkole, 2019; Kingsley et al., 2009; Morris et al., 2017; Orsini et al., 2013; Pirrera et al., 2010). However, when the impact of the built environment on health is commonly accepted, it is not supported by evidence globally (Grant, 2015). The only extensive assessment of the effects of planning interventions took place in the field of infectious diseases and sanitation for short time-lags only (Grant, 2015), the main reason being that for infectious diseases, environmental determinants of diseases are in small numbers and time lags between exposure and illness are small (Rothman et al., 2008). These characteristics allow easier identification of a "dose-effect", and therefore governance endorses effective direct interventions investing more in preventive measures (WHO, ,). Determinants of health that are hardly traceable to their cause in space or time scale, or causality, otherwise called distal according to Morris et al. (Morris et al., 2017), are likely not to resolve. Instead, determinants of health in non-communicable diseases are many and heterogeneous within the population. Furthermore, multi-causality in population health does not allow easy identification of the causal pathway from illness to urban environments (Grant, 2015; Tesh, 1994).

The collection of urban health issues deals with many diseases, a large number of characteristics of cities and multiple sectors of urban planning (Elsey et al., 2016; Lawrence and Gatzweiler, 2017; WHO, 2020). Urban planning is the tool considered in this article to address urban health by managing the built environment. Urban planning is a transdisciplinary process that spatially develops and designs the land use (Levy, 2016). This process implements optimal solutions to solve conflicts among multiple sectors and harness synergies (Levy, 2016). Similarly, HUP encompasses multiple sectors of planning, such as transportation, housing and environmental protection, to promote health promotion and prevention (WHO, 2020).

In contrast to the multidisciplinary nature of urban health, monodisciplinary approaches adopt biomedical models based upon symptom and treatment, rather than integrating multidisciplinary interpretations able to confront the impact levels of different built environment features on health (Diez Roux, 2007; Reis et al., 2015). Disciplinary approaches to assessing single determinants of health miss the synergic and conflictual effects of multiple features of urban environments on population health and its spatial coherence. Besides, health cannot be disconnected by other dimensions, such as the natural and social environment, in which cities are deeply tangled within the same ecosystem. At the current state of research, assessments of the healthiness of the built environment are widely performed on multiple urban health issues separately, and they are not geographically contextualised (Barton et al., 2013; Barton and Grant, 2013; Gomez et al., 2015; Northridge et al., 2003; Schulz et al., 2018; Wierzbicka et al., 2018; Yang et al., 2013b).

For example, Health impact assessment (HIA) may be considered a broad assessment for its potential application on a wide range of policies, programs and projects (Harris-Roxas and Harris, 2011). HIA is defined as "a combination of procedures, methods and tools by which a policy, program or project may be judged as to its potential effect on the health of a population, and the distribution of those effects within the population"(European Center for Healthy Policy, 1999). HIA serves as a fundamental approach for health protection and promotion to support planning as an active agent and an integrated part of planning in all its phases through six steps: screening, scoping, assessing, recommending, reporting, monitoring and evaluating(Health in Impact Assessments: Opportunities not to be missed, ; WHO, 2020).

Despite being initially conceived with methodological shortcomings (Krieger et al., 2003; Winkler et al., 2013), HIA has been applied to a broader range of sectors with success (Rogerson et al., 2020). For example, in the Healthy Cities network, HIA initially introduced in Phase IV followed a wide range of applications in Phase V (Leeuw and Simos, 2017a). Reviewing HIA and equity, Buse et al. reported a limited but increasing number of HIAs addressing inequalities (Buse et al., 2019). In particular, 53 of the 89 items reviewed included multiple risks, hazards and impacts for cases of healthy cities and urban planning issues, cumulative health risk assessment, corporate health impact assessment, climate change-focused HIA, intersectionality-based assessment, and global health HIA (Buse et al., 2019). On the one hand, HIA has been voluntarily implemented to climb over barriers related to decision-making acceptance, from the other hand, HIA is not usually seen as a pro-active, preventive and supportive actor in urban planning: health promotion and prevention is added as a condition and not regularly as a final objective (Carmichael et al., 2012). HIA is a pragmatic and powerful approach to integrate HiAP systematically (Harris-Roxas and Harris, 2011; Leeuw and Simos, 2017a), yet HIA faces multiple bureaucratic, methodological and political barriers needing support from external agents, such as the Healthy City network or NGOs (Carmichael et al., 2012; Winkler et al., 2013). HUP could profit from HIA to integrate health as a primary goal and address health equity, prevention and promotion through a wide range of health issues that can stratify disproportionally within the city area (Buse et al., 2019; Rogerson et al., 2020).

Beyond HIA, other examples of urban health research display various advantages and shortcomings in building knowledge to inform planners and decision-makers that protocols of assessment such as HIA could undertake. For example, the protocol created by the Canadian Urban Environment Health Research Consortium sets a broad assessment characterised by spatial contextualisation (Brook et al., 2018). they merged environmental measures to provide a protocol for exposure analysis of air pollution, transportation, noise pollution, greenness, climate and neighbourhood factor by postal codes aggregate metrics. However, despite the large size of the dataset involved, health outcomes are investigated as a product of the built environment within the area covered by postal codes containing residence which belongs to rural and urban areas. Therefore, the size of a spatial unit of analysis is highly variable, and the spatial unit of analysis may be not small enough to represent the relation of the built environment with population health (Elsey et al., 2016; Gomez et al., 2015; Verma et al., 2017).

A final example is the BE Tool created by the Center for Disease Control and Prevention to study obesity and its determinants only (Eyler et al., 2015). The BE Tool is made to assess the spatial characteristics of the environment able to promote active mobility, recreational activities and healthy nutrition following measurements of selected features of the built environment. The BE Tool is restricted to the study of obesity but remains multi-sectorial and based on measures of the urban environment, such as street pattern characterisation of crossings and sidewalks pathway (CDC, 2019).

Many other studies are listed in the geospatial assessment for urban health in the fields of heat exposure, cardiovascular diseases, air quality, food environment, health care accessibility, active mobility, among the many (Lu and Delmelle, 2019). WHO itself offers multiple open-source analytical tools to assess urban environments, such as GreenUr for urban green spaces, AirQ+ for air pollution, HEAT for walking and cycling and also the Health Impact Project's cross-sector toolkit, which collects HIA experiences and guides (WHO, 2020). Also, indicators are overused in defining healthy urban forms (Pineo et al., 2018; Rothenberg et al., 2015; Stauber et al., 2018) and are rarely spatially explicit within the city area. The representation of composite indicators to represent the healthiness of the built environment broadly has been criticised because it summarises complex information or because the adequate weighting of the composing indicators has not been addressed yet (Pineo et al., 2018). While overall composite scores are not clear, the joint representation of multiple indicators or multiple tools could have a meaningful and valuable utilisation when spatially explicit. When proposing a global urban environment and health index representing ten categories and 58 indicators generated by a causal pathway framework through iterative stakeholder engagement, Pineo et al. (Pineo et al., 2018) called for neighbourhood-scale data gathering to enable smaller-scale analysis.

As opposed to sector-specific assessments based on measurement protocols seen before, comprehensive approaches are primarily theoretical. While the former is not able to capture synergies and conflicts between urban health issues, the latter is not prone to environmental and individual health measures. Among comprehensive frameworks that outline urban health, Galea et al. proposed four generic urban health characteristics: population characteristics, physical environment, the social environment and health and social service system (Galea et al., 2005). Grant (Grant, 2015) identified eight important issues for HUP: climate change and public health emergencies, exposure to noise and pollution, healthy urban planning, healthy transport, healthy urban design, housing and regeneration, safety and security, creativity and liveability. Otherwise, the "Social determinants of health and environmental health promotion" scheme from Northridge et al. display the multiple causal pathways from environmental features at different scales to health outcomes through intermediate steps (Northridge et al., 2003). The previous conceptual framework describing the relationship between health and the built environment, like many others, do not set a basis for spatial analysis and measurements. However, conceptual models, i.e. eDPSEEA, are already used to engage stakeholders in facing a broader conceptualisation of urban health (Reis et al., 2015). Still, the previous theoretical examples are instead meant to embrace multiple urban health issues, interdisciplinarity, and causal path and feedback loops to inform and guide the planning process. In summary, future approaches could benefit converging measurements of the built environment and transdisciplinarity, thus tackling multiple health determinants based on what has been diagnosed in the city to address health prevention and promotion (Barton et al., 2013; Healthy urban design, 2019; Northridge et al., 2003; WHO, 2020).

1.2.6 Geospatial analysis applied to urban health

Since urban health is not an established discipline, and since it collects a vast range of studies, just as many, if not more, are the geospatial approaches tested on many urban health issues. Therefore there is not a comprehensive meta-analysis of geospatial models employed in urban health literature, while attempts can be found for separate disciplines (Auchincloss et al., 2012a; Blatt, 2015; Franz W. Gatzweiler, ; Lawson et al., 2016; Maantay and McLafferty, 2011; Shen, 2012; Sun et al., 2018).

Foremost, geospatial studies are affected by multiple issues. The calculation, measurement, specification, sampling, and stochastic error are the five leading sources of uncertainty with particular relevance in geospatial studies, including urban health (Griffith, 2018). While the first three are a relevant source of error, we can deal with them; stochastic and sampling error are challenging to solve due to heterogeneity in the spatial distribution of the population and the aggregation of data, respectively (Griffith, 2018).

Therefore, the study of the relation of the spatial distribution of health data played an essential role in exploring environmental causes of illness since the early experience of John Snow (Snow, 1855; Yang et al., 2013b). In particular, the study of spatial autocorrelation allowed the identification of hotspots of health conditions in a large number of health disciplines, so that consequently, association with places were explored (Anselin, 1995; Getis, 2010; Griffith, 2018; Lawson et al., 2016; Rushton, 2003). Instead, the study of spatial heterogeneity, has been scarcely adopted in the spatial studies of health since it requires the collection of multiple spatial data (Geniaux and Martinetti, 2018; Griffith, 2018; Oshan et al., 2019).

Two problems are rooted in the spatial analysis of health and HBE. The first is the bias introduced by the spatial aggregation of data, the Modifiable Areal Unit Problem (MAUP), a problem shared by geospatial analysis applications (Openshaw, S, 1984). The second is the Uncertain Geographic Context Problem, which is related to the bias introduced depending on how contextual units or neighbourhoods are spatially designated may alter findings on the impacts of area-based features on individual behaviours or outcomes (Kwan, 2012). The latter is exclusive in studying the relation of places with individuals, hence in geospatial studies of health, sociology, transportation, among the many.

Geospatial research has been moving toward finer spatial resolution and improved data collection (Elsey et al., 2016; Lee et al., 2019; Miller and Tolle, 2016). In fact, to a great extent, advancement in urban health geospatial studies took advantage of the development of technologies able to collect more and better data. Geographic Information System (GIS) already played an essential role, for example, in public health and planning separately (Ago Yeh, 1999; McLafferty, 2003; Rushton, 2003) by handling the data under the lens of place. Further advancements allowed the collection of more and better data, thanks to Remote Sensing and Geographic Positioning Systems; while more recently thanks to Social Media, Volunteer Geographic Information, Sensors and Internet-of-Things (Lu and Delmelle, 2019).

Instead, advances in methods for geospatial analysis are somewhat sporadic and based on theories developed decades ago (Arlinghaus et al., 2020; Gelfand et al., 2010; Gesler, 1986). The current geospatial methods are derivable of two early approaches to relate objects and places, the density of objects or events (e.g. disease cases, or services) within an area, namely regional ratio, and the distance-based methods (Gesler, 1986). While the study of places only, allowed the application of advanced physical and statistical model (Batty, 2019; Iltanen, 2012; Skidmore, 2017), the uncertainty introduced by the human factor, hinder the application of advanced geospatial models following the intrinsic complexity of studying urban health issues, such as in the case of non-communicable disease (Kwan, 2012; Rydin, Bleahu, Davies, Dávila, Friel, De Grandis, Groce, Hallal, Hamilton, Howden-Chapman, Lai, CJ Lim, et al., 2012). The explanation of health conditions by HBE characteristics recently implemented artificial intelligence (AI) approaches in health to perform regression and classification tasks (Kamel Boulos et al., 2019). The emerging AI implementation allowed the data mining and learning of high-dimensional data collected by the new technologies (Kamel Boulos et al., 2019; Lu and Delmelle, 2019). According to the review of geographic AI models applied on health, current approaches lack labelled training data, mainly supervised learning and expertise integration, to avoid the uninformed use of data (Kamel Boulos et al., 2019). On the one hand, AI is a powerful tool to improve the data collection through new technologies, for image classification al labelling in cases of the paucity of data on HBE (Maharana and Nsoesie, 2018). On the other hand, AI can be integrated to detangle the multidimensional nature of HBE and health data (Kamel Boulos et al., 2019; McAllister et al., 2017). Also, implementation of geospatial AI is mainly AI approaches applied on spatial data, so that geographic location is only an additional dimension used in a global approach, rather than AI models that implement geographic location locally or in the function of geographic location (Georganos et al., 2021; Kamel Boulos et al., 2019).

The intrinsic complexity of urban health issues can also be studied under the lens of behaviour, including place as a geographic factor, such as in the agent-based model (Badham et al., 2018). Furthermore, geospatial analysis can include time to thoroughly detangle the Spatio-temporal contextualisation of health in the HBEs (Matthews and Yang, 2013; Saarloos et al., 2009). Since we did not address the temporal evolution of HBE and health in this work, further consideration is discussed in the paragraph of the study limitation and future research perspectives (Chapter 6).

1.3 Methods

The thesis attains to understand the spatial distribution of the HBE for a broad range of urban health issues relevant in the study area, the canton of Geneva. The study addresses this task by employing geospatial analysis methods by the statistical analysis of both HBE and health data. The thesis does not aim to test the inference between health conditions and HBE or explore the new causal path from HBE to health. Instead, it studies the spatial distribution of HBE, and geospatial health data based on prior scientific evidence.

The methodology used in this study does not estimate the health impact of the HBE but study the spatial distribution of HBE, of a health dataset and in the end their spatial association. The objective of addressing all relevant urban health issues in the study area, gather the HBE determinants of all three types of health burden, communicable and non-communicable diseases, and injuries (Rydin, Bleahu, Davies, Dávila, Friel, De Grandis, Groce, Hallal, Hamilton, Howden-Chapman, Lai, C Lim, et al., 2012). Different diseases-specific measurements can evaluate this macro-area of health group health conditions, and they could be compared using global aggregate measurements. For example, relative risk, mortality, life expectancy, morbidity, disability-adjusted life years (DALYs), years of life lost (YLL), and quality-adjusted life-years (QALYs) are frequently used among the many (McDowell et al., 2004; Plass et al., 2019). However, the relation between HBE and health conditions is not linear nor univocal, so that we cannot correspond all HBE characteristics to an estimate of a global aggregate measurement of health impact at individual level. This estimate of health impact can be accurate in case phenomena attributable to a "dose-effect" mechanism, such as exposure or injuries, or can be modelled by collecting data at individual levels. However, an estimate of health impact is not feasible for the totality of urban health issues since no agreement or standard were found in the scientific literature about their respective health impact. For example, it can be assumed that if the active mobility network is expanded in a district, an increase in walking and cycling can follow the intervention and consequently shape the health of the population. However, beside measuring and understanding a change in mobility behaviour, modelling the spatial extension of the change, and its distribution within the population is a complex task (Morelle et al., 2019). An additional barrier to traduce HBE characteristic into health impact estimates, is the spatial analysis at small geographic scale, which is necessary to optimize understanding and address inequities (Paragraph 1.1.2). Therefore, we employed geospatial statistics approaches to understanding the spatial distribution of urban health issues by studying the spatial variability of HBE characteristics and their stratification within the study area. In the end, we compared the HBE with a spatial health dataset of cardiovascular risks.

Therefore, we diagnose the healthiness of the BE in the study area by summarising the metric that represents HBEs by indicators. Urban health indicators are extensively employed because of their benefits in synthetising the search for a more effective translation of health into planning, in terms of increased communication with decision-makers and advocacy through participatory processes or the press and media (Galea and Vlahov, 2005; Lowe et al., 2015; Pineo et al., 2018; Rothenberg et al., 2015). In 2015, Rothenberg et al. reviewed the current status of urban health indicators and reported no leading standards despite the abundance of examples (WHO et al., 2014). Only a few sectors concerned with urban health make extensive use of standards, such as environmental measure thresholds and construction standards. (An et al., 2018; UN, 2020; *WHO*, 2018b). Rather than selecting arbitrary indicators, we developed a framework that enabled us to build a set of indicators for the entirety of relevant urban health issues by utilising the existing indicators' measurement. Existing urban health frameworks were incomplete, overlapping, or too generic to be represented by HBE measures (Paragraph 2.1.1). Thanks to the role of indicator as facilitators of HUP, urban health indicators can be a bridge to integrate the perspectives of experts and decision-makers in evaluating and amalgamate them (WHO et al., 2014).

Another key concept of the methodology is the employment of both local and global geospatial approaches. Geospatial studies can be split into those that make broad strokes in search of 'global' insights and those that seek to understand local variation (A. Stewart Fotheringham et al., 2002; Harris et al., 2011). The spatial dimensions that represent the geographic location are not merely additional dimension because, as simply summarised by Tobler's first law of geography: "everything is related to everything else, but near things are more related than distant things" (W. R. Tobler, 1970). In fact, places exhibit homogenous characteristics and gradual variation at variable geographic scales, so that is not randomly distributed in space (W. R. Tobler, 1970). Even if this concept was first applied to topographic surfaces, cities are no exception (Miller, 2004). In urban health research, geospatial data are frequently studied with a global approach by studying differences in geographic distribution under the assumption that the relation between HBE and population health are the same within the study area (Griffith, 2018; Wei et al., 2016). Instead, local approaches can lead to significant insight into the non-stationarity of the observed phenomena (Anselin, 1995; Geniaux and Martinetti, 2018; Getis, 2010; Griffith, 2018; Harris et al., 2011). Since local approaches provide an interpretation variable depending on the location, their output should be used with caution, as it is based on a model that may differ within the study area and depending on the definition itself of local space. Compared to a global model applied to the same geospatial dataset, the output of a local statistical model is represented by an additional dimension for each object in the dataset. Adopting a local approach is also coherent with the concept of accessibility, a key concept to contextualise health in the geographic space (J Lu et al., 2021; Matthews and Yang, 2013).

Recalling the urban health system (Figure 5) in simplified version (Figure 5 a), the hypothesis of the thesis focus on the geospatial diagnosis of HBE (H1), and the study is subsequently extended by understanding the viewpoint on HUP (H2), and by integrating the geospatial health data (H3). The methodology is set on a generic framework developed and used throughout the thesis structure, following an adaptation to the case study. The study is based on multiple statistical and geospatial methods (Table 4), where the hypothesis first and third hypotheses are dedicated to spatial analysis, and the second hypothesis provides insight into HUP and implements its findings in the HBE diagnosis.

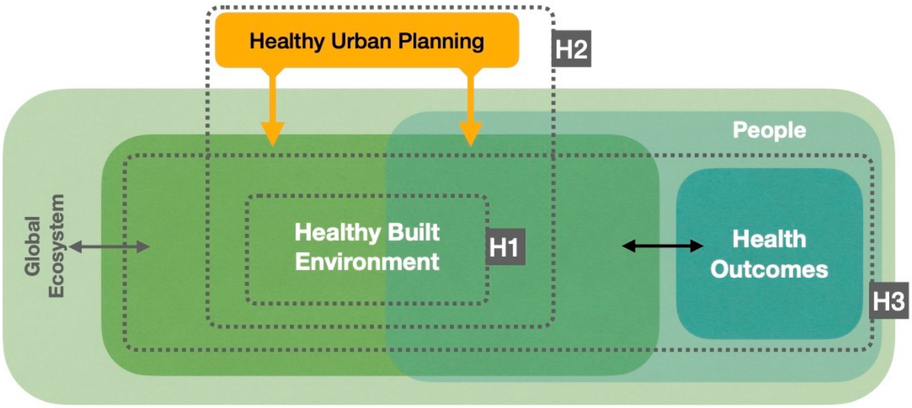

Figure 5: Workflow (a) application area of the hypothesis in the urban health system. (b) The workflow of the thesis according to the three hypotheses.

	METHOD	OBJECTIVE
SECTION 1 **(HYPOTHESIS 1 & 2)**	Semi-structured review	Identification of relevant BE determinants (and relative metrics) of health for the framework creation
	K-Means Clustering (and criteria loading)	Dimensionality reduction and grouping of BE determinants in Urban Health Issues (UHI) for the framework creation
	Statistical analysis (Pearson, Spearman, Anova)	Comparison between BE metrics within and between UHIs in the case study
	Kernel Density Estimator	Spatial interpolation of discrete BE metrics to represent their spatial decay
	Principal Component Analysis (PCA) (and Factor Analysis)	Generation of global UHI indicators, identification of outliers
	Skater clustering	Generation of contiguous spatial clusters of UHI indicators
	Geographically Weighted PCA (Explained variance ratio, loadings and Discrepancy score analysis)	Generation of local UHI indicators, identification of outliers, study of the heterogeneity by the spatial variation of loadings, performance comparison between local and global indicators model
	Spearman correlation	Ranking conservation between UHI indicators calculated by PCA and GWPCA
SECTION 2 **(HYPOTHESIS 3)**	Direct weighting	Collection of perspective on health integration in planning, experience, and UHIs rating
	Statistical analysis (Pearson, Spearman, Anova, Odds)	Comparison of responses between and within groups in assessing UHI
	K-Means Clustering /PCA	Profile analysis
	Spatial association and spatial clustering	Association between the perception of UHIs in residents and UHI indicators,
SECTION 3 **(HYPOTHESIS 4)**	Statistical analysis (Pearson, Spearman, Anova)	Description of the health dataset
	Spatial Autocorrelation (Local Indicators of Spatial Autocorrelation)	Spatial clustering of health data.
	Deep Neural Network	(Global) Predictive power of BE data (Land cover, BE metrics and UHI local and global indicators) at multiple scales. Predictive power of spatial cluster and health data of spatial clusters.
	Shapely values analysis	Interpretation of predictors' contributions
	Multiscale Geographically Weighted Regression	Local Predictive power of BE data (Land cover, BE metrics and UHI local and global indicators), identification of spatial cluster f better predictors.

Table 4: Main methods used in the thesis per each chapter.

1.4 Structure of the thesis

The thesis is divided into six chapters, where the first one introduces the thesis, the second deal with the development of a conceptual framework, the third, fourth and fifth chapters address each of the thesis hypotheses, while the last one consists of a final discussion and conclusion. The first two research gaps, the comprehensive approach, and the spatial analysis of the HBE, are tested in the second and third chapter. Then, the fourth chapter addresses the third research gap about stakeholder perspectives integration. Then, the fifth chapter includes the findings of the third chapter and addresses the last research gap, the study of health data, and its relationship with the HBE.

More precisely, the second chapter develops a framework of urban health issues (UHI) to diagnose the HBE for a generic urban health application. Then, three chapters address the test of the three hypotheses respectively. The third chapter targets the first hypothesis. The framework is then adapted to the case study, the canton of Geneva (Switzerland). The third chapter deals with data preprocessing by presenting the spatial aggregation and interpolation of data, which structure is employed in the spatial representation of HBE across the rest of the thesis. Afterwards, it is shown how HBE metrics generate UHI indicator by employing a global and local statistical approach to reduce dimensionality in input data. The use of indicators allows the spatial analysis of multiple urban health issues by studying outliers, interpreting variability of indicators, comparing the global and local approach, mapping their stratification and measure inequities.

The fourth chapter addresses the second hypothesis. In the first paragraph, a short survey is developed to evaluate the integration of health among the objectives of planning and understand the perspective in addressing the urban health issues according to the structure of the previous framework. The survey responses in three groups of stakeholders, international urban health experts, local planners and local citizens are then compared (4.3). Also, the responses provide a weighting of the urban health indicators for the case study (4.3.3). Additionally, the responses in the residents in the study area, are used to study the spatial distribution of perspectives from the place of residence, and ratings are compared with objectively measured data in the third chapter.

The fifth chapter focuses on the last and third hypothesis, also integrating findings of the second chapter. The chapter starts describing the health dataset, a cross-sectional study about cardiovascular diseases and cardiovascular risk in the state of Geneva, and later, it provides the spatial analysis of the dataset studying its spatial clustering. After, the comparison of health measures of cardiovascular risk factors with HBE is addressed across multiple dimension dimensions: by global and local approaches, emplying different HBE datasets, at multiple scales of spatial aggregation and across different health measures. Then the regression is tested for a subset of the health dataset, the spatial clusters identified in the first paragraph of this chapter.

In the last chapter, we summarise the main findings, we discuss the future perspective for the development of research in urban health and the integration of health in spatial planning.

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Chapter 2 Addressing a broad range of disciplines: a framework of Urban Health Issues

Abstract : In this chapter, we describe the choice of the conceptual structure to represent the built environment's healthiness. We adopt a semi-structured approach to generate categories to represent the wide range of urban health issues. The purpose of this chapter is to compile the most pertinent urban health concerns that have been broadly acknowledged in the literature and to build a framework for use on a generic case study and with built environment data to aid in spatial planning. The conceptual framework developed in this chapter is employed in the other chapters to structure the multiltiple disciplines of urban health and study the healthy built environment.

2.1 Introduction

To develop better cities, it is vital to understand the relationship between the Built Environment (BE) and population health (Elsey et al., 2016; WHO, 2020). The complicated interaction between health and the BE generates a plethora of challenges which have been studied by separate sectors of urban health research (D'Alessandro, 2020; Glanz et al., 2016). The latter generated a substantial body of evidence on each of those issues, which prompted successful interventions through planning and policies tackling proximal determinants of health, or partially improved health addressing distal determinants of health (Krieger Nancy, 2011; Rydin, Bleahu, Davies, Dávila, Friel, De Grandis, Groce, Hallal, Hamilton, Howden-Chapman, Lai, CJ Lim, et al., 2012). Even if the solutions to this challenges are known, action for health prevention and promotion through planning have not been implemented systematically in both developing and developed countries or within countries (Leeuw and Simos, 2017b).

In urban health, either practice or research have developed and tested approaches to assess each of those challenges within a sector or a limited number of spatial planning sectors, but still lack a standardized method to gather them. In fact, in urban health there is no agreement yet on a conceptual structure that simply lists those challenges. For example, the SDGs fixed 17 strategic objectives for sustainable development which includes urban health challenges as well as other governance's objectives. Primarily, the advantage of such a broad framework that encompasses all relevant challenges, is that none is omitted a priori. Also, among the founding principles used for SDGs creation, UN aimed to create objectives which are oriented to action, limited in number and universal (UN and World Economic Forum, 2016; UN, 2015). As well as broad topics, such as human development, urban health could also be compartmentalised into categories that collect this multiple dimension of factors and impact sources (Shannon, 1990). In Healthy urban planning (HUP) those categories have been named in research as urban health challenges (Vardoulakis et al., 2016) or issues (Grant, 2015; LHUDU, 2017; Shannon, 1990). While studying the collection of schemas, frameworks, and models that address urban health within each sector is not realistic and would require additional research, the number of frameworks that collects the broad range of challenges of urban health is limited.

In the first section of this chapter, we develop a conceptual framework which collects a broad range of urban health issues for a generic case study so that it optimizes the representation of both health and BE data. The generation of urban health issues follows an iterative process which identifies the links between BE and health, and subsequently groups them to represent those issues according to multiple criteria. We adopted a semi-systematic review of scientific literature to identify connections between BE characteristics and health conditions. Then the links between BE environment and Health conditions were gathered by K-means clustering and by criteria constrain; and in the end, the resulting groups were validated by experts and by narrative review.

2.1.1 Review of urban health frameworks

Two types of urban health framework were identified in the literature: conceptul framework and operational frameworks. Conceptual urban health frameworks were conceived to describe the interactions between its composing sectors, or between multiple determinants. For example, the schemas of Northridge et al. or Nieuwenhuijsen et al. are conceived to outline the connections between the BE and health displaying intermediate levels that shape health, such as mechanisms that explains how BE shape health, i.e. behaviour and exposures (Nieuwenhuijsen, 2016; Northridge and Sclar, 2003). Similarly, Rydin et al. displayed the connection between urban environment and health outcomes, summarised by four core groups, chronic diseases, mental health, injury and violence and infectious diseases (Rydin, Bleahu, Davies, Dávila, Friel, De Grandis, Groce, Hallal, Hamilton, Howden-Chapman, Lai, CJ Lim, et al., 2012). The health map, or the settlement health map of Barton and Grant is probably the most cited and widely used of urban health framework. The health map displays how individuals and their health are incorporated within multiple ecosystems showing the indirect interconnection between determinants (Barton and Grant, 2006). Galea et al. depicted urban Health by using a framework where a hierarchic structure of governance manages different BE levels to shape health determinants (Galea and Vlahov, 2005). The review of Bird et al. on healthy planning principles gathers studies in four groups, neighbourhood design, housing, food environment, natural and sustainable environment and transport (Bird et al., 2018). Kent and Thompson identified three domains that challenges urban planning for health and wellbeing, obesity, physical activity and social isolation (Kent and Thompson, 2014). Grant elicited eight important issues for HUP: climate change and public health emergencies, exposure to noise and pollution, healthy urban planning, healthy transport, healthy urban design, housing and regeneration, safety and security, creativity and liveability (Grant, 2015).

Otherwise, operational urban health framework has been realized in order to be applied directly on planning practice and address a broad range of issues. For example, Place Standard structured a strategic tool to address urban Health in 14 classes rearranging the content concerning urban planning within the SDGs (NHS, 2019). The London Healthy Urban Development Unit (HUDU) of the NHS, created a checklist for healthy urban planning (LHUDU, 2017). The HUDU checklist is based a framework which groups 24 planning issues into four general themes, namely healthy housing, active travel, healthy environment and vibrant neighbours. The checklist also allows users to qualitatively verify if each urban health issue is relevant by key questions, and link it with policies, from strategic plans to design standards. Similarly, the Centre of Population Health of NSW created the Healthy Built Environment Checklist to integrate health in policies plans and proposals (NSW, 2020). The NSW checklist lists eleven topics, provide key questions to assess the BE and provides supporting evidence as well as example of practice. The NSW also suggests supporting the use of the checklist with data and evidence. The Active Design Guidelines provide guidance to healthy planning, but specifically target physical health while including other challenges of urban health. The Active Design Guidelines provide a checklist for planners which address multiple topics mainly split in urban design (outdoor public space) and indoor design (for indoor spaces) (Centre for active design, 2010). Recently the WHO published a sourcebook to integrate health in planning, which adopts an entry point chosen between setting, outcome, principle or sector to develop an approach of urban health intervention (WHO, 2020). Despite not providing a fixed structure of challenges of urban health, the WHO source provides examples as well as tool of assessment for many urban health challenges, allowing practitioners to understand quantitatively the healthiness of the BE. Supporting reports and handbooks for the procedure of Health Impact Assessment of WHO provides strategies, principles, guidance and examples; but suggests to employ literature review or experts consultation in order to elicit subjects of assessment (PAHO and WHO, 2013; WHO Europe, 2005). Also other frameworks, such as the eDPSEEA are design to strategically support HUP, rather than provide a list of objectives or subjects (Reis et al., 2015).

The choice of a list of urban health challenges could be oriented different principles, so that it can be representative of most of the urban health challenges and is designed for the use on real cases. Therefore, a framework of urban health could gather different challenges from both developing and developed countries, also belonging to different climates (UN, 2020; UN and World Economic Forum, 2016; WHO, 2020). The elicitation can be supported by literature review as well as experts interviews such as in the case of the HUDU checklist (LHUDU, 2017).Then the urban challenges should facilitate action for healthier planning, thus being designed to be supported by measures, and policies (LHUDU, 2017; NSW, 2020). Action can be supported by integration of data in each phase of planning (Grant, 2015; Sallis et al., 2016), a role which can be played indicators (Rothenberg et al., 2015; UN, 2020; WHO et al., 2014). Ideally, urban challenges could be supported by multiple tools such as the one provided in the sourcebook of WHO, i.e. AirQ for air pollution (WHO, 2020). Moreover, the creation of an urban health framework which is prone to e use with real data; should reduce the overlap between its composing parts. In fact, the arbitrary choice of the urban health challenges could cause different topics or disciplines addressing twice the same issue. For example, in the checklist of NSW, physical activity is addressed directly as an intermediate determinant of health in the second thematic, and it is included again in the seventh thematic about open spaces (NSW, 2020).

2.1.2 Framework development

We developed a framework for urban health in this research that focuses on the relationship between BE and population health, rather than on specific health problems or planning sectors. In the fields of urban health, those relationships are not defined and are differently named, such as challenges, opportunities, problems and issues (Galea et al., 2007; Urban Health Collaborative, 2020; WHO, 2010). WHO mainly adopted "challenges" to address macro-area of urban health, therefore by using a positivistic interpretation of urban health, so that problems correspond to potential solutions? Otherwise, the term "issue" has been widely used (Boslaugh et al., 2008; Grant, 2015; LHUDU, 2017), and we employ it in this work.

In this research, we used the term "Urban Health Issues" (UHI) to refer to a category of features of the built environment that potentially contribute to a set of linked health outcomes. The choice of UHI is equal to the wording of Urban Health Indicators provided by WHO to represent the indicator resulting from the amalgamation of multiple indicators of urban health (WHO et al., 2014). The concept of UHIs can correspond to an urban health indicator or gather a set of indicators. In Chapter 3 BE characteristics of the study area are grouped per each UHI to generate indicators that correspond to UHIs.

The conceptual framework used in the theoretical representation of urban health, such as the one of Northridge and Sclar, or the one of Nieuwenhuijsen et al. (Nieuwenhuijsen, 2016; Northridge and Sclar, 2003), displayed how multiple pathways relate BE and health conditions. Those streams can be described by multiple levels of intermediate determinants which relate places with people. As shown in the health map of Barton and Grant, variables mediating the link between BE and health conditions may be located closer to people or to physical features of the environment (Barton and Grant, 2006). Both intermediate determinants, as well as BE characteristics and health outcomes are source of information capable to input HUP (WHO, 2020). In the previous conceptual map (Figure 1), the field of research of for potential UHI overlap with both characteristics of the BE and Health conditions, including intermediate determinants of health (Figure 6). The global ecosystem does influence the BE and health conditions, but spatial planning of a single city, can only mitigate the effects of the global ecosystem, i.e., climate change, rather than being able to control it.

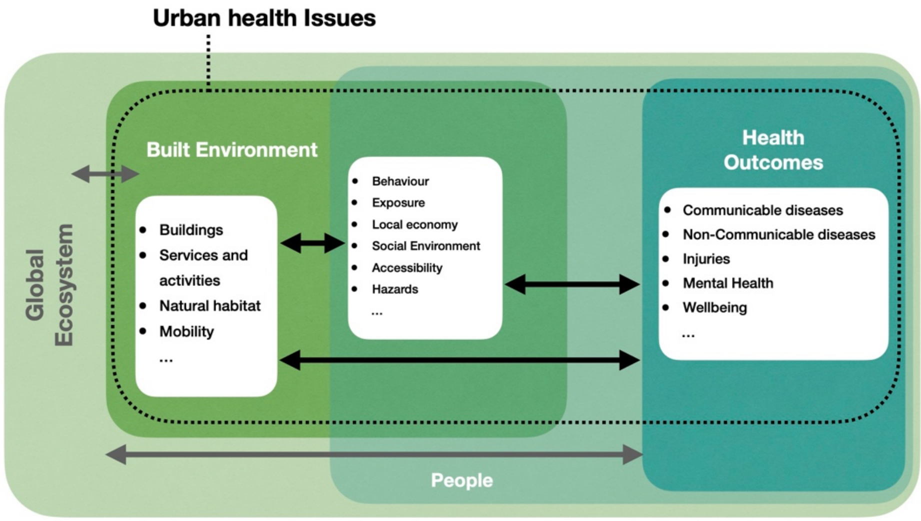

Figure 6: Conceptual map based on the health map of Barton and Grant; and the Urban health Framework of Galea and Vlahov (Barton and Grant, 2006; Galea and Vlahov, 2005).

2.2 Methods

Three steps were adopted to develop the UHIs: the identification of linked BE characteristics and health conditions from the literature, their grouping, and the groups validation. Depending on the validation of the generated groups, the process was iterated. We used both semi-systematic and statistical methods identify an optimal structure of UHIs according to four criteria:

I. The reduction the overlap between BE characteristics and health outcomes,
II. The selection of relevant UHI for a generic city,
III. The subdivision of UHIs so that they address public or private spaces,
IV. The separation of UHIs so that they are predominantly related to passive mechanisms (such as accidental injuries or exposures) or to behavioural mechanisms.

The first two criteria adhere to the WHO's sourcebook for urban health indicators, which recommends indicator identification based on scientific evidence and indicators that minimise duplication of information while ensuring component independence (WHO et al., 2014). The third and fourth criteria are derived from the example of the London HUDU checklist (LHUDU, 2017), which was developed to facilitate the translation of theory into practise by integrating different levels of HUP implementation (Paragraph 1.2.2).

The generation of UHIs follows the approach displayed in the Figure 7 so that the four criteria are addressed. Firstly, BE features and health conditions are tabulated to display their mutual relationship. Secondly, BE features are grouped into an optimal minimum number of clusters so that three criteria (I, II, IV) are addressed. In the end, the robustness of clusters produced in this way is evaluated by experts interviews and by a semi-systematic review to address the second criterium (II). This step validated the developed groups, either iterated the approach of UHIs' generation.

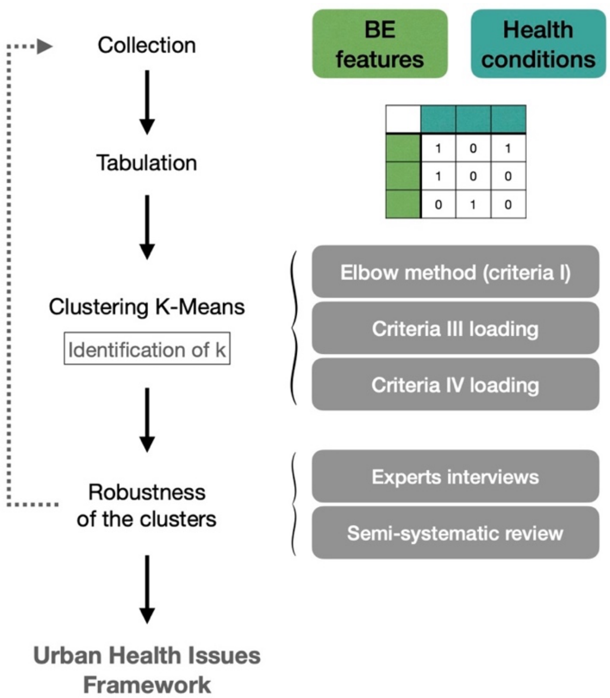

Figure 7: Framework creation workflow: from elicitation of attributes to the generation of Urban Health Issues.

Clusters' generation

Initially we collected the extremes of the streams, the characteristics of the BE and the health outcomes which show mutual relationship in scientific literature. In this research we refer to each measure, metric or characteristic of the BE with the generic term BE features. Literature research allowed a narrative synthesis of connections between BE features and health conditions based on the cross search of keyword identified from multiple sources (Popay et al., 2006). The sources employed in this phase were the existing examples of broad urban health frameworks; reports produced by international agencies (UN; WHO; UNHABITAT, GRI), or by public health agencies of UK, Switzerland, US and EU; and systematic reviews of urban health topics. The identified measures of BE features and health condition were tabulated, so that a resulting binary matrix displayed the links between BE features and health conditions (Nebot and Berlanga, 2016). For example, a measures of ambient air pollution, such as particular matter concentration, would display a null link with accidental injuries, while displaying a link with lung cancer and stroke. The link between BE and health was considered in case of scientific literature that identified either causation or association.

Afterwards the binary matrix was used to form groups of BE features by semi-supervised approach, thus by employing statistical methods and criteria constrains (Nebot and Berlanga, 2016; Qin et al., 2019). The first criterium (I) aim to reduce the overlap between groups using a statistical method on the binary matrix previously created. Therefore groups collect elements by similarity by employing K-Means clustering, so that groups ar composed of issues with similar impacts on health and similar BE features (Nebot and Berlanga, 2016; Tomaselli et al., 2021). Statistical methods, such as K-means clustering, can be used to generate frameworks, and coupled with criteria into semi-structured statistical approaches (Fordellone and Vichi, 2020; Nebot and Berlanga, 2016; Qin et al., 2019; Tomaselli et al., 2021). The intention was to group similar BE characteristics, so that the number of clusters, is reduced as much as possible while the error introduced is acceptable. To calculate the error introduced by dimensionality reduction in k clusters, we used the Elbow method, a heuristic to minimise k and the sum of squared error (SSE) produced by clustering (Thorndike, 1953). In parallel, we controlled the partition so that cluster respected the third (III) and fourth (IV) criterium. The third criterium allows the separation of BE features into sectors that rely on different spatial planning regulation mechanisms, a direct control of the governance of public spaces, and indirect control on private spaces by regulations (Carmichael et al., 2012). The fourth criterium better addresses the subdivision into different health burdens of urban health that are more or less related with behaviour or exposure and injuries, so that groups address different phases of health integration in planning (Rydin, Bleahu, Davies, Dávila, Friel, De Grandis, Groce, Hallal, Hamilton, Howden-Chapman, Lai, CJ Lim, et al., 2012). Also, the fourth criterium tends to split respectively BE features related with urban advantage, such as the availability of services provided by urban environments, e.g. public transports; and with urban penalty, such as the adverse side effect of urban environments, e.g. extreme ambient temperatures (Choi et al., 2015; Vlahov et al., 2005). Following these two criteria, two additional matrices were generated to outline whether the link between BE features, and health conditions respected the third and fourth criteria. However, the criterium do not perfectly identify complementary urban heath issues. For example, air pollution can increase the risk of respiratory diseases and discourage outdoor physical activity (Tainio et al., 2021). Hence, we considered only the direct and leading relation for each link between BE features and health conditions.

To evaluate how criteria were respected by clustering, we calculated the mean percentage of each BE features loading correctly to a cluster according both third and fourth criteria. Following the K-means clustering in k clusters, BE features loaded differently to a criterium *c.* We measured loading as follow:

$$\mu_{i,c} = \begin{cases} \bar{x}_{i,c}\ , & \bar{x}_{i,c} > 0.5 \\ 1 - \bar{x}_{i,c}\ , & \bar{x}_{i,c} \leq 0.5 \end{cases} \qquad load_{k,c} = \frac{\sum_{i=1}^{k} \mu_{i,c}}{k} \qquad i = 1, .., k$$

where $\bar{x}_{i,c}$ is the mean value of a BE feature assigned to a cluster *i,* and $\text{load}_{k,c}$ is the mean loading of a criteria c of the partition in k cluster. For example, a cluster that evenly grouped BE features of both private and public spaces, will display a mean $\mu_{i,c}$ equal to 0; while a cluster that is characterised by only public or private places, will display a mean $\mu_{i,c}$ equal to 1. Therefore, for the whole partition in k clusters, a loading percentage $load_{k,c}$ of 50% means BE features are homogeneously split between clusters according to one criterium, while 100% represents a subdivision that load perfectly according to a criterium. The optimal number of clusters k was identified so that:

- k is larger or equal of the number of clusters which shows a sudden change in the decay of SSE.
- k is the smallest number of clusters that produce a 100% loading for the third and fourth criteria.

Narrative review of clusters

Afterwards, we qualitatively evaluated the robustness of the resulting clusters to address the second criterium (II). By addressing three questions, we examined whether clustering enabled the identification of relevant UHIs through the elicitation of BE measures and health conditions: "Is any Urban Health Issue missing?" "Are the cluster addressing relevant Urban Health Issues?" "Do cluster identify case-specific Urban health Issues rather than for a generic case study?". To answer these questions, we used two approaches. Firstly, ten experts in the field of urban health evaluated the UHI identified by clustering and criteria by in person interviews. Secondly, a semi-systematic literature evaluated if the identified UHIs were relevant. The review of the clusters created by the semi-structured clustering aims to confirm that the BE features, and health conditions were chosen based on sound evidence; and that no aspects were omitted from the selection process. In case of missing issue, the whole process was reiterated. Instead, in case of irrelevant clusters, we proceeded with the withdrawal of the respective BE features and iterated the cluster generation.

Experts' viewpoints were evaluated using open-ended interview questions in person, which resulted in the first iteration of UHIs generation. Experts in the field of urban health were recruited during the International Conference of Urban Health (2018). Additional information is provided in the Chapter 3, where the study of experts' viewpoint is further developed. The experts' evaluation followed a semi-systematic review (Flemming et al., 2018; Higgins, 2019). We followed the guidance of Popay et al. for semi-systematic reviews, employing clustering, and after a thematic analysis (Popay et al., 2006). The approach that was employed, can be considered semi-structured since items retrieved in the review were not representative of the literature's totality in urban health. Fragmentation of sources deals with the transdisciplinary nature of urban health and source type, such as websites, reports, protocols, and regulations (Pineo, Glonti, et al., 2020). Indeed, semi-systematic reviewing approaches are often adopted in fields widely conceptualised among multiple disciplines (Snyder, 2019). The topic's broadness limits a sound, systematic approaches, which simply cannot rely on the systematic collection of the totality of sources, such as in the case of potential, relevant research identification or theoretical models (Snyder, 2019). Urban health is a topic that merges various disciplines belonging to macro disciplines of health and spatial planning. Hence, narrative, and integrative reviews are frequent in urban health publication that addresses the wide range of disciplines such as the urban health conceptual models described in the Paragraph 2.1.1. For example, in reviewing urban health indicators application, Pineo et al. adopted a semi-systematic review (Pineo, Glonti, et al., 2020).

As a result of the dispersion of sources in various formats and sectors, the evaluation process was limited to two source types and limited in the number of retrieved items (Gusenbauer and Haddaway, 2020; Higgins et al., 2021; Snyder, 2019). Items published between 2008 and 2018 were selected when belonging to one of the following source types:

- Reports: website reports and official documents produced by international agencies (UN; WHO; UNHABITAT, GRI), or by public health agencies of UK, Switzerland, US and EU.
- Systematic reviews: systematic review articles were extracted from Scopus, PubMed, Medline, and Google Scholar.

All items retrieved were downloaded into reference management software (Zotero) and analysed by keywords related to BE features and health conditions (Python package PyPDF2). Titles, abstracts, and tables of contents were scanned by one reviewer (AS) to understand whether a publication reported a relation between BE features and Health conditions. The semi-systematic review was constrained by the fact that the research process came to a halt when at least four and ten items in the reports and systematic reviews groups, respectively, were identified. Also, systematic reviews research stopped when one hundred results were retrieved. A UHIs was classed as relevant when at least or four reports or at least ten systematic reviews reported a significant association between BE and health. We set a search threshold because this work does not aim to understand which UHIs are more relevant in literature. Cluster classed as weak and irrelevant were either removed, either reassigned to another cluster to generate a UHI.

2.3 Results

The semi-structured approach previously described was used to identify UHI, so that they represented groups of links between BE features and health conditions according to four criteria. This approach was iterated five times, and therefore findings are presented for the final iteration.

The elicitation of BE features, and health conditions led in the construction of a binary matrix of liked data illustrating their relationship. For the last iteration, the matrix collected 271 BE features, and 169 health conditions. We acknowledge that elicitation of the latter is not comprehensive of the totality of measures of the BE and health that can be employed to describe the totality of their link. In fact, BE features and health conditions could be characterised by several characteristics that has not been measured or listed yet. The elicitation of BE features, and health condition took advantage of an initial merging of items that presented similar links. For example, *NO* and NO_2 concentrations were merged into *NOx* among BE features; or *ischemic stroke* and *haemorrhagic stroke* were merged into *stroke* among health conditions. BE measures revealed an average of 2.3 (IQR: 1.2, 2.8) connections to health conditions. Also, health impacts and BE features related to work occupation were not considered, due to its independence from spatial planning.

BE features were grouped into *k* clusters where *k* ranged from 1 to 30. The upper limit of 30 was chosen as the maximum desirable number of clusters that could summarise the relationship between BE and health in UHIs. The SSE and the $load_{k,c}$ were calculated per each clustering in k groups (Figure 8). The Elbow method did not identify a sudden slope change but rather shows a gradual decrease in SSE by increasing cluster number. Instead, the percentage loading of the third and fourth criteria is entirely successful at *k* equal to 20 (Figure 8). As a result, at the conclusion of this stage, we grouped the BE features into 20 clusters.

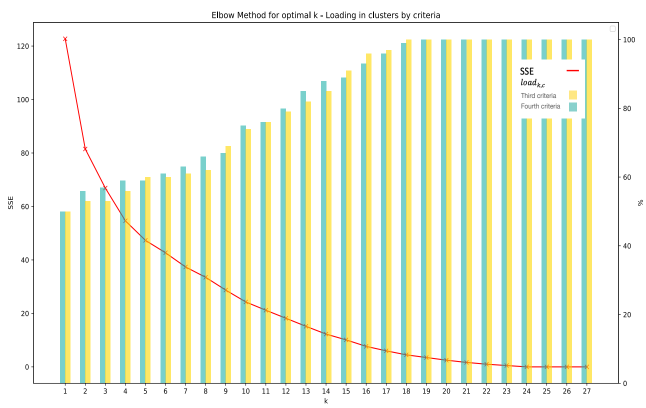

Figure 8: Sum of Squared Error (SSE) and criteria loadings of BE features in Health conditions by k-mean clustering in k clusters.

Experts' interviews mainly addressed the identification of missing UHIs in the first iteration of the generation of cluster and elicitation of BE features and health conditions. Experts' viewpoint allowed the creation of two additional UHI, by the integration of multiple additional BE features as input. Seven experts on ten reported a missing inclusion of climate change or natural environment hazards. Natural environment hazards and climate change issues were initially excluded since they mainly depend on the global environment at macro-scale. However experts pointed out that spatial planning, can tackle and contain those impacts and that the effects of climate change can differently impact distinct area of a city and produce inequities in HBEs (Fagliano and Roux, 2018). Four experts suggested the inclusion of the accessibility to healthcare services. Accessibility is also related with geographic accessibility and the physical distribution of those assets, playing as mediator between health conditions and healthcare (Brondeel et al., 2014; Kelly et al., 2016a). Also, experts identified missing BE features, namely radon exposure, electromagnetic pollution, radiation pollution, and unsafe design for accidental injuries. After the experts' interviews, the semi-systematic review determined if the identified UHI were considered relevant for BE spatial planning. The validation by the systematic review allowed the generation of 14 UHIs (Table 5). The characteristics of the BE features grouped in each cluster allowed the identification of a generic name for each UHIs.

We eliminated two clusters in this phase because they lacked supporting evidence: electromagnetic pollution and light pollution, and safety and criminality. Four clusters were integrated or included in other UHIs: radiation pollution cluster in Contaminated Land; Radon pollution in Household Air Pollution; and Overcrowding in Safe Design and Accessibility. Also, four clusters were merged into two: Safe water with Sanitation; and Dampness in indoor environments with Thermic comfort.

In the end, fourteen relevant UHI were then split into three domains, following the third and fourth criteria introduced to identify the clusters' optimal number. The domain of Outdoor Environment collects four UHIs that are predominantly related with exposure mechanisms, and two that are related with accidental injuries. The domain of Indoor Environment gathers housing indoor characteristics. The domain of Healthy Places collects UHIs associated with the use or experience of public services, with publics in terms of potential accessibility to those services. The last domain is significantly related with lifestyle, habits, and behaviour. The resulting structure of UHIs and UHI domains as outlined in Table 5. A full description of UHIs is provided in the Appendix. Additionally, each UHI was summarised by a single sentence employed in the survey in the third chapter (Paragraph 4.2).

The health conditions linked to BE features within UHIs were differently split across UHIs and the respective domains. In addition, we explored how domains of UHI gathered in macro-groups of health condition. Therefore, we grouped health impacts into four groups accordingly to Rydyn et al.: Communicable Diseases, Non-Communicable Diseases, Injuries and Wellbeing and Mental Health (Rydin et al., 2012). The rank of counts is used as the UHI domain's representation since the number of counts is biased by our arbitrary initial selection. The rank of loaded numbers of health conditions within each UHI domain is shown in Figure 9. Consequently, UHI domains addresses health impacts type differently: Outdoor environment addresses more non-Communicable diseases and injuries, Indoor environment address more Communicable Diseases and Healthy Lifestyle more Wellbeing and Mental Health. Also, the number of Healthy lifestyles UHIs dealing with Non-Communicable Diseases is slightly overpassed by Outdoor Environment. The conceptual framework of UHIs (Table 5) have been created also as guidance of broad diagnosis of the HBE. Notably, the framework can be a track to group measurements of the HBE, such as urban health indicators.

Domains	***UHI: Urban Health Issues***
Outdoor environment	**Air pollution**
	Noise pollution
	Hydro-geologic risk
	Extreme outdoor temperatures
	Contaminated land
	Road injuries
Indoor environment	**Thermo-hygrometric comfort**
	Safe design and accessibility
	Sanitation & Safe Water
	Household air pollution
Healthy places	**Healthcare (geographic) accessibility**
	Active mobility
	Community spaces
	Food environment

Table 5: Framework of Urban Health Issues (UHIs) and UHI's domains.

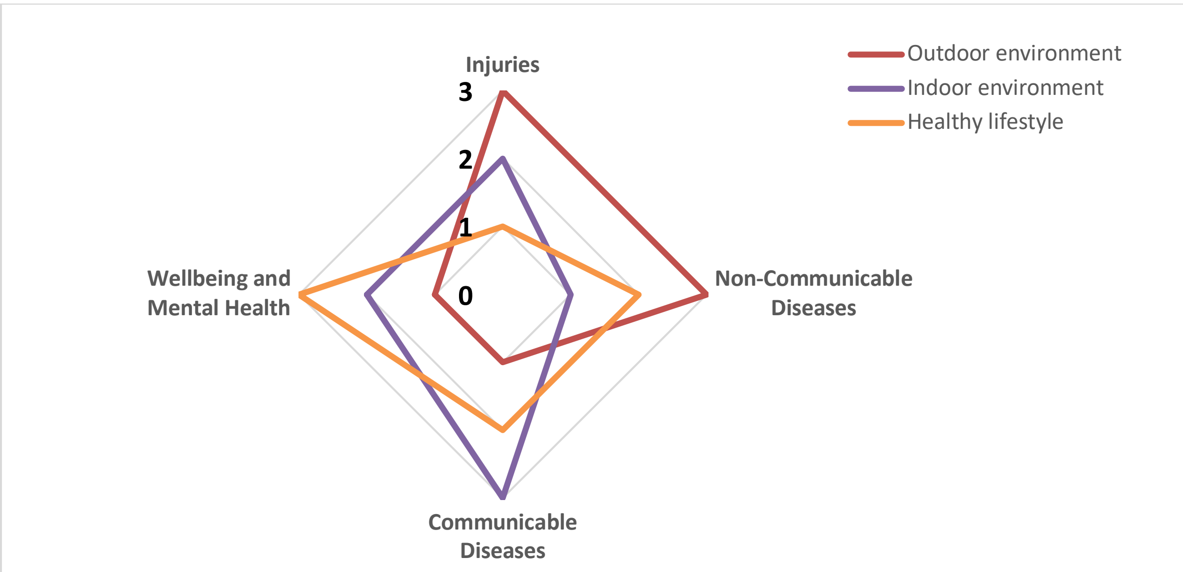

Figure 9: UHI's domains ranking in addressing four categories of health outcomes.

2.4 Discussion

The scientific literature has not produced yet a standard categorisation of the multiple challenges of urban health. The multidisciplinary nature of urban health is barrier itself to a systematic approach to identify a theoretical structure able to represent urban health (D'Alessandro, 2020; Glanz et al., 2016). In the first section of this chapter, a semi-structured approach was employed to identify urban health issues to develop conceptual framework of urban health, with the aim of identify all relevant connections between BE and health for a generic case study and provide guidance for the evaluation of HBEs.

Firstly, we identified connections between BE features and health conditions by content analysis of scientific literature. Secondly, BE features were grouped according to four criteria. An optimal number of clusters was chosen based on the loading of two criteria (III and IV). The error (SSE) did not hint an optimal number of clusters, but rather displayed a gradual decay by increasing number of clusters. Afterwards, the evaluation of the robustness of the clustering allowed the iteration of the process of generation of UHIs by removing minor urban health issues by identify the missing issues. Experts' viewpoint contributed to identification of missing elements in the first elicitation of BE features and health conditions, while the semi-systematic provided a qualitative pruning of the clusters. In the end fourteen UHIs were identified and grouped in three domains.

The creation of the conceptual framework of UHIs is affected by different limitations. Firstly, literature review was based on a semi-systematic approach, allowing a coarse screening of the many studies in the fields of urban health (Flemming et al., 2018; Popay et al., 2006). Secondly, since the framework is intended to identify general issues of urban health, it is far from exhaustive in representing the complexity of urban health (Batty, 2009; Gatzweiler et al., 2017; Rydin, Bleahu, Davies, Dávila, Friel, De Grandis, Groce, Hallal, Hamilton, Howden-Chapman, Lai, CJ Lim, et al., 2012). Additional criteria would increase the number of UHI, resulting in more precise groupings but also in the generation of an excessive number of UHIs that are unsuitable for this research. The supernumerary of UHIs could potentially impact the translation of the UHI in practice, by failing in providing a summary of urban health issues (Pineo, Glonti, et al., 2020; Sallis et al., 2016). However, the adoption of additional criteria to generate UHI is not excluded to generate sub-levels of UHIs similarly to SDGs' structure, which could be employed on case-specific application (UN, 2020). Therefore, the conceptual framework is suitable to be used at strategic level (Rocco and Plakhotnik, 2009), and it can be adapted depending on the case study. In the end, the overlap between urban health challenges cannot be completely avoided due to the multiple interactions between health conditions and BE (Franz W. Gatzweiler, ; Nieuwenhuijsen, 2016; Rydin, Bleahu, Davies, Dávila, Friel, De Grandis, Groce, Hallal, Hamilton, Howden-Chapman, Lai, CJ Lim, et al., 2012), but rather reduced by limiting the elicitation of BE and health conditions to the more direct connections. The necessity of reducing the overlap, affect also the use of urban health indicators, which in turn are based conceptual categorization of urban health challenges (Rothenberg et al., 2015).

The conceptual framework of UHI is coherent with the content reported by the existing frameworks of urban health since they were used to generate it. The novelty of the framework stands in providing a rearranged structure of existing contents for the study HBE data, and in gathering the content from multiple disciplines. Furthermore, only a small number of publication use statistical approaches for creating a conceptual framework for urban health were identified when this text was drafted.

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Chapter 3 Spatial analysis of the Healthy Built Environment in the canton of Geneva

Abstract : In this chapter, we conducted a spatial analysis of the healthy built environment in the canton of Geneva, Switzerland. The conceptual framework of urban health issues is employed as the guiding structure after adapting it to the case study. Initially we collected a broad range of geospatial data providing a spatial aggregation of datasets in small-scale spatial and taking into account accessibility. Afterward we employ two statistical methods to summarise the global spatial variation of the healthy built environment (principal componenent analysis), and and the local one (geographic weighted principal component analysis). The global approach enables the comparison of urban health indicators and the quantification of disparities in the distribution of a healthy built environment.Rather than that, the local approach enables comprehension of the heterogeneity of the research area's healthy built environment, as well as the limitations of the global approach in interpreting geographical data as independent. This chapter provides an overview of the canton of Geneva's healthy built environement, allowing for a better understanding of the priorities and areas to examine in order to improve the built environment's health.

3.1 Introduction

Spatial planning has the potential to shape multiple determinants of health related to the place where we live (WHO, 2020). The evidence of the relationship between health and the healthy Built Environment (HBE) is widely accepted and gathers a broad range of positive and negative impacts. However, data are not widely used in planning to integrate health across policies, programs and plans (Grant, 2015). Understanding the status of BE is the first step in driving healthier intervention in spatial planning (Sallis et al., 2016). The main goal of planning healthier cities cannot be accomplished, leaving apart equity (Organization and WHO Centre for Health Development (Kobe, 2010; Thomson et al., 2018). Tackle inequities in the healthy built environment (HBE) require understanding its spatial variation (Elsey et al., 2016). Many urban health issues displayed how differences can be identified within cities, not only between cities or countries (Chaix et al., 2009; Matthews and Yang, 2013; Rothenberg et al., 2015). Knowing spatial inequities in the HBE can optimise planning intervention where it is needed more, making sure that the most deprived areas and populations are not excluded a priori or hidden by averaging measurements in large geographic areas (Verma et al., 2017). Equity can also be considered regarding the lost opportunity of considering all relevant potential Urban Health Issues in studying the HBE, and not only in term of population. Strategic tools, such as the healthy Built Environment Checklist, gather multiple challenges of urban health intending to avoid the stratification of multiple acceptable impacts across multiple challenges (LHUDU, 2017; Rydin, Bleahu, Davies, Dávila, Friel, De Grandis, Groce, Hallal, Hamilton, Howden-Chapman, Lai, CJ Lim, et al., 2012).

Firstly, geospatial data quality is critical for comprehending the spatial variation of the BE. In particular, the scale at which data are aggregated carry larger biases when larger geographic scales (Openshaw, S, 1984; Wong, 2009). This issue is frequent because studies are mainly based on available geospatial data at administrative units, rather than at small scale or on disaggregated data (Elsey et al., 2016; Rothenberg et al., 2015). Secondly, studies that investigate the spatial distribution of BE in urban health are often limited to a single health issue and lack multi-attribute approaches. However, approaches that include a broad range of BE attributes demand methods to summarise the consequent complex information. This duty can be attained by merging data into synthetic indicators, which can be either constructed or statistical (Rothenberg et al., 2015). While the composite indicators are widely used in the context of urban health(Rothenberg et al., 2015), methods employed usually treats independently observation regardless their spatial context (Greco et al., 2019; Harris et al., 2011; Wei et al., 2016). As opposed to global approaches to summarise the information of multiple attributes and reduce dimensionality, local approaches, such as geographic weighted methods, can also take into account effects such as spatial heterogeneity and spatial autocorrelation (Harris et al., 2011, 2015). While the latter have been shown to more accurately characterize the source data than aspatial techniques, they do not give a means of comparing all items inside the study area (Harris et al., 2015; Wei et al., 2016). The joint use of global and local approaches have been tested to provide a complete understanding of an observed phenomena, such as in few examples of environmental health determinants (Chi et al., 2013; Saib et al., 2015; Wei et al., 2016). A precise approach able to understand where the BE potentially shape health, is the first and essential step to drive healthier intervention, specifically through spatial planning (Corburn, 2015; Friel, Vlahov, et al., 2011; Sallis et al., 2016).

This chapter aims to understand the spatial distribution of HBEs in the canton of Geneva. This work uses the conceptual framework of Urban Health Issues (UHIs) created in the first section as a track to represent the characteristics of the HBE. Then in brief, as synthetised in Figure 10, we deal with the spatial aggregation of data and after we adopt a global and local approach to understand the spatial distribution of the HBE and the inequity within the study area. Firstly, we describe the data sources according to the conceptual framework adopted for the case study. Secondly, we address the spatial aggregation of geographic data to represent the density of HBEs at a fine spatial scale and address the concept of accessibility. In the end, we generate indicators for each UHIs employing global and local statistical approaches (PCA and GWPCA), also allowing the amalgamation of indicators. The resulting indicators are analysed to understand the spatial variation, their significance in representing geospatial data, the inequalities, and the extreme values.

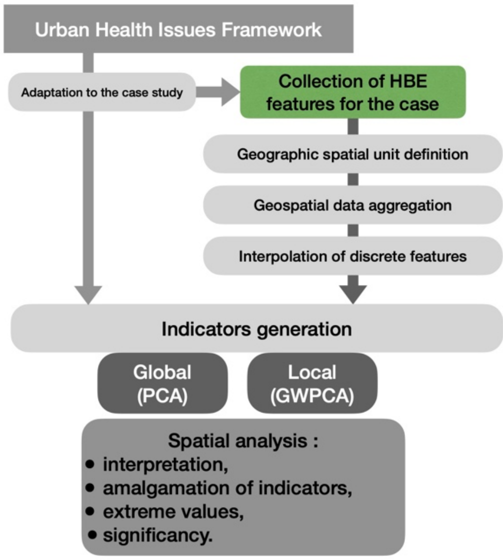


Figure 10: Workflow of spatial analysis of the HBE.

3.1.1 Health indicators

The multitude of characteristics of the BE, which are health determinants, are frequently summarised by indicators (Greco et al., 2019; Rothenberg et al., 2015). Indicators of urban health are widely used in both urban health research and Healthy Urban Planning (HUP) practice (Rothenberg et al., 2015; WHO et al., 2014). A single metric is not sufficient to serve the many purposes of spatial planning and represent the complexity of the interactions between health and BE (WHO et al., 2014). Instead, when are transparent in combining the information the HBE, indicators are more likely to summarise information efficiently and be representative (Corburn and Cohen, 2012; Pineo, Glonti, et al., 2020; WHO et al., 2014). Indicators are synthetic constructs based on various techniques, ranging from simple linear combinations to more complex mathematical transformations and combinations (Rothenberg et al., 2015; WHO et al., 2014). By reviewing urban health indicators, Lawrence et al. and Rothenberg et al. both call for the employment of indicators at more minor geospatial scales (Lawrence, 2008; Rothenberg et al., 2015). The study of Costa et al., which employs the EURO-HEALTHY Population Health Index to study inequities in health determinants and outcomes, identified how inequities are present in multiple contexts of Europe within metropolitan areas regardless of differences between metropolitan areas (Costa et al., 2019).

While there is broad agreement on the importance of urban health indicators, there is a lack of standardised indicators (Pineo, Glonti, et al., 2020; Rothenberg et al., 2015). Indeed, the proliferation of various indicators is likely to negatively impact the systematic integration of health in spatial planning (Pineo, Glonti, et al., 2020; Rothenberg et al., 2015). Also, the Kobe centre of WHO developed a handbook for urban health index creation (WHO et al., 2014). The handbook provides operational guidance for eliciting health determinants, spatial aggregation and standardisation of indicators, the combination of data, geographic visualisation and the calculation of disparities (WHO et al., 2014).

3.1.2 Spatial aggregation issues

The discipline of urban health is entangled with spatial analysis in order to put "people into a place" so that health and HBE could be linked (Entwisle, 2007). The first step consists that HBEs and geospatial health data must be represented in space under various assumptions to aggregate geospatial data. Two problems affect the aggregation of geospatial in urban health: the Modifiable Areal Unit Problem and the Uncertain Geographic Context Problem, which is related to the uncertainty introduced by the human component.

According to (Wong, 2009), the "Modifiable Areal Unit Problem (MAUP) refers to the latter type of aggregation based upon space, and many data in geographical research are provided in spatially aggregated formats or sometimes also known as ecological data".The MAUP is typical of spatial analysis, and it is composed of two aspects: the scale effect and the zoning effect (Openshaw, S, 1984). The scale effect introduces uncertainty in spatial representations when the scale of the spatial unit (SU) is not coherent with the spatial arrangement of the observed phenomena (Manley, 2019). On the one hand, SU smaller than the observed phenomena scale does not allow the comparison of data within a SU. On the other hand, SU that is too large fails in representing local variation (Kirby and Taylor, 1976). However, smaller SUs can be aggregated in a second moment depending on the phenomena (Wei et al., 2016) or allow the use of local approaches of spatial analysis such as moving windows, convolution, contiguity, interpolation or spatially weighted methods (Anselin, 1995; Huang et al., 2018; Lloyd, 2010b; Wei et al., 2016). Instead, the uncertainty introduced by the aggregation at large spatial scales cannot be addressed, despite being able to deliver stronger correlation (Fotheringham and Wong, 1991). The zonation effect introduces uncertainty by the way the study area is subdivided (Manley, 2019). The correlation between data sources is highly variable depending on the arbitrary choice of how the study area is subdivided (Openshaw, S, 1984), thus when SUs are irregular in shape and size. Studies on place and health are widely based for convenience on aggregated data on irregular geopolitical units, such as administrative boundaries, postal codes or census districts (Elsey et al., 2016; Gomez et al., 2015; Kanaroglou and Delmelle, 2016; Rothenberg et al., 2015; Schulz et al., 2018; Yang et al., 2013b). While the zonation effect is reduced with regular SUs, the latter requires input geospatial data characterised at more minor spatial scales or disaggregated data (Manley, 2019; Wong, 2009). The primary impediment to urban health research in dealing with the MAUP is the lack of disaggregated health data, determined mainly by individual data privacy protection (Andrew Swift et al., 2014).

The Uncertain Geographic Context Problem (UGCP) is a significant issue related to the uncertainty introduced by the human component. The UGCP, firstly theorised by Kwan, refers to "the problem that findings of the effects of area-based contextual variables on individual behaviours or outcomes may be affected by how contextual units (e.g., neighbourhoods) are geographically delineated and the extent to which these areal units deviate from the true geographic context" (Kwan, 2012). The problem can include the concept of the ecological fallacy of linking place with the individual (and therefore their health) (Dorling et al., 2009; Entwisle, 2007), and it encompasses the concept of spatial polygamy (Matthews and Yang, 2013). In urban health, the uncertainty introduced by the UGCP is related to heterogeneity among individuals depending on multiple factors, i.e. activity space (Kwan, 2012). The inclusion of activity space by the study of accessibility is often considered in defining the BE that has potential in shaping health determinants (Chaix et al., 2009; Martino et al., 2021; Sun et al., 2018; Wang et al., 2019). The inclusion of accessibility in studying BE about individuals is done mainly by employing two approaches: by building SUs which includes BE features that are equally accessible, thus as a simple regional ratio; either by modelling the distance decay (Jr and Delamater, 2019; Pun-Cheng, 2016; Stępniak and Jacobs-Crisioni, 2017). The first approach is often used across disciplines of urban health, while the second has been confined to the study of service accessibility, particularly in healthcare services geographic potential accessibility (Jr and Delamater, 2019; Kelly et al., 2016b). Furthermore, the inclusion of accessibility by distance decay approaches can be implemented regardless of the knowledge of points origin and destination by modelling the density of HBE feature and by using interpolation techniques (Shi et al., 2019; Yu and Ai, 2014).

In general, the aggregation of data in small-size SUs aims to reduce the error but create more sparse data so that information is usually sampled successively at larger geographic scales (Chen et al., 2019; Gotway and Young, 2002; Hampton et al., 2011; Wong, 2009). Otherwise, sparse geospatial data can be interpolated to represent the spatial variation of certain phenomena, such as air pollution (Shi et al., 2019; Stein, 2012). Spatial interpolation methods (SIMs) includes a broad range of methods, either geostatistical, i.e. kriging methods, either non-geostatistical, i.e. nearest neighbour and inverse distance weighting (Li et al., 2011; LI Xin and LI Xin, 2000; Scheuerer et al., 2013; Stein, 2012). Interpolation is often used to provide a continuous representation of environmental variables obtained with spatial sampling (Li et al., 2011) but can also be applied to represent accessibility to places, i.e. public services (Higgs, 2004; Langford et al., 2008; Langford and Higgs, 2006; Schröter et al., 2015; Sun et al., 2021). Indeed, potential accessibility to services, i.e. healthcare services, has often been modelled by employing the same mathematical equations (i.e. Quartic, Gaussian) integrated into geostatistical interpolation methods to account for the distance decay in trips density (Jr and Delamater, 2019; Kelly et al., 2016b; Luo and Qi, 2009). In addition, spatial interpolation of the density of a BE feature addresses both its accessibility and frequency in the geographic space, compared to a nearest-neighbour analysis (Shi et al., 2019; Yu and Ai, 2014). The complete explanation of the uncertainty of UGCP would require a complete characterisation at the individual level, which is adopted in exposome studies (DeBord et al., 2016).

In the conjoint study of the BE and individual characteristics, i.e. health, many approaches have been tested to address the uncertainty caused by the aggregation of geospatial data. Sun et al. studied the application of both regular and irregular SUs testing the aggregation of blocks to measure the liveability of urban environments in dense urban areas of Hong Kong to predict socioeconomic status (Sun et al., 2018). In the latter, estimations by both regular circular buffers and constructed buffers based on mobile networks and services were inconsistent between small and large scales and inconsistent in predicting socioeconomic status in terms of rank correlation (spearman) (Sun et al., 2018). Martino et al. used mobility network radii to predicts socioeconomic status by BE indicators finding those larger radii (ranging from 400m to 4.8 km) were better predictors of socioeconomic status, despite providing a smoothed representation of diversity within the study area (Martino et al., 2021). Wei et al. studied the association of health outcomes with public service inequality in Quito (Ecuador) by using census block or by aggregating census block with tree removal (SKATER) and self-organising map (SOM) algorithms from social, environmental and health-related indicators (Wei et al., 2016). They reported better association by using the clusters obtained by the aggregation of census block compared to the disaggregated geospatial data. Indeed, neighbourhoods have been used as the activity space and spatial unit, despite the inconsistency in the perception of its spatial extension (Chaix et al., 2009; Matthews and Yang, 2013; Saarloos et al., 2009). Otherwise, the SU can be defined by the perceived neighbourhood by residents (Coulton et al., 2013; Diez Roux, 2007) rather than objectively experienced neighbourhood (Chaix et al., 2009). Meanwhile, neighbourhoods, districts or blocks do not exist in isolation since attributes describing the BE do not shift immediately and discreetly but display different gradients of variation at different geographic scales (Chaix et al., 2009; Martin and Michael, 2004). In general, small-scale and regular SUs are suitable because they are suitable for exploring the aggregation at larger scales, and they better outline spatial gradients of BE variation.

3.1.3 Composite indicators

Due to a lack of standard assessment approaches and the fact that urban health is a complex problem, it lends itself to the development of composite or synthetic indicators (Becker et al., 2017; Bluszcz, 2016; Nardo et al., 2005). According to Arechavala and Trapero, a synthetic indicator is “a numerical measure reflecting the situation of an objective state of affairs made up by many components meant to be integrated into a single comprehensive value” (Arechavala and Trapero, 2014). The use of composite indicators has the principle advantage of providing a synthesis of a multidimensional problem, thus being prone to be employed at different social levels, therefore at expert, political and general social levels (Bluszcz, 2016; Nardo et al., 2005). Multiple advantages and weaknesses are identified in the sourcebook for composite indicators building, created by the Joint Research Centre of the European Commission (Nardo et al., 2005). The synthesised content of composite indicators allows a straightforward interpretation, facilitating ranking, the alternative comparison, the study of trends and signs of progress, the management of complex issues and the communication with multiple audiences promoting accountability. However, composite indicators are sensitive to errors in their construction, require transparency to avoid instrumental uses, may fail in the representation of the problem due to local heterogeneities, which weak the correctness of the indicator (Bluszcz, 2016; Nardo et al., 2005). Composite indicators are more likely to be helpful at the strategic or explorative levels of planning instead of requiring the understanding of the role of its components at the following stages (Bluszcz, 2016; Nardo et al., 2005). The composition of indicators can be coupled with weightings provided by stakeholders, for example allowing the trade-off at the political level or integrating the participation of citizens (Greco et al., 2019; Nardo et al., 2005). For a better insight on composite indicators, the methodological review of Greco et al. discusses the issues of weighting, aggregation and robustness of composite indicators (Greco et al., 2019).

In particular, the composition of indicators can be based on weighting driven by stakeholders using methods such as budget allocation process, hierarchic analytic process or conjoint analysis, or being data-driven, by equal weighting, i.e. geometric mean, or by methods such as correlation analysis, multiple linear regression, principal component analysis and factor analysis, or data envelopment analysis (Greco et al., 2019). The data-driven approach offers an "objective" interpretation, a desirable quality for preventing manipulation or instrumentalization, opposed to the "subjective" interpretation generated by stakeholders (Greco et al., 2019). General criticism of data-driven approaches argues that indicators may fail in capture the intrinsic value of a concept extrapolating it from facts, which is an objection to the use of data itself (Greco et al., 2019). Also, the inaccuracies that make an indicator poorly constructed by selecting and characterising the input of indicators affect equally data-driven indicators and the one constructed subjectively (Becker et al., 2017; Nardo et al., 2005).

Principal Component Analyisis

Among the data-driven approach, principal component analysis (PCA) is suitable for understanding drivers of inequity in HBE. The PCA, firstly theorised by Pearson in 1901 (Pearson, K., 1901), following its calculation by Hotelling in 1933 (JRC,), has the objective of capturing the higher variance as possible in input variables aiming at reducing dimensionality. The PCA is a widely used approach in building composite indicators (Greco et al., 2019; Nardo et al., 2005). The first application of PCA in building composite indicators merged both individual and BE characteristics to study the physical quality of life (Noorbakhsh, F., 1996; Ram, 1982). The PCA helps address the problem of multicollinearity in data so that variance could be preserved. The spatial study of urban health takes advantage of the conservation of variation because it allows the understanding of differences in the study area, thus the inequalities. Indeed, in studying the spatial association of the HBE with health, characteristics that do not vary in space do not contribute to the comprehension of differences in health conditions (Getis, 2005; Shi and Kwan, 2015). Part of the issues of PCA has been addressed by variants of PCA, such as the non-linear PCA methods about the input linearity assumption (Greyling and Tregenna, 2017) and the Robust PCA to address sensibility in the construction of data (Ruymgaart, 1981). Also, Factor Analysis can improve the understanding of indicators' components by employing varimax rotation to minimise the number of indicators with high loading on each component (Nicoletti et al., 2000). Another fallacy of PCA is related to its application on spatial data because of its inconsistency in the geographic space, making it hard to compare indicators (Greco et al., 2019; Harris et al., 2011). PCA is frequently utilised in geospatial studies (Demšar et al., 2013; Keast et al., 2010).

However, spatial data do not simply add two dimensions to the n-dimensional space of BE metrics because of two effects, spatial heterogeneity and spatial autocorrelation (Demšar et al., 2013). The application of PCA has been made without distinction on irregular and regular SU and points characterised by homogenous and heterogeneous spatial distributions.

Geographic Weighted Principal Component Analyis

PCA application can be implemented by methods that integrate the spatial arrangement of data, such as the Geographic Weighted PCA (GWPCA), which adapt PCA at a local geographic scale. The GWPCA proposed by Harris et al. (Harris et al., 2011) allow the calculation of principal components, in this case, different per each object of the dataset, by accounting for two crucial spatial processes, spatial heterogeneity (i.e., spatial non-stationarity) and spatial autocorrelation (i.e., spatial dependence) (Anselin, 1989, 1990). The first GWPCA was dependent on the choice of a (distance) bandwidth to determine the geographic scale of the local PCA. Subsequently, GWPCA has been implemented to automatically calculate the scale at which it should operate locally by cross-validation and provide a method to identify multivariate outliers (Harris et al., 2015).

The GWPCA has been widely used in environmental science and geology (Chang and Chen, 2016; Chen et al., 2021; Faraji Sabokbar et al., 2014; Fernandes et al., 2018; Sarra and Nissi, 2020; Wu et al., 2019); in the study of wellbeing, quality of life or deprivation (Benita et al., 2020; Cartone and Panzera, 2021; Lloyd, 2010a; Mishra, 2018; Park and Xu, 2021; Robinson et al., 2019; Sepúlveda Murillo et al., 2019). In both fields, GWPCA has been used for the creation of composite indicators, similar to the application of PCA (Benita et al., 2020; Cartone and Postiglione, 2020; Mishra, 2018; Park and Xu, 2021). According to the study of Mishra et al., which employed both PCA and GWPCA in constructing an indicator of human deprivation based on characteristics of the HBE; both PCA and GWPCA display useful findings: the first can describe the global process to understand the aspatial process, while the latter can better describe the local processes and optimise local interventions (Mishra, 2018). Despite the potential of GWPCA in studying or comparing geospatial health data (Wang, 2020), only a few publications applied it. Saib et al. applied GWPCA to build composite indicators of exposure to heavy metals, socioeconomic status (SES) and cancer mortality at the regional scale in the region of Picardy (France), confirming the benefit of GWPCA on the study of spatial heterogeneity (Saib et al., 2015). At the city scale, Wei et al. studied the geographic variation of public services related to health and wellbeing in Quito (Peru) by employing PCA and GWPCA and varying the aggregation of geospatial data and validating indicators with indicators surveyed data on subjective health and wellbeing (Wei et al., 2016). In two recent publications, Das et al. modelled the occurrence of COVID-19 in different metropolitan areas of India by GWPCA on SES indicators, allowing the identification of hotspots of the epidemic outbreak (Das et al., 2020, 2021). The advantage of GWPCA is significant across multiple studies, underlining the undisclosed potential of employing GWPCA in the fields of urban health (Wang, 2020). Nonetheless, GWPCA should be carefully interpreted due to the complexity related to spatial variation of its findings (Cartone and Panzera, 2021; Demšar et al., 2013; Harris et al., 2015; Saib et al., 2015).

3.2 Methodology

3.2.1 Built environment dataset

The framework of UHIs previously created guided the elicitation of HBE features by adapting it for the study area of the canton of Geneva. Firstly, the framework has been adapted by excluding issues that were not relevant for the study area. Secondly, open-source geographic data were collected to represent each UHIs. Again the study area has been modified, removing the enclave territory with a spatially contiguous space. The enclave territory's exclusion carries a limited loss of 0.1% of the residential population and 1.4% of the geographic surface (which is composed of 15.9% by built surfaces) (OFS, 2014). Geospatial data were gathered from multiple open-source existing geospatial sources. Due to the broad range of UHIs, we chose to use available data rather than collect data on the HBE. The convenience of using existing data is motived by the overall quality of open-source data in the study area and as a facilitator of research translation (Sallis et al., 2016; WHO Europe et al., 2003). HBE geospatial data were researched in multiple opensource databases, namely: (SITG, 2021); FOEN, the Federal office for the environment (FOEN,); Swisstopo (Geocat), the geospatial portal of the swiss federal service of topography (Federal Office of Topography swisstopo,); Opendata-swiss portal (Swiss Confederation, 2020), OSM, Open Street Map (OpenStreetMap,). An additional source of open-source geospatial data was identified by web-search. The search was based on UHIs, and keywords identified by HBE features. Moreover, data were required to display a geographic variation within the study area. Precisely, geospatial data were considered if they showed at least three classes or values or categories, and in the case of aggregated data, the spatial unit should not exceed the size of the spatial unit (SU) of analysis (Paragraph 3.2.2). Applying the generic framework of UHIs to the case study resulted in the entire or partial exclusion of certain UHIs. More precisely:

- *Sanitation and access to safe water*: wastewater treatment is regulated in Switzerland to prevent adverse impacts on population health (WHO, 2018c). The quality of tap water is considered about health impacts through its mineral content, while the biologic hazard of wastewaters is mitigated and considered irrelevant in Switzerland (WHO, 2018c).
- *Safe design and accessibility*: structural failure issues are monitored and regulated, while safety is addressed by design regulation, e.g. for electrocution and accidental falls. However, domestic injuries, such as falls, despite regulations, still impacts population health (BFU, 2019). We do not have access to spatial data of measures of indoor hazards, such as poor design for the elderly or people with reduced mobility. However, similarly to the BFU pilot study, we used the building's age as a proxy of safe design and accessibility for people with reduced mobility (BFU, 2019).
- *Thermo-hygrometric comfort*: thermic isolation and dampness prevention are regulated in Switzerland (SIA, 2021). However, building standards are needed to meet new targets due to climate change and the heat island effect (Burgstall et al., 2019). Also, dampness health issues related to unsafe housing are commonly underestimated in Europe (Mendell Mark J. et al., 2011; WHO Europe, 2009). Since we lacked data about housing systems and insulation, we used the building age and the yearly energy expenditure per surface unit as proxies.
- *Household air pollution*: the influence of indoor sources on health is managed by regulations on heating systems and installed cooking equipment to avoid indoor sources from having a negative impact on health. Instead, outdoor air pollution is a relevant contributor to indoor pollution (Meier et al., 2015) and is considered separately. Also, Radon pollution, which is mapped on the whole swiss territory, is considered irrelevant within the study area (UFSP, 2019).
- *Hydro-geologic risk*: hydrogeologic risks are limited to flooding risk. Due to the study area's location on the lakeside and at the confluence of two rivers and past events, flooding is the only relevant issue that can systematically affect the study area. Instead, the risk of slope instability phenomena, such as landslides, is irrelevant in the study area (Lateltin et al., 2005). Also, other hydrogeologic risks are assumed to be not relevant in the study area, e.g. tectonic instability (FOEN, 2018a; UFSP, 2019).
- Contaminated land: features related to waste management were considered irrelevant for their direct impact on health (FOEN,). Similarly, radioactive pollution was not considered for the study area (Radioactive waste - safe disposal in Switzerland, ; SFOE,).

Consequently, we deliberately excluded UHIs or part of them due to the local context. The application of standards, regulations, and policies systematically prevent specific hazards and diseases, particularly in addressing communicable diseases and injuries. Therefore, *Sanitation and Safe Water* and *Household Air Pollution* were excluded from the case study analysis. Instead, the lack of HBE data generally affects the domain of *Indoor environments*, needing proxies to represent jointly *Thermo-hygrometric comfort* and *Safe design and accessibility*. The lack of data impacted mainly the *Indoor environment* domain, which collects information belonging to private property, which is less likely to be collected and shared on open-source portals for privacy protection. Therefore, the two UHIs belonging to the domain of *Indoor environment* were replaced by the domain itself while two UHIs were excluded; so that the generic framework of fourteen UHI was reduced to eleven UHI. Most data related to the UHI framework reported by federal datasets did not display geographic resolution below the cantonal scale. Finally, most geospatial data was collected by SITG sources, and the elicited data and respective sources are displayed in Table 6. Overall, HBE features chosen for this study count 61 variables. Data were retrieved in geospatial file formats, except local food markets and physicians' cabinets automatically geocoded by postal address lists. The totality of geospatial data was converted in the same coordinate reference system (EPSG 2056, CH 1903+/ LV95).

	Environmental measures	***Source***
Air pollution	Modelled NO^2 concentration	SITG (SITG, 2021)
Noise pollution	Daytime and noise level calculated by noise models of road and rails traffic.	SonBAse (FOEN, 2018b)
Extreme ambient temperatures	Physiologic Equivalent Temperature (PET) in a daytime situation of maximal thermal load, modelled for 2010 and 2020.	SITG (SITG, 2021)
Water quality	Water hardness of the tap water network.	SITG (SITG, 2021)
	Physical object and networks	
Buildings	Physical extension of buildings registered in the cadastre (surface, height, shape, location and postal address location); use of buildings according to four categories: housing, activity, collective, mixed.	SITG (SITG, 2021)
Indoor thermic performance	Mean energy consumption per year per m^2.	SITG (SITG, 2021)
Mobility	Mobility networks (nodes and length) of roads, public transports, pedestrian, and bike trails. Active mobility network divided into an exclusive and shared network and commuting and leisure network. Road network was also characterised by hierarchy (4 categories). Location of public transports and rail stops, taxi waiting area, car-sharing services, and bike parking.	SITG (SITG, 2021) and OMS (*OpenStreetMap*,)
Green areas	Location and surface of green surfaces OTEMO-Corine, parks and leisure green areas	OSM (*OpenStreetMap*,)
Flooding	Past flooding events location and areas; the scale of severity of the event; surface and location of potential flooded events characterised by modelled return time.	SITG (SITG, 2021)
	Places and locations	
Services and community places	Location of services and places for education, entertainment, culture and recreation, sports facilities, and administrative services	SITG (SITG, 2021)and OMS (*OpenStreetMap*,)
Local food markets	Postal addresses of local markets geocoded from the cantonal website of local temporary markets	Genève Marchés(Ville de Genève, 2020a, 2020b)
Food places	Location of general groceries, specialised food shops, fast foods, bars, cafés and pubs.	OSM (*OpenStreetMap*,)
Industrial sites	Location of industrial sites (operational and dismissed)	SITG (SITG, 2021)
Contaminated sites	Location and surface of contaminated sites, physical medium contaminated, state of the site (monitored, treated) and type of contamination source (storage, productive activity or accidental event)	SITG (SITG, 2021)
Road accidents	Location and number of accidents, injured, severely injured and deaths; black points of road accidents calculated by MISTRA VUGIS.	SITG (SITG, 2021)
Healthcare services	Location of hospitals, ambulatories and clinics, social aid centres (EMS), geocoded addressed of a registered physician to the Association of Physicians of the Canton of Geneva (AMGE), and pharmacies.	SITG (SITG, 2021), AMGE (*AMGE*,), and OSM (*OpenStreetMap*,)
Population	Count of the resident population by postal address and the postal address location	SITG (SITG, 2021)

Table 6: List of HBE features collected for the case study. Geospatial data were characterised for different years ranging from 2015 and 2018 (80% updated to 2018).

3.2.2 Spatial aggregation

Geospatial data that collect different geometries and occupy different locations must be aggregated to be compared (Apparicio et al., 2017). The HBE features belong to three macro-categories of spatial data: ambient measures, physical objects and networks, places, and locations. These categories respectively corresponded to three different morphologic representations: representation of a feature on the whole surface of the case study by geospatial units; representation by the physical extension of an object or its approximation by a network, and the representation by postal address or the location of the centroid of a physical object. In general, the geospatial data employed includes:

- numerical values related to the quality of the HBE, such as noise level estimate.
- numerical values of the geometric characteristics of the HBE, such as the length of roads.
- binary values (including categorical values transformed in dummies), related to the availability of HBE, like the presence of a pharmacy.

The topography of the study area was not included in the study since the slope gradient does not exceed 50 meters in 1 km in linear distance. The only information collected about z-dimension is the height of buildings. Thus, geospatial data were represented in two spatial dimensions.

Spatial Unit of analysis

The Geospatial data of HBE were aggregated within spatial units (SUs) of analysis. The meaning of the SU is to represent a portion of the case study surface by characteristics of the HBE that potentially shape health. In particular, an individual who experiences or is exposed daily to a set of SUs is supposed to be likely to develop certain health conditions depending on the BE's healthiness characterised in that set of SUs (Kwan, 2012). Also, the SU is a portion of the surface in which the characteristics of the HBE can be considered homogeneous (Wong, 2009). We choose SU size and shape to reduce the spatial uncertainty introduced by the spatial sampling of HBE features, therefore to address the Modifiable Areal Unit Problem (MAUP) (Delmelle, 2014; Li et al., 2018) integrating consideration about the Uncertain Geographic Context Problem (Kwan, 2012; Shi et al., 2019; Yu and Ai, 2014).

The first option was to consider administrative units. The SITG provides two spatial subdivisions finer than the municipalities: administrative sub-statistic sectors, namely GIRECS and the partition by parcel (SITG, 2021). Both spatial datasets are composed of irregular shapes and count 475 and 71912 objects, respectively. The use of parcels provides a spatial partition that overlaps with land use and does not compare multiple BE features in the same SU. The use of sub-sectors provides a spatial partition that distinguishes the different neighbourhoods in urban areas and villages and hamlets from agricultural or forest areas in rural areas. However, the subsectors offer a coarse spatial resolution, where surfaces increase with the distance from the town centre (Figure 11). In both parcel and sub-statistics sectors, the irregularity of shapes, measured in perimeter over area ratio, highly overcome a squared SU's perimeter over area ratio. Also, the presence of concave shapes does not allow spatial operations requiring the use of centroids. To overcome these issues, we opted for a regular SU to represent the study area.

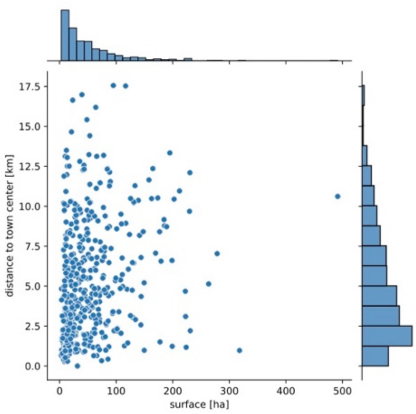


Figure 11: Distribution of sub-statistical surface area against the distance from town centre.

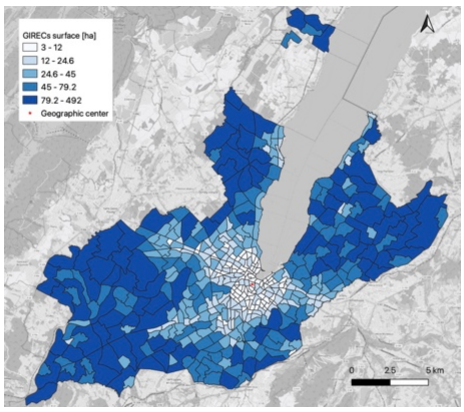


Figure 12: The sub-statistical administrative units of the canton of Geneva (GIRECs), classed by Euclidean distance from the geographic town centre.

We adopted a hexagon shape as SU. The hexagon shape, when compared to a rectangular grid, has several advantages (Birch et al., 2007). The subdivision of space in hexagons reduces the edge effect (having a high perimeter over area ratio), allowing the best fit of space with no overlap, keeping the number of vertices low. Consequently, spatial sampling bias is reduced, in particular when objects with different geometries are collected. Hexagons are less affected by distortion in large areas due to the projection of the reference system. Also, hexagons are suitable for spatial operations that implement movement path and connectivity measures. However, the hexagon geometry is more complex, and big geospatial data may suffer a higher computational load than rectangular grids. Also, hexagon SU makes the computation of spatial subdivisions more difficult.

Data points aggregated in surface spatial units are less affected by spatial sampling error with decreasing size of the spatial unit and are generally preferred to address the MAUP (Fotheringham and Wong, 1991; Gerell, 2017; Wong, 2009). However, spatial units would drastically carry less information when size is smaller than the majority of sampled objects (*Wiley.com*,). Thus, we chose the smallest SU, which was large enough to include the 0.99 quantiles of the building's surface. Also, the size of SU should account for the population distribution, so each SU is not over the representative of the population. In our case, we chose SU so that the 0.999 quantile of the sampled population in the most populated SUs is lower than the 0.1% of the total resident population in the study area.

Therefore, following those criteria, we adopted a hexagon size of 1 hectare (10 000 m^2) as SU of analysis, corresponding to a circumcircle radius of 62m and an apothem of 53m. The furthest points belonging to the same hexagon are 124 m away in terms of spatial aggregation precision. The study area was therefore represented through 24690 hexagonal SU, which entirely covered the study area.

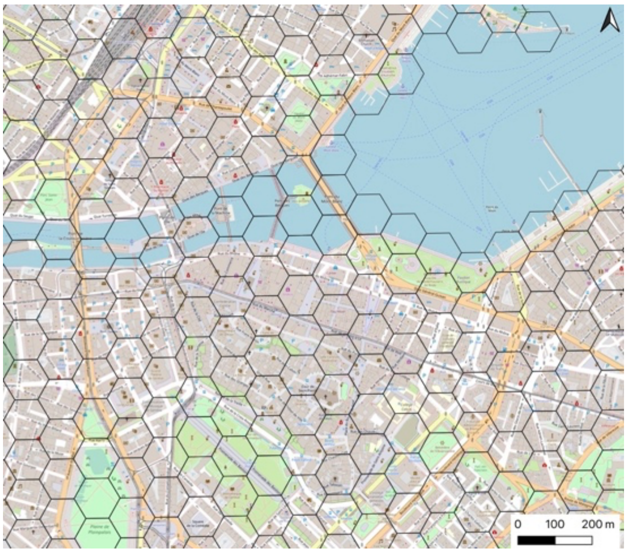


Figure 13: Example of spatial subdivision generated by the hexagonal spatial units of one hectare.

Spatial interpolation

Geospatial data were interpolated except for HBE features that are already provided at continuous spatial scale, i.e. noise and air pollution estimates and ambient temperature estimates; or for features which impact do not vary in space, so that its influence is limited to its location, such as characteristics of the indoor environment characteristics and flooding. Since contaminated sites are regulated and monitored to contain their impacts, those features were not interpolated (Romy I. et al.,). Geospatial data were interpolated using Kernel Density Estimators (KDE) employing quartic function, which is mathematically equivalent to kriging (Scheuerer et al., 2013). Depending on the type of the HBE feature, interpolation used different distances and bandwidths, weighting the interpolation on the measures represented in Table 6.

Firstly, different variables were used to calculate UHIs related to passive mechanisms, such as exposure, which is represented by the first domain of UHI employing Euclidean distances. Discrete variables related to air pollution were interpolated using a bandwidth of 500m, coherent with other studies to represent the distance at which dispersion makes pollutants negligible, despite being highly variable due to meteorological conditions and the building geometry (Pasquier and Andre, 2016; Shi et al., 2019). Instead, a bandwidth of 1000m was used for discrete variables linked with noise pollution and urban health island. For noise level, the bandwidth corresponds to the reduction of 20 dB(A) in standard environmental conditions to represent the difference between outdoor harmful noise level and moderate annoyance noise level (Attenborough, 2014; *WHO*, 2018a; *WHO*,). The bandwidth represents a precautionary value for urban heath islands at which heath island effect decay can be neglected in standard environmental conditions for tight urban areas (Bao et al., 2016; Gartland, 2012).

Secondly, variables were used to calculate UHIs related to accessibility. Thus, the third domain of UHI employed transport network travel time. We modelled the distance decay (in terms of travel time) around service location to outline the likelihood of individual to shape is activity space depending on walking distance on the pedestrian network. Daily destinations shape the daily activity space of individuals we could not control, such as workplace, residence, school etc. (Liu et al., 2020; Matthews and Yang, 2013). Instead, we choose to represent the distance decay around services as the potential influence that a service has in attracting an individual located at a specific distance by modifying their activity space by walking (Apparicio et al., 2017; Giles-Corti et al., 2005; Gutiérrez et al., 2011; Iacono et al., 2008; Kolcsár et al., 2021). This choice does not assume that individuals commute only by walking but outlines how; independently form the transportation mode between daily destinations; individuals modify their activity space behaviour by walking. The utilisation of other transportation modes could have smoothed significantly spatial variation of features, therefore missing local differences able to outline accessibility in urban areas.

Figure 14: Example of walking travel time on the pedestrian network from a random point of origin.

Distance between SUs was represented by network travel time on the pedestrian network with a constant speed of 4.5 km/h using QNEAT3 plugin on QGIS (QGIS Python Plugins Repository,). An example of network travel time by random origin is displayed in Figure 14. The bandwidth choice aimed to consider significant features within a distance of 400m which is the adequate value for walking activity space (Alfonzo, 2005; Azmi et al., 2012; Hwang et al., 2016; Larsen et al., 2010; Villanueva et al., 2014). Hence, interpolation by KDE was calculated on a bandwidth of 500m so that weights over 0.25 characterised SUs within 400m. The use of network distance rather than linear distance does not impact the calculation of distance between the centroids of SU significantly since Origin Distance (OD) matrices calculated by network distance, and linear distance are significantly similar (by ANOVA with p-value>0.05). Networks distances in the OD matrix were more significant than the Euclidean distances in areas characterised by natural constrains, such as forests, lakes, and rivers, as shown by the percentage difference of network distances over linear distances (Figure 15). Also, the difference between the two distance calculations is smaller than the sampling error introduced by the spatial representation with SU, thus in the approximation related to the calculation of distances between centroids of SUs. The secondary importance of the distance calculations compared to aggregation and calculation methods of accessibility has been tested by Apparicio et al. (Apparicio et al., 2017). In general, the weighting provided by the quartic equation decays with increasing bandwidth distance, inversely to the increasing number of neighbour SUs (Figure 16). Also, weights drop below 0.01 respectively at 480m and 912m by adopting a bandwidth of 500m or 1000m. Furthermore, interpolation of geospatial data contributes to the spatial smoothing of discrete features so that their exponential distribution tends to be transformed in quasi-normal distribution (Stein, 2012).

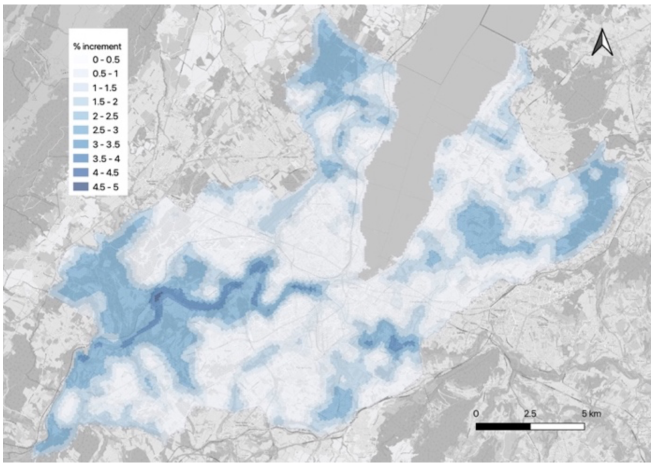


Figure 15: Mean ratio of distances calculated employing network OD matrix on the Euclidean OD matrix.

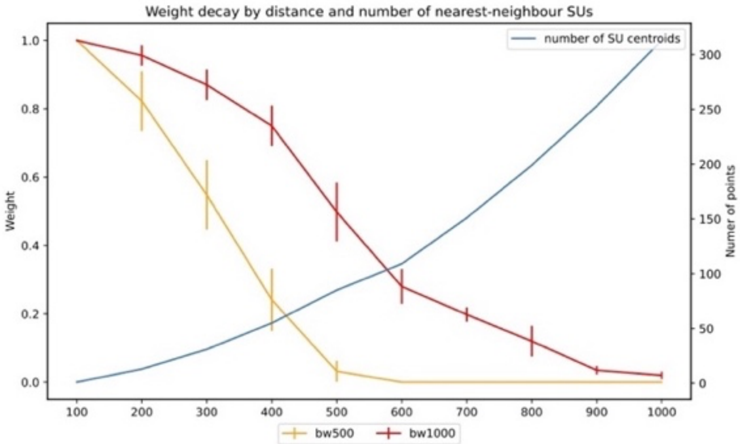


Figure 16: Local weight decay and number of neighbour SUs by distance. The weight decay is calculated by quartic function by distance [m] for fixed bandwidth of 500m and 1000m for centroids of neighbouring hexagonal SUs. Vertical lines display the range of weights within an interval of 100m. Also, the figure displays the number of neighbouring SU centroids by distance. These curves represent the case of a non-boundary spatial unit based on Euclidean distance measure between the respective centroids.

Loading of HBE features in UHIs

Geospatial data of BE features assigned to each SUs were subdivided into 11 subsets of metrics according to the eleven UHI chosen for the case study (Table 7). The features do contribute to different UHIs as displayed in Figure 17, because they can have different impacts on health, such as motorized vehicles are related to noise and air pollution. Furthermore Figure 17 allow to visualize how many BE features converge into UHIs and then into domains depending on connection widths. The maps of single features are not shown, while a synthetic thematic map (Figure 18) displays few relevant features, such as physical constrains (borders, waterbodies), and transportation networks and hubs.

UHI number	UHI name	BE features
UHI1	Air pollution	Nitrogen bioxide mean concentration estimate, building count, road nodes, road length, road hierarchy, index of building energy consumption, airport.
UHI2	Noise pollution	Day-time and night-time noise level (modelled from road and rail traffic), noise protection area, road nodes, length and hierarchy, rail nodes and lenght, airport.
UHI3	Flooding	Predicted flooded area by return time (inverse of return time), flooding event gravity, flooding event count, river
UHI4	Heat island effect	Physiologic equivalent temperature modelled for 2010 and 2020, total built surface, building number, index of building energy consumption, road nodes, length and hierarchy, river, lake, rural green areas, urban green areas.
UHI5	Contaminated land	Contamination count, surface water contaminaton, groundwater contamination, soil contamination, air contamination, contamination accident, contamination by exploited area, contamination by storage area, treated contamination, monitored contamination, industrial area (current and dismissed).
UHI6	Road injuries	Road injuries, Serious road injuries, road deaths, black point road accidents index, road nodes, length and hierarchy, active mobility exclusive network and length, active mobility shared network nodes and length.
UHI7	Healthcare services acc.	Pharmacies, physician cabinets, social healthcare services, hospitals, clinics and ambulatories,
UHI8	Indoor environment	Building age, index of building energy consumption, tap water hardness, building height, building mean surface.
UHI9	Active Mobility	Active mobility exclusive network and length, active mobility shared network nodes and length, urban green areas, public transport quality index, road speed limit, public transport stops, train stations, taxi waiting area and car sharing facilities, bike parking.
UHI10	Community places	Urban green areas, weekly local market, education facilities, commercial activities, collective building, administrative services, sport facilies, entertainment facilities.
UHI11	Food Environment	Fastfood, restaurant, bars pubs and other beverage shops, weekly local market, general groceries, specialised food shops.

Table 7:List of BE attributes assigned to each UHIs.

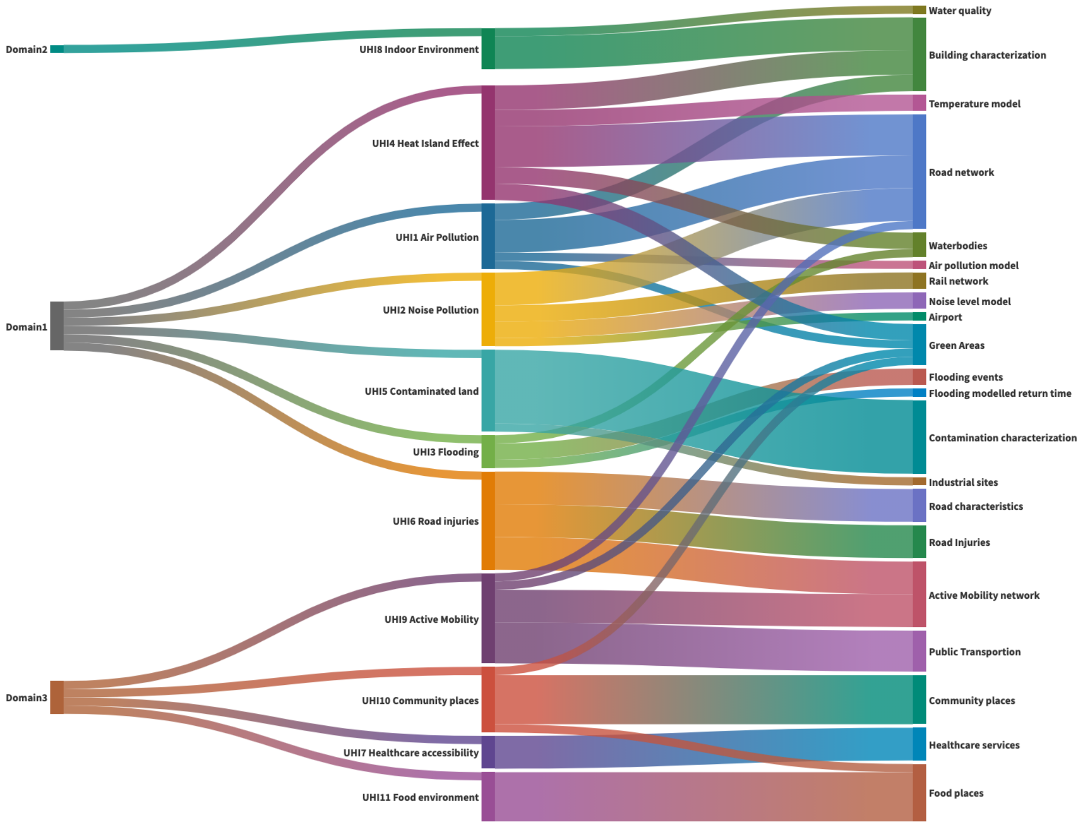


Figure 17: Sankey diagram of the grouping of HBE features in the UHIs and domains. The width of the connections is proportional to the number of features flowing to a UHI. This diagram allows to understand how BE attributes can contribute to multiple UHIs.

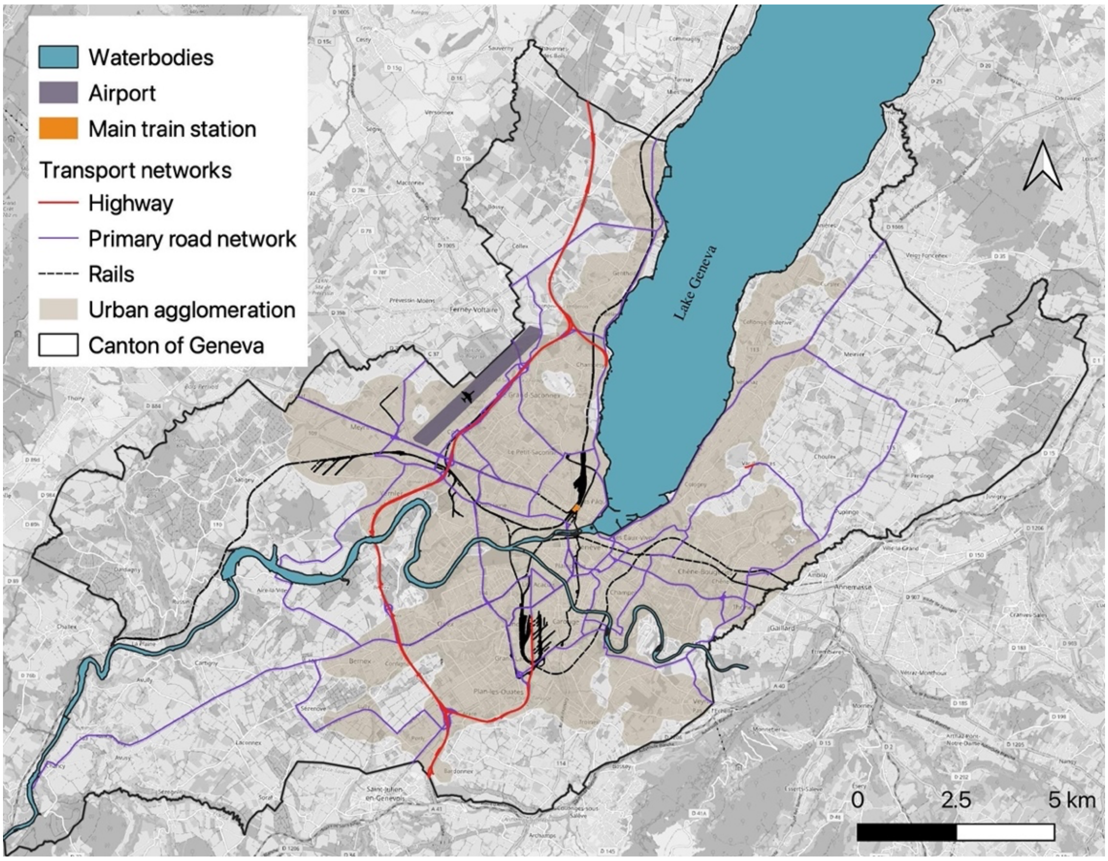


Figure 18: Summarised thematic map of the canton of Geneva. The urban agglomeration is defined in the following paragraph.

3.2.3 Urban agglomeration

The in studying the relation between places and health, rural and urban areas are usually separated or compared because they are characterised by different BE attributes and therefore by different environmental health determinants. However, those geographic areas are usually identified by the predominant attributes within administrative units, rather than relying on spatial pattern of land-cover. To outline the urban edge in the study area, land-use data in the study area areas input a convolution-based method (Bosch, 2020). In brief the latter classifies as urban area a pixel that had 15% of urban land-use classes in a radius of 400m. The area identified as urban propagate outside the municipality of the city of Geneva along the lake shores, and in multiple directions towards east, south-west and west (Figure 19). This study does not explore the differences between rural and urban areas in BE or in health outcomes. The definition of the urban agglomeration is employed to describe the location of objects in the study area.

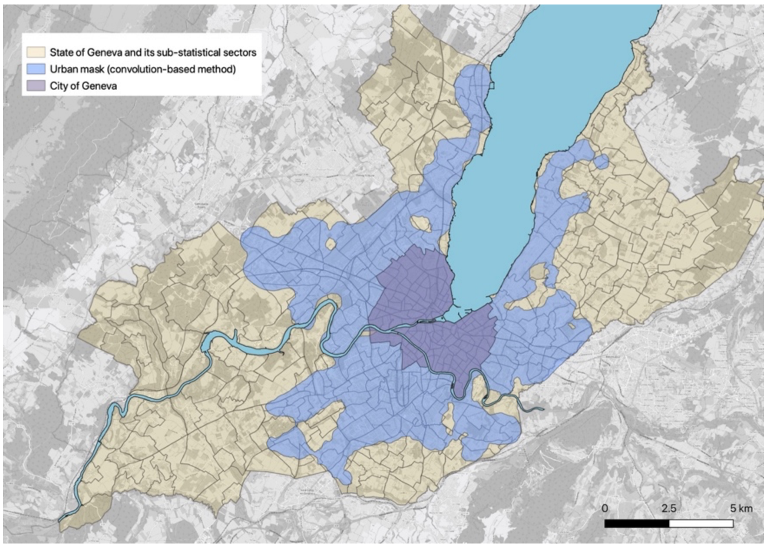


Figure 19: Urban agglomeration (urban mask) calculated with a convolution-based method, compared to the whole canton of Geneva and the municipality of Geneva.

3.2.4 PCA and GWPCA

We performed PCA and GWPCA on each UHI group of standardised and normalised BE features. We performed a PCA using the Scikit-learn packages on Python (Pedregosa et al., 2011) to calculate the cumulative explained variance by the number of components. The number of components was chosen, so the cumulative explained variance (EV) was above 0.70 for each UHI. The EV was used instead of Eigenvalues since the latter are not automatically calculated in the GWPCA. In addition, we applied the varimax rotation to maximise the variance among factors (*Factor Analysis: Varimax Rotation*, 2017). The varimax rotation is usually employed in factor analysis to improve the interpretation of PCA components. However, PCA is already set to maximise the variance while performing a dimensionality reduction (Demšar et al., 2013). Therefore, unrotated PCA was used for further calculations, while rotated factors were used to ease loadings interpretation. For each UHIs, we represented loadings per each component and mapped the first component.

Secondly, we performed GWPCA using the GWmodel package on R (B Lu et al., 2021), adopting the same number of components identified by the cumulative EV in PCA. The calculation of the adaptive bandwidth (with bisquare kernel) suggested that bandwidth over 11km, which considering the study are surface, would have produced similar results to the PCA. Therefore, we opted for a fixed bandwidth of 500m coherently with a previous approximation of walking activity space. Differently from PCA, a set of loadings and EV per component was produced per each SU (n=24690), allowing the mapping of the latter two. Also, maximum loadings of the first components were mapped per UHI to understand which HBE features deliver the maximum contribution heterogeneously in space. By employing the mvoutlier package on R (Gschwandtner, 2021), outliers were identified by calculating the local discrepancy generated by the GWPCA. The latter measures the sum of individual discrepancies between the actual values of HBE features with one reconstructed with the respective loadings. Principal components calculated with PCA and GWPCA were normalised and scaled so that the HBE related with a potential positive impact (the HBE belonging to the third domain) displayed the exact information of the one representing potential negative impact. Thus, components displayed values between 0 and 1, where 1 indicates a context associated with negative impacts, and 0 indicate a context related to neutral or positive impacts.

3.2.5 Amalgamation of indicators and global disparities

The components calculated with PCA were amalgamated per each UHI to create their respective indicators. The amalgamate indicators were calculated with geometric means following the guidelines for Urban health indicators of WHO (WHO et al., 2014). Therefore we calculated each UHI_u indicator as follow:

$$UHI_u = \left(\prod_{i=1}^{j} c_{UHI,s,i} \right)^{\frac{1}{j}}$$

Where j is the number of standardised principal components $c_{UHI,s,i}$ per each UHI. The resulting UHI indicators were mapped, we calculated the correlation between them in the study area. Instead, the amalgamation of GWPCA components has not been recommended (Harris et al., 2011). Indeed GWPCA provides a local interpretation that do not allow its principal components to be directly compared or combined (Harris et al., 2011, 2015). Afterwards, we studied extreme values of each UHI indicator calculated with PCA by identifying the outliers of the Box function (Spear, 1952). Therefore, we calculated the threshold to identify superior and inferior outliers (out_{head}, out_{tail}):

$$out_{head} \geq q_3 + 1.5 * (q_3 - q_1) \qquad out_{tail} \geq q_1 - 1.5 * (q_3 - q_1)$$

Where q_1 is the first quartile and q_3 is the third quartile. We represented the variability of outliers by calculating the percentage of the ratio between the difference of the outlier and the threshold; and the inter-quantile range ($q_3 - q_1$). In addition, similarly to components amalgamation per each UHI, we merged UHI indicators belonging to different domains to calculate an indicator per each domain, and we merged all UHI indicators to produce a single summary indicator of all UHI indicators.

According to the handbook of WHO for Urban Health Indexes, two key measures can outline disparities identified by indexes at the global level (WHO et al., 2014). By using the rank distribution chart, thus by ranking objects (SU) according to a target indicator and comparing them to the indicator values, two measures can be identified: the disparity slope and disparity ratio, which quantify the average variation of central and extreme values. The disparity slope measure how the central segment tilt, displaying how heterogenous are central values within the study area. The disparity ratio measures the difference between mean values of outliers (respectively highest and lowest decile). Indicators that are homogenous within the study area can contribute to impact health both positively and negatively, but they are less likely to deliver inequities within the study area. We calculated disparity ratios and slopes for each UHI indicator obtained with PCA and GWPCA and displayed their respective rank distribution charts.

3.3 Results

3.3.1 PCA results

Aggregated HBE features at the level of SU were processed using a global and local approach, respectively PCA and GWPCA. The PCA allowed identifying a variable number of components that delivered a cumulative EV of 70% by employing a variable set of HBE features (Table 8). The PCA reduced the dimensionality in the dataset by conserving the variance in data, using a maximum of three components for nine UHI on ten, while only the Food environment UHI was explained by one single component. Overall, the UHI first components explained variances ranging from 0.32 to 0.74, with an average of 0.48 (Table 8). The PCA first components mapped in Figure 20, display how potential impact of the HBE are distributed in space. Take note that because the UHI are computed using scaled characteristics, values closer to 1 indicate an expected adverse effect on health or the absence of a beneficial HBE; while values closer to 0 indicates an expected beneficial impact on health or the absence of an adverse HBE. The major loadings (in terms of absolute value) for each component are displayed in Table 10.

UHI	*N° Inputs*	*N° Comp.*	*Cumulative EV [%]*	*1°*	*2°*	*3°*	*4°*	*5°*
Air pollution	11	2	70.9	0.48	0.13	-	-	-
Noise pollution	11	3	76.1	0.4	0.16	0.11	0.09	-
Flooding	5	3	92.1	0.34	0.21	0.2	-	-
Heat island effect	13	4	73.4	0.37	0.17	0.09	0.07	-
Contaminated land	11	5	72.7	0.32	0.13	0.1	0.09	0.09
Road injuries	12	2	75.0	0.6	0.15	-	-	-
Healthcare access.	4	2	79.9	0.57	0.23	-	-	-
Indoor environment	5	3	83.4	0.44	0.2	0.19	-	-
Active Mobility	11	3	72.8	0.51	0.13	0.09	-	-
Community space	8	3	72.7	0.50	0.13	0.09	-	-
Food Environment	6	1	74.0	0.74	-	-	-	-

Table 8: Dimensionality reduction by PCA. The number of input HBE features, components, and cumulative explained variance (EV) per UHI. Explained variance by principal components for each UHI.

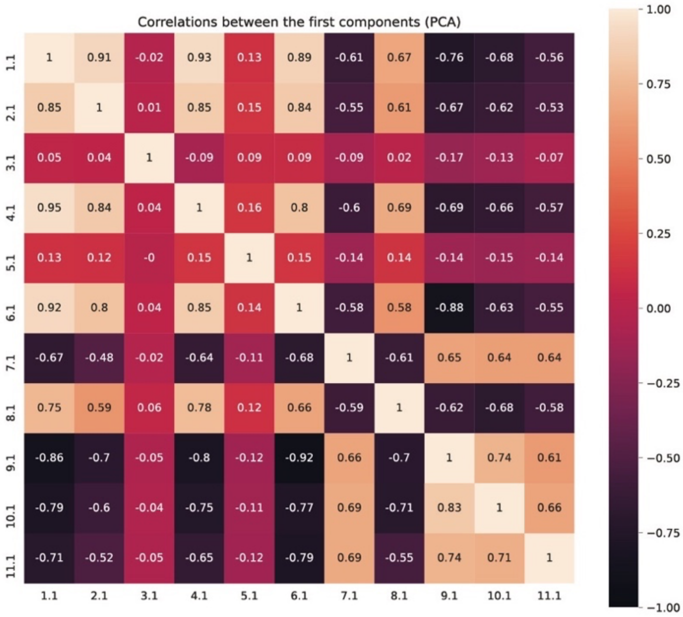


Table 9:Correlations between first components (PCA). The table displays the Pearson correlations in the bottom left corner, while the top right corner displays the Spearman correlations.

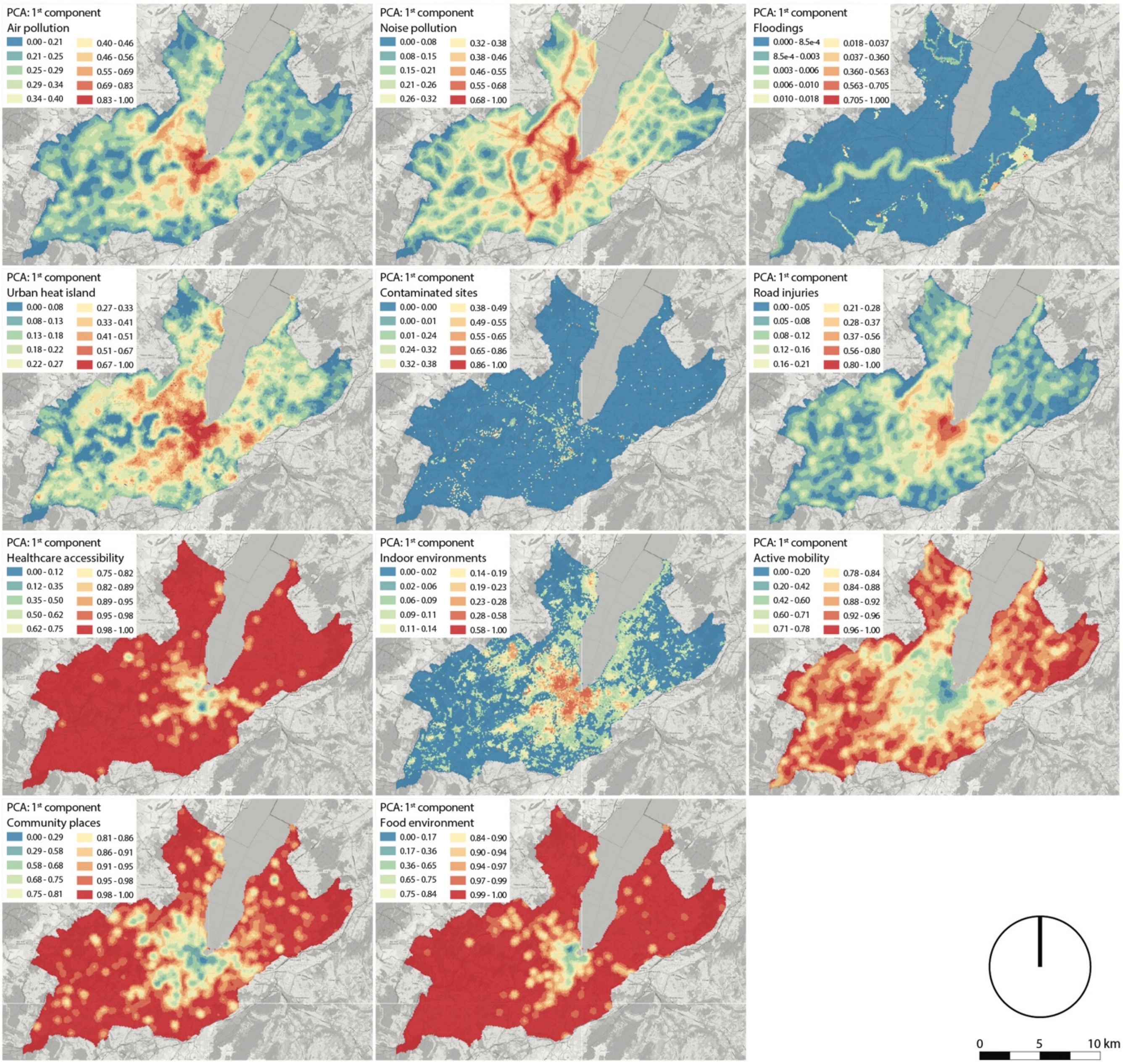


Figure 20: First principal components for each UHI and correlations among the latter. Values are classified into ten classes by Natural Breaks.

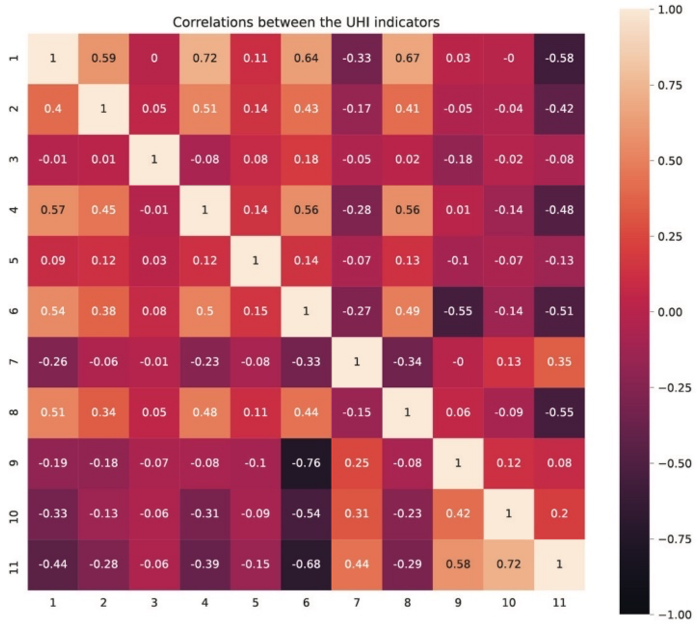
UHI	Component	Major Loadings -1 ... 1		
Air Pollution (UHI1)	1	Roads nodes (0.47), length (0.45) and hierarchy (0.42)	Index of building energy consumption (0.4)	Building count (0.3)
	2	Airport (0.83)	NO2 (0.49)	Building count (-0.24)
Noise Pollution (UHI2)	1	Roads hierarchy (0.44), length (0.42) and nodes (0.41)	Night-time noise level (0.39), Day-noise level (0.38)	Rail-noise lengths (0.24), rail axes (0.23)
	2	Rail-noise lengths (0.66), rail axes (0.65)	Highway (-0.17)	
	3	Noise protection area (0.60)	Airport (0.49)	Roads nodes (-0.32), length (-0.28)
Flooding (UHI3)	1	Flooding events severity and counts (0.71)		
	2	River count (0.72)	Flooding Return Time (-0.7)	
	3	Flooding Return Time (0.71)	River count (0.7)	
Urban Heat Island (UHI4)	1	Roads nodes (0.41), length (0.40) and hierarchy (0.39)	Index of building energy consumption (0.35)	Rural green (0.3)
	2	PET 2010 and 2020 (0.58)	River (-0.31)	Index of building energy consumption (0.22)
	3	River (-0.81)	River (0.48)	Rural green (0.26)
	4	Building surface (0.55)	Roads length (-0.39)	Buildings count (0.38)
Contaminated land (UHI5)	1	Contamination monitoring (0.51)	Contamination count (0.49)	Contamination by storage (0.38)
	2	Contamination by exploitation (-0.53)	Contamination by storage (0.45)	Surface water contamination (0.31)
	3	Soil Contamination (0.58)	Treated contamination (0. 47)	Air contamination (0.44)
	4	Contamination by accidents (0.7)	Air contamination (0.52)	Treated contamination (0. 39)
	5	Industrial area (0.56)	Contamination by accidents (-0.54)	Air contamination (0.43)
Road accidents (UHI6)	1	Active mobility shared network nodes (0.36) and length (0.34)	Roads nodes (0.34)	Injuries count, serious injuries count (0.33)
	2	Active mobility exclusive network length (-0.57) and nodes (-0.5)	Highway (0.38)	Roads hierarchy (-0.34), and length (0.32)
Healthcare accessibility (UHI7)	1	Physicians cabinets (0.61)	Pharmacies (0.52)	Hospitals, clinics, ambulatories (0.5)
	2	Social care (-0.82)	Hospitals, clinics, ambulatories (0.5)	Physicians cabinets (0.2)
Indoor (UHI8)	1	Building height (0.63)	Building age (0.55)	Index of building energy consumption (0.5)
	2	Water quality (-0.99)		
	3	Building (mean) surface (0.93)	Index of building energy consumption (-0.36)	
Active Mobility (UHI9)	1	Active mobility shared network nodes (0.39) and length (0.38)	Public transport stops (0.34)	Car sharing or taxi area (0.33)
	2	Active mobility exclusive network length (0.55) and nodes (0.45)	Speed limit (-0.39)	Public transport quality index (-0.36)
	3	Train stations (0.81)	Bike parking (0.33)	Speed limit (-0.26)
Community space (UHI10)	1	Education buildings (0.40)	Collective buildings (0.39)	Administrative services (0.37
	2	Sport facilities (-0.57)	Shopping activities (0.49)	Local markets (0.45)
	3	Sport facilities (0.7)	Local markets (0.39)	Administrative service (-0.39)
Food Environment (UHI11)	1	Restaurants (0.45) and bars (0.44)	Fast foods and specialised groceries (0.42)	Groceries (0.39)

Table 10: Major loadings (in terms of absolute values) of each principal component per each UHI.

3.3.2 Amalgamation of PCA components: UHI indicators

The principal components generated with PCA were amalgamated using the geometric mean to generate an indicator for each UHI. We refer to the latter as the UHI indicators. Firstly, Table 11 shows the correlations between values and rank in UHI indicators. Non-null correlations are observed since multiple HBE features were use to generate different HBE indicators, or since those issues take place in the geographic areas.

The eleven UHI indicators' values are mapped in Figure 21 using the same color scheme. Further, the UHI indicators were combined with the same method to represent each domain of UHI (Figure 22) and a single HBE index by combining domains (Figure 23). The outliers for each UHI indicator were identified by the Box function (Figure 24): the outliers represents the extreme values observed per each UHIs. For Flooding UHI and Contaminated land, almost all values were classified as outliers since data are highly unbalanced, so the interquartile range calculated for the Box function is null. Consequently, the representation of the outliers is equal to Figure 21 and it is not shown. Instead, the Indoor Environment UHI would represent few SUs since the outliers represent approximately one hundred elements that display values above 0.33, and thus it is not shown.



	1	2	3	4	5	6	7	8	9	10	11
1	1	0.59	0	0.72	0.11	0.64	-0.33	0.67	0.03	-0	-0.58
2	0.4	1	0.05	0.51	0.14	0.43	-0.17	0.41	-0.05	-0.04	-0.42
3	-0.01	0.01	1	-0.08	0.08	0.18	-0.05	0.02	-0.18	-0.02	-0.08
4	0.57	0.45	-0.01	1	0.14	0.56	-0.28	0.56	0.01	-0.14	-0.48
5	0.09	0.12	0.03	0.12	1	0.14	-0.07	0.13	-0.1	-0.07	-0.13
6	0.54	0.38	0.08	0.5	0.15	1	-0.27	0.49	-0.55	-0.14	-0.51
7	-0.26	-0.06	-0.01	-0.23	-0.08	-0.33	1	-0.34	-0	0.13	0.35
8	0.51	0.34	0.05	0.48	0.11	0.44	-0.15	1	0.06	-0.09	-0.55
9	-0.19	-0.18	-0.07	-0.08	-0.1	-0.76	0.25	-0.08	1	0.12	0.08
10	-0.33	-0.13	-0.06	-0.31	-0.09	-0.54	0.31	-0.23	0.42	1	0.2
11	-0.44	-0.28	-0.06	-0.39	-0.15	-0.68	0.44	-0.29	0.58	0.72	1

Table 11: Correlations between UHI indicators. The table displays the Pearson correlations in the bottom left corner, while the top right corner displays the Spearman correlations.

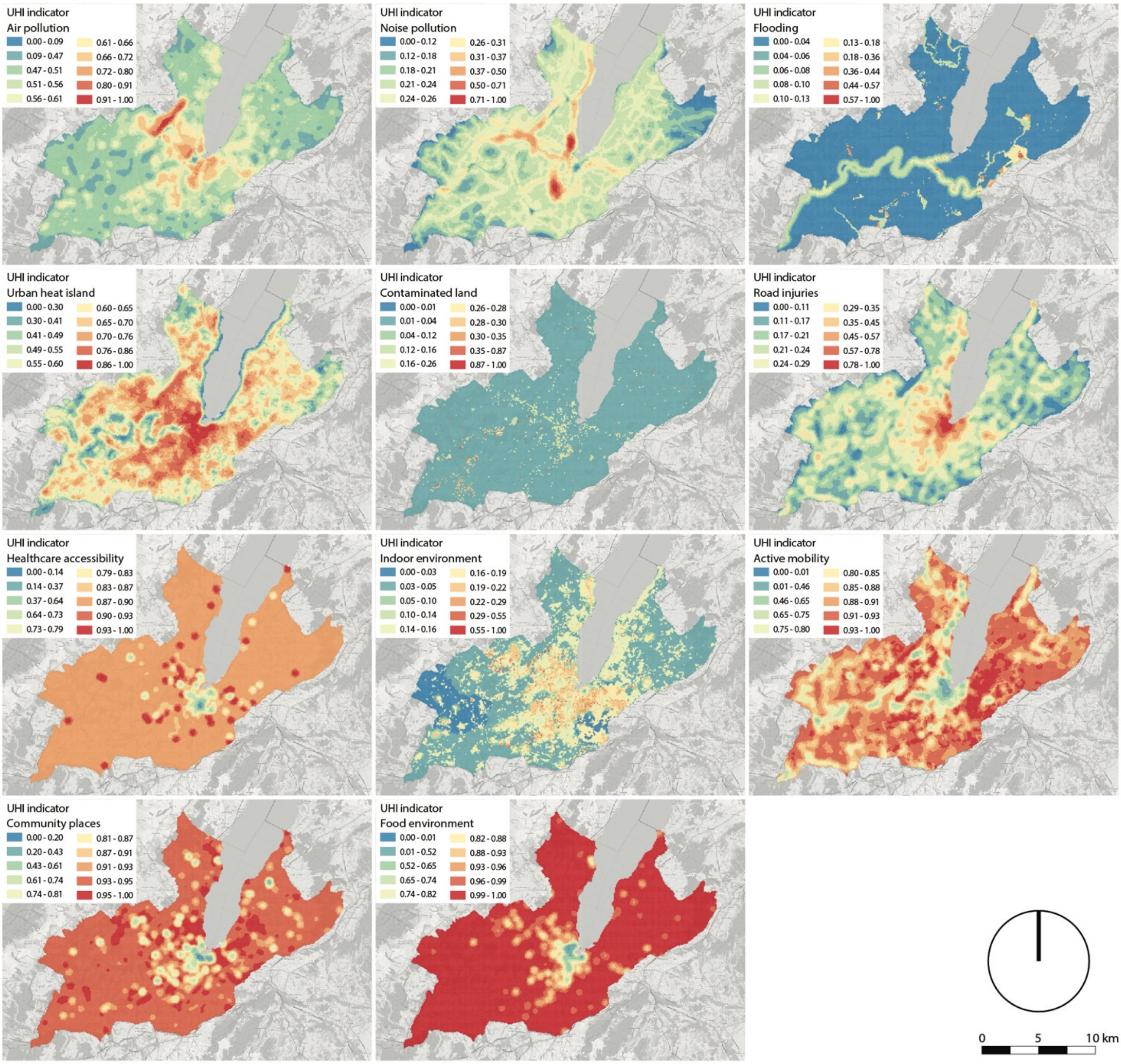


Figure 21: UHI indicators calculate by the amalgamation of PCA components. Values are classified into ten classes by Natural Breaks. The table shows the correlations between UHI indicators: the bottom left corner displays the Pearson correlations, while the top right corner the Spearman correlations.

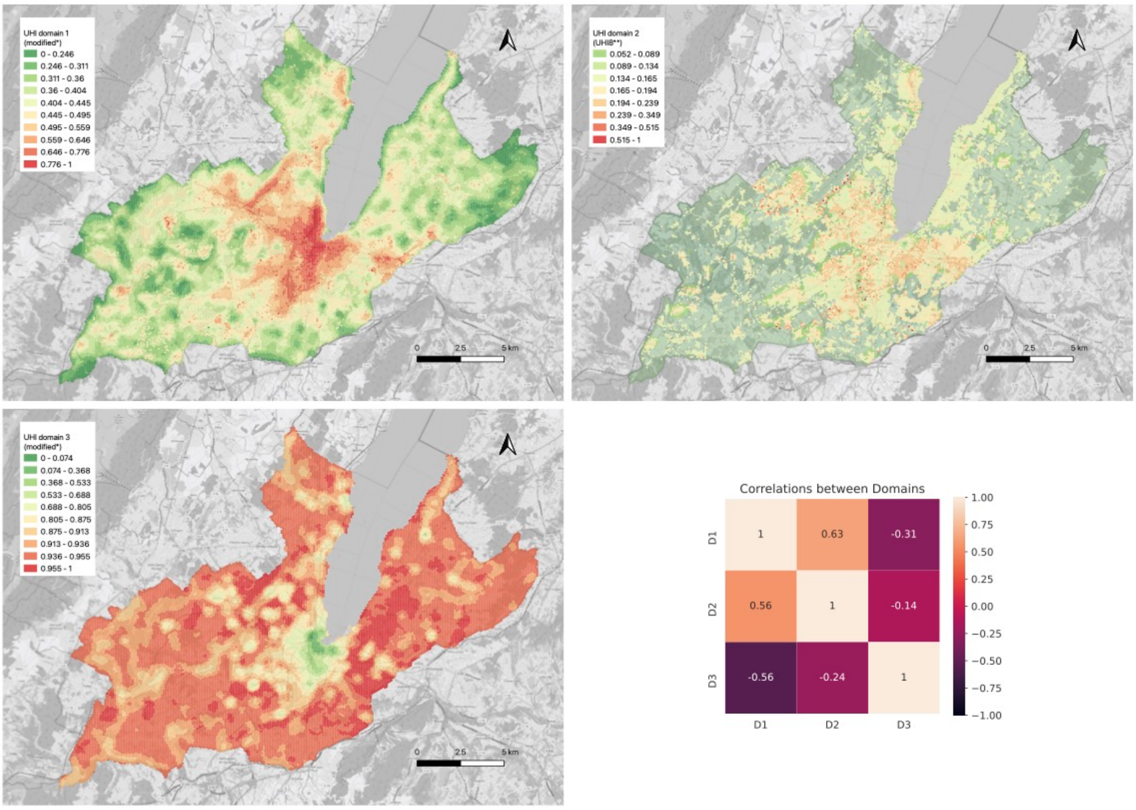


Figure 22: UHI domains calculated by combining UHI indicators. Values are classified into ten classes by Natural Breaks. The Table shows the correlations between UHI indicators: the bottom right corner displays the Pearson correlations, while the top right corner the Spearman correlations.

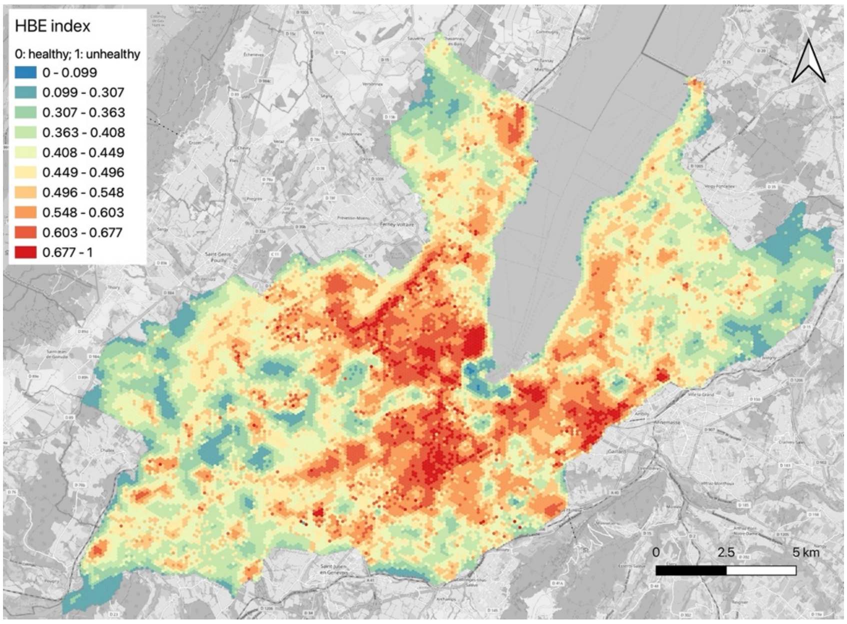


Figure 23: HBE index calculated by combining UHI domains. The HBE index summarise the spatial distribution of the HBE through a single index to show how multiple UHIs are stratified within the study area. Values are classified into eight classes by Natural Breaks.

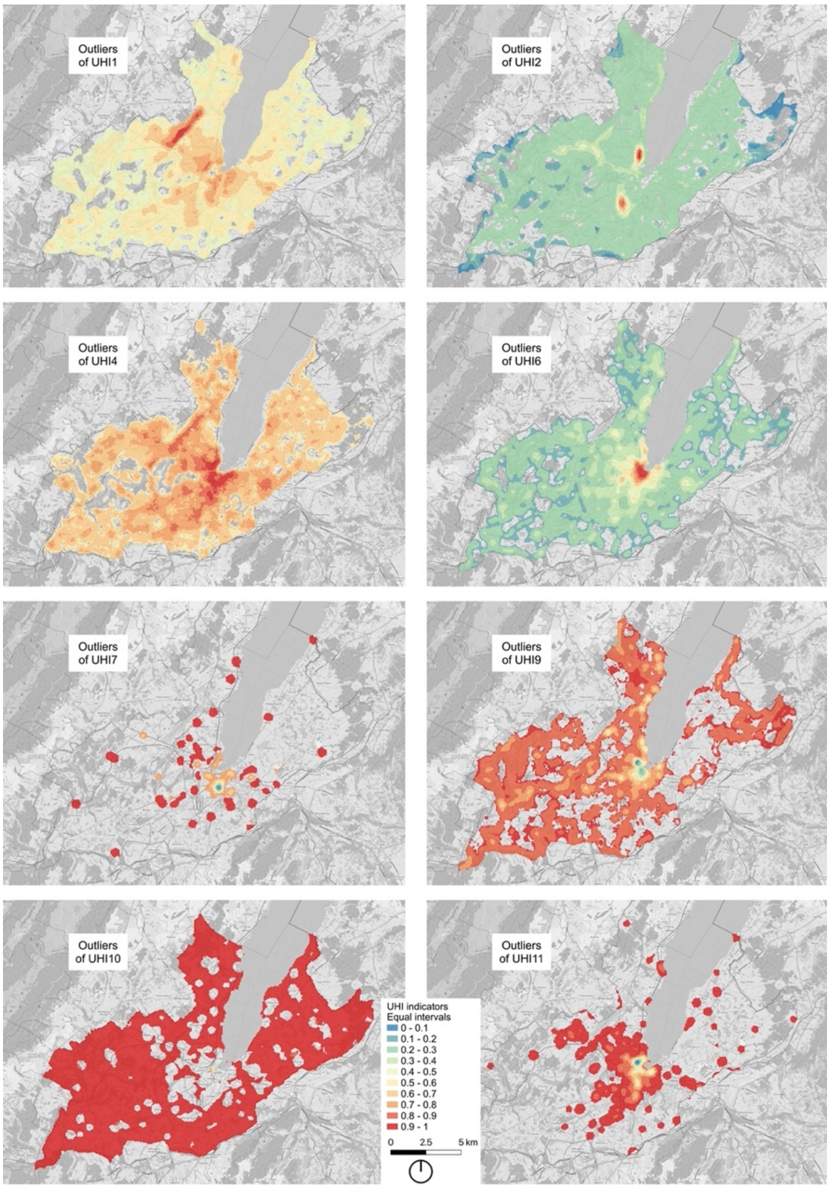


Figure 24: Extreme values identified by the Box function for eight of the eleven UHIs. We chose to not represent Values are classed by ten equal intervals identically per each map.

Because of the spatial pattern displayed by HBE index, in addition we show the change of the HBE index in function of the population and function (Figure 25 , on the left) of the distance from the city center (Figure 25 , on the right) for the SUs with positive residential population density. In the end, we performed a correlation analysis (Pearson) between all indicators (UHI indicators, domains and HBE index) to understand their relationship with population density, distance from the town centre and median revenue (characterized at the geographic level of the sub-statistical sectors displayed in Figure 26. Thus, the latter displays how issues are associated with different geographic contexts, with different residential densities and socio-economic status.

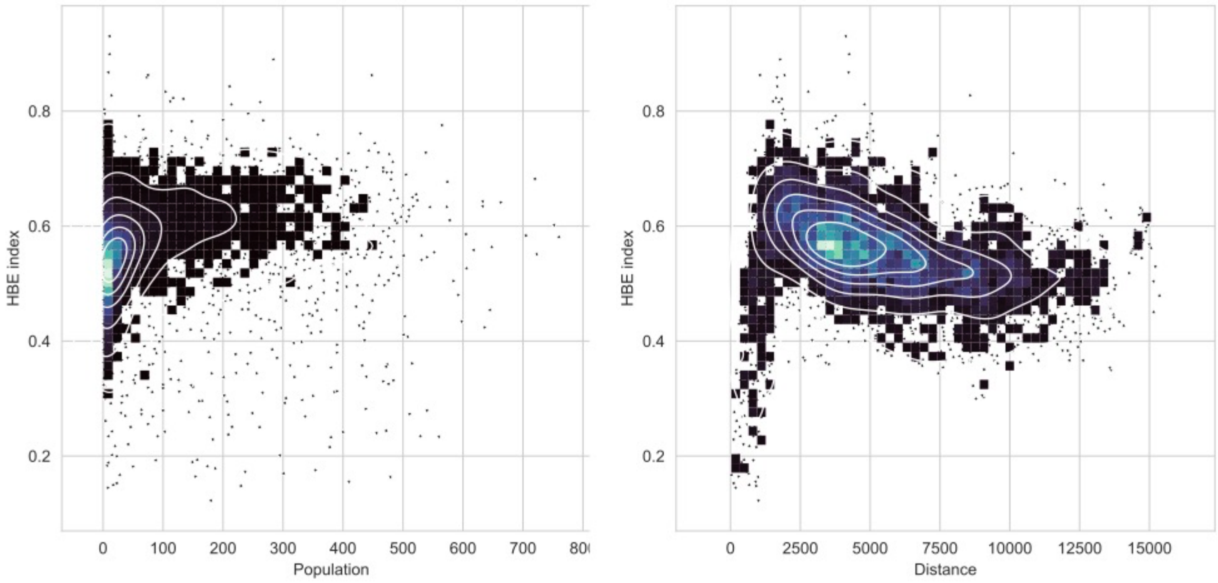


Figure 25: Density of SU by HBE index and residential population (left) or distance from town centre (right). The charts surpose a Kernel density plot on a scatterplot when at least 50 observations are concentrated. Pixels display the density of points (over the thresholds of 50 points) by colour. Five levels are used to describe the kernel density plot.

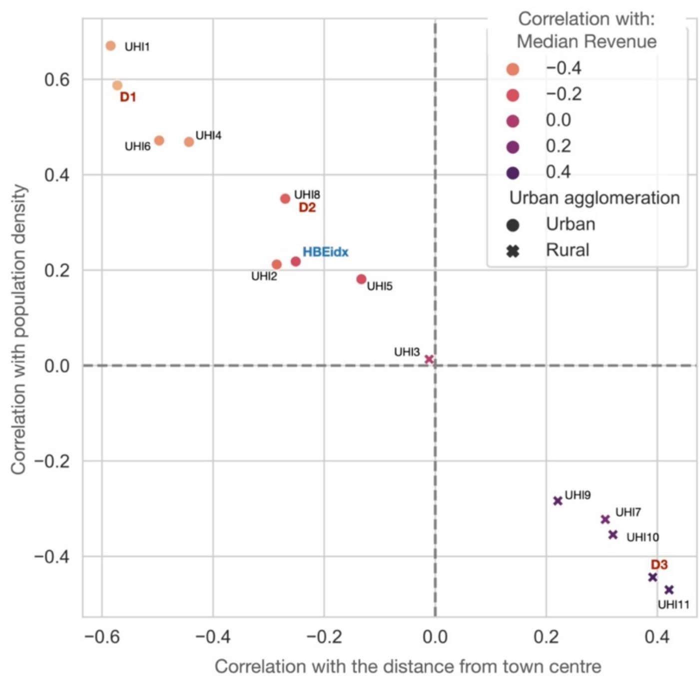


Figure 26: Correlation (Pearson) of UHI indicators (UHI), UHI domains (D), and the HBE index with distance from the town centre, population density, and median revenue. The points are classed as Urban or Rural, whether they were positively correlated with the membership to the urban agglomeration (marked with a dot) or negatively correlated with it (marked with a cross). The correlations are displayed for SU with non-null residential populations. The colour palette displays the approximative correlation with median revenue (at the spatial scale of the administrative units in Figure 12).

Correlograms and autocorrelation:

To understand if UHI indicators are randomly distributed in space, we calculated the autocorrelation of the latter in function of the distance (Euclidean). Autocorrelation between SUs is shown in the correlograms by increasing spatial lag (Figure 27). UHI indicators are split into two correlograms depending on their distribution: they decrease for five UHI in Figure 27 (left) or decrease and peak for six UHI in Figure 27 (right). At smaller distances autocorrelation values can be considered high, meaning that the UHI indicators' values are not randomly distributed in the geographic space. However, the autocorrelation is affected by the employment of kernel density estimators, meaning that Figure 27 includes the consideration of accessibility related to the spatial sub-division in small SUs.

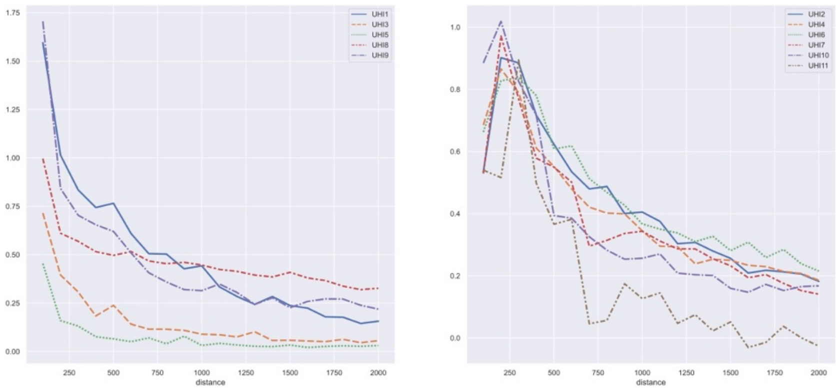
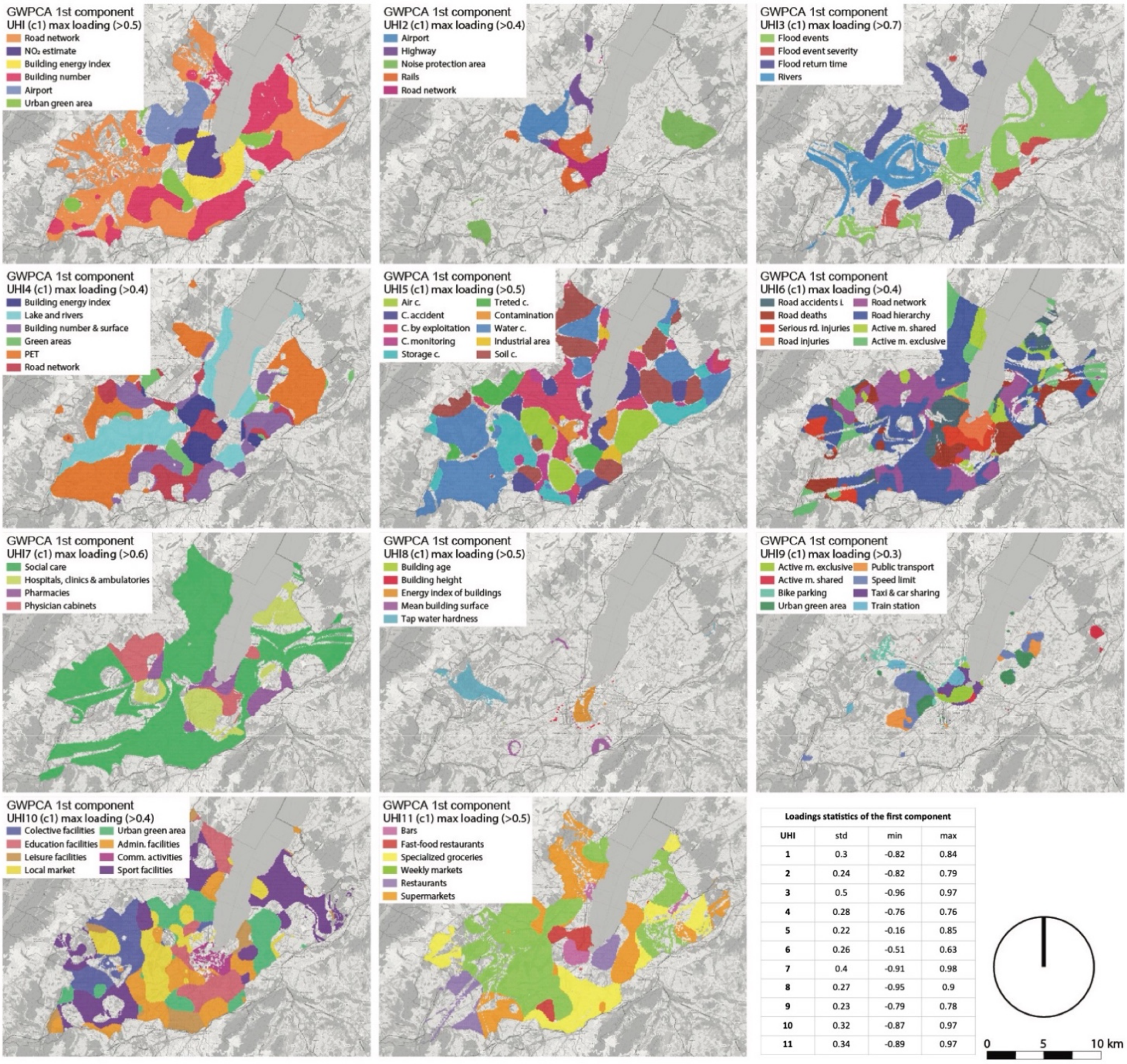


Figure 27: The autocorrelation decay by increasing spatial lag of UHI indicators (left) and the autocorrelation decay with a peak (right).

3.3.3 GWPCA results

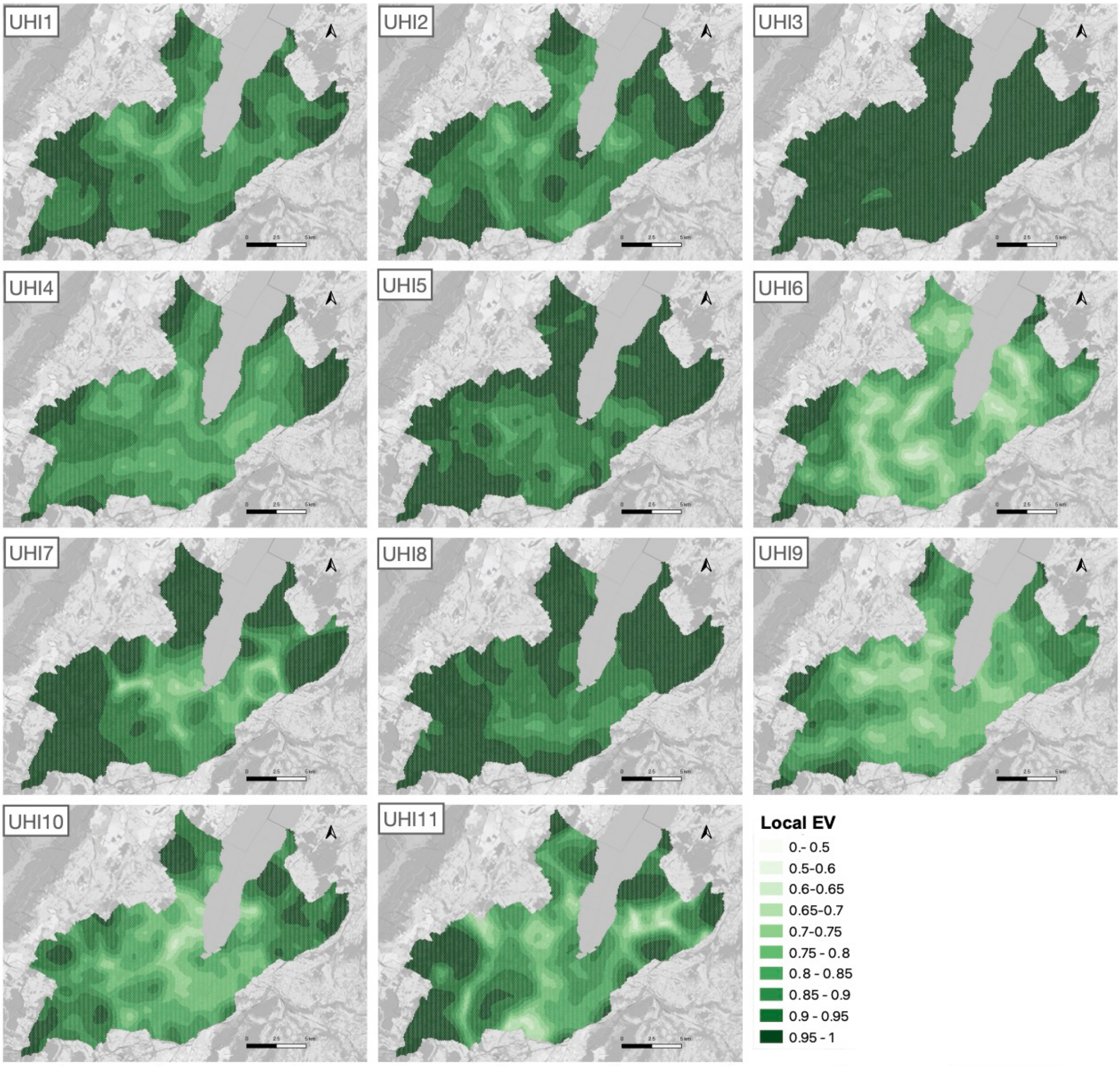
Contrarily to PCA, the outputs of the GWPCA allow to understand the spatial variation of local loadings and EV, thus of individuals loadings unique to a specific location. The Figure 28 shows the local loadings of the first component of GWPCA for the eleven UHI. We displayed only the maximum local loading per each UHIs that were greater than the PCA loading. In this way, we can observe from the maps the diversified patters of loadings, which are not stationary within the study area, neither display smaller values compared to PCA loadings. Only one HBE feature is identified as maximum loading in more than the half of the SUs (56.2%), the social-care services in the UHIs of healthcare accessibility. The Table attached to Figure 28 displays the descriptive statistic of the loadings of the first components. The multi-patch patterns of loadings show how spatial approach, do not average the variation of data, but represents the heterogeneity of the latter in the local geographic context. Then, the local EV (for the complete sets of components) is mapped in Figure 29 to visualize how GWPCA locally describe the variance of input variables in space. The Table of Figure 29 displays the descriptive statistics of the local EV of GWPCA. The local EV by GWPCA components can be considered high, and its mean values are greater than the PCA EV. Since it has not been proved yet under which assumptions GWPCA components could be aggregated, a direct amalgamation such as the one performed for PCA as not been performed. Afterward, the enhancement of Harris et al. (Harris et al., 2015) allows the computation of multivariate outliers considering all components (Figure 30). The local "discrepancy" describe the grade according to which values are locally different from neighbouring values but do not display directionality. However, the interpretation of discrepancies can rely on the values visualized by the HBE features in Figure 31. The latter, shows the profile of the HBE features used to generate principal components in the circled areas in Figure 30, compared to the values of all athers SUs. Indeed, those location display extreme values (low and high values) of only few BE features, while other features do not contribute to the identification of the multivariate outliers. The characterization of the outliers allow to understand not only what is related to discrepancy measure, but to understand also what neighbouring areas misses, hence to understand spatial gradients. Also, the discrepancy maps are coupled with a table of descriptive statistics for each UHIs. The correlations between the first components generated with PCA and GWPCA are displayed in Table 12. The two methods provide a different interpretations of the HBE, which can be correlated if the local variation is similar to the global variation within the study area depending on the UHI.



Loadings statistics of the first component

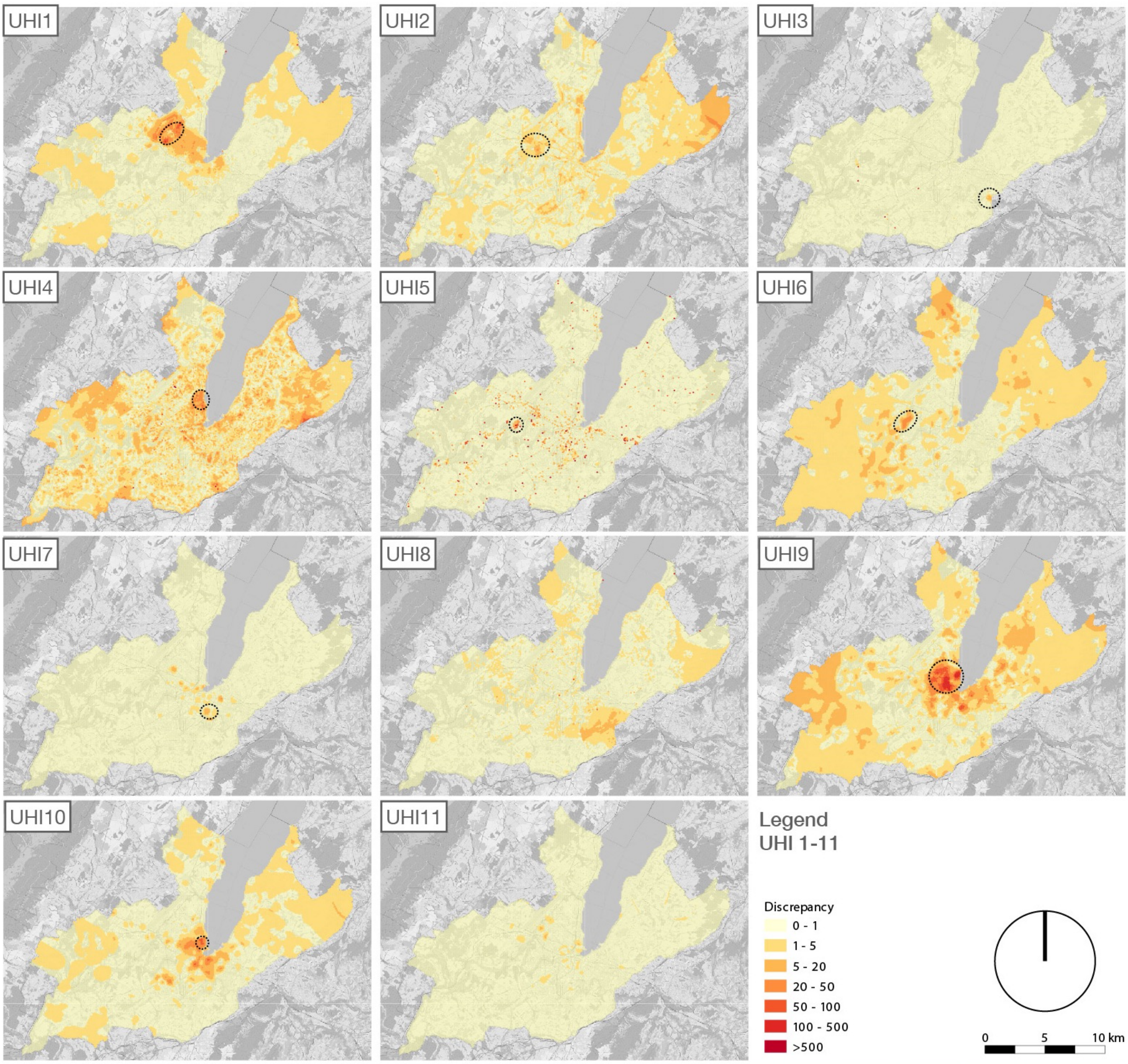
UHI	std	min	max
1	0.3	-0.82	0.84
2	0.24	-0.82	0.79
3	0.5	-0.96	0.97
4	0.28	-0.76	0.76
5	0.22	-0.16	0.85
6	0.26	-0.51	0.63
7	0.4	-0.91	0.98
8	0.27	-0.95	0.9
9	0.23	-0.79	0.78
10	0.32	-0.87	0.97
11	0.34	-0.89	0.97

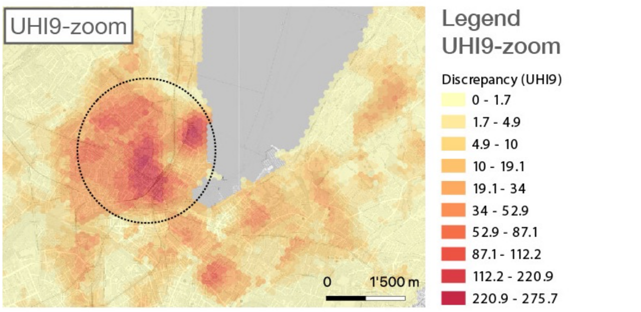
Figure 28: Maximum local loadings by GWPCA. The local loadings are displayed whether they shown values greater than the PCA loading for each respective UHI. The attached table in the corner shows the descriptive statistics of loading for each UHI.



UHI	mean	std	min	25%	50%	75%	max	EV(PCA)
1	0.92	0.05	0.75	0.89	0.93	0.95	0.99	0.73
2	0.92	0.04	0.75	0.9	0.93	0.96	0.99	0.76
3	1	0.01	0.89	0.99	1	1	1	0.75
4	0.89	0.05	0.75	0.85	0.88	0.93	0.99	0.7
5	0.95	0.04	0.81	0.92	0.96	0.99	1	0.73
6	0.81	0.08	0.63	0.75	0.81	0.87	0.99	0.75
7	0.92	0.08	0.67	0.87	0.95	0.99	1	0.8
8	0.95	0.04	0.82	0.93	0.97	0.98	1	0.83
9	0.84	0.07	0.65	0.79	0.84	0.89	0.98	0.73
10	0.86	0.07	0.64	0.81	0.87	0.93	1	0.73
11	0.88	0.08	0.61	0.82	0.88	0.95	1	0.74

Figure 29: Local explained variance (EV) by GWPCA. The Table shows the descriptive statistics of the local EV calculated with GWPCA and the EV calculated with PCA. Values of local EV are classed in ten equal intervals identically per each UHI.





UHI	mean	std	min	25%	50%	75%	max
1	1.55	4.71	0.0	0.2	0.67	1.32	178.76
2	1.43	2.63	0.0	0.12	0.62	1.6	33.33
3	0.2	8.71	0.0	0.02	0.09	0.09	879.33
4	3.61	15.38	0.0	0.38	1.59	4.39	1879.06
5	3.3	74.3	0.0	0.06	0.1	0.16	5214.77
6	2.21	2.61	0.0	0.48	1.81	3.07	41.29
7	0.13	0.59	0.0	0.02	0.06	0.13	21.93
8	0.69	3.41	0.0	0.13	0.4	0.9	431.75
9	4.0	11.45	0.0	0.53	1.79	3.57	275.71
10	1.4	3.5	0.0	0.12	0.59	1.52	75.39
11	0.31	0.37	0.0	0.03	0.22	0.52	7.44

Figure 30: Multivariate outliers identified by the local discrepancy calculation obtained with GWPCA. The table attached above the maps collects the descriptive statistics of the discrepancy's values per each UHI. The circled area corresponds to the elements showing high discrepancy values, whose composition is highlighted in the parallel coordinates plot in Figure 31.

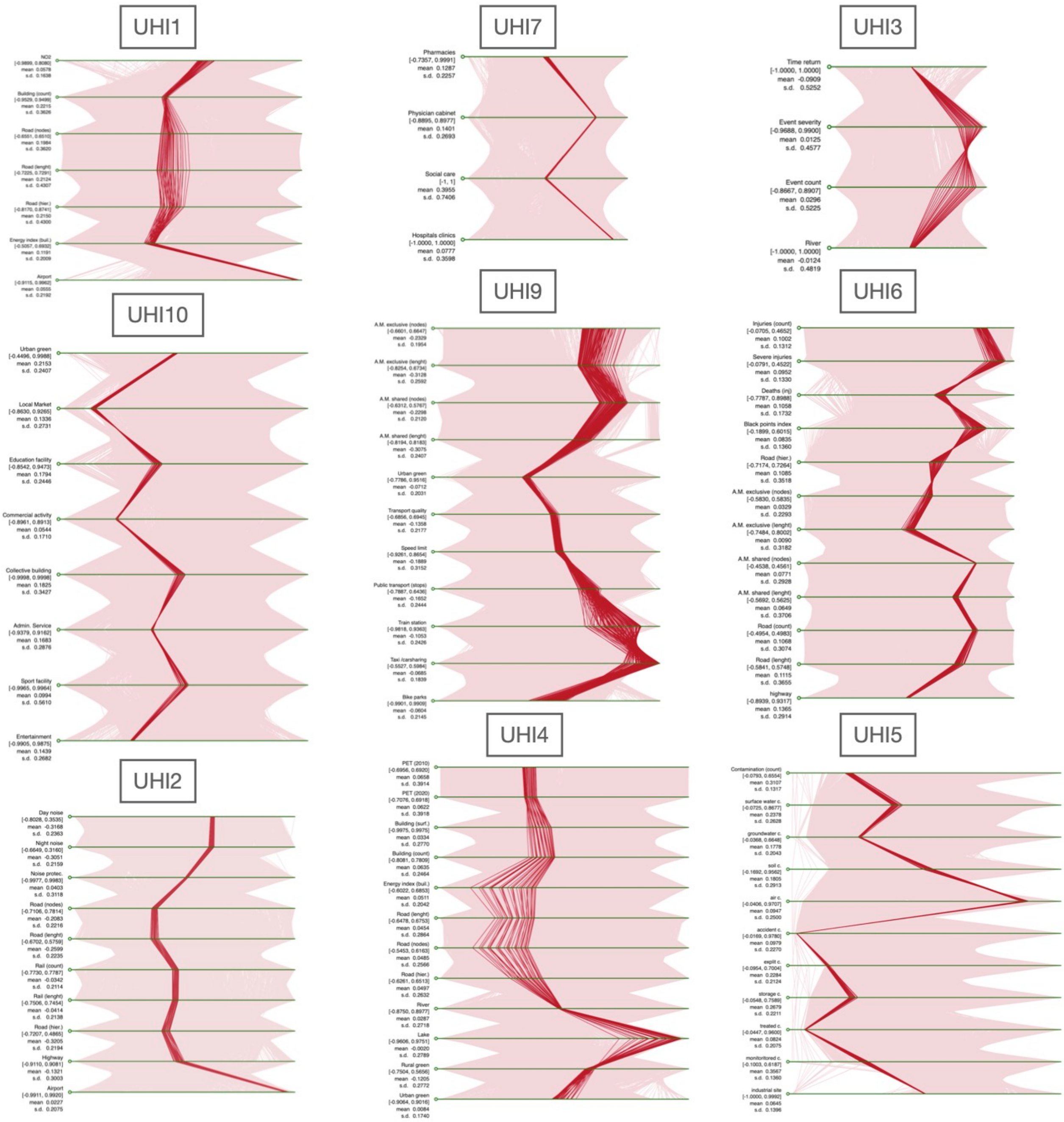


Figure 31: Parallel coordinates plot of the HBE features' values within the circled area displayed in the map of multivariate outliers calculated with GWPCA. The circled areas were chosen due to higher level in discrepancies, meaning that those areas were significantly different from the others within smaller spatial lag the chosen one (400m). The dark red lines display according to which HBE feature values, those circled areas differs from the rest of the study area SUs which are shown in pink. Therefore the plots displays which HBE features values are highly heterogeneous in space for each UHIs, and if those values are higher or lower than the others. The ordering of HBE features is casual for each UHI.

UHI	Spearman c.	Pearson c.
Air pollution (1)	0.56	0.6
Noise pollution (2)	-0.25	0.08
Flooding (3)	0.08	0.11
Urban heat island (4)	0.44	0.44
Contaminated land (5)	0.91	0.94
Road injuries (6)	0.63	0.69
Healthcare service acc. (7)	0.62	0.76
Indoor environment (8)	-0.6	-0.48
Active mobility (9)	-0.48	0.1
Community places (10)	0.61	0.37
Food environment (11)	0.79	0.94

Table 12: Correlations (spearman and Pearson) between PCA and GWPCA first components for each UHI.

3.3.4 Global disparities

The inequities in HBE observed in the study values can be studied by rank distribution charts. Hence, the disparity ratios and slopes were calculated from the respective rank distribution charts (Figure 32). In addition, since the study area includes rural areas or in the general area without settlements, the rank distribution charts, disparity ratio and slopes were calculated for the urban agglomeration only (Paragraph 3.2.3) by displaying the population density in each SU (Figure 32). Similarly, rank distribution charts, disparity ratio and slopes were calculated by combining GWPCA components with geometric mean within the urban agglomeration (Figure 32). The latter provide a global interpretation of the local inequities but are not representative of the total inequities in the study area.

	UHI ind. (PCA)		UHI ind. (PCA) urban agglomeration		GWPCA components mean urban agglomeration	
UHI	D. Ratio	D. Slope	D. Ratio	D. Slope	D. Ratio	D. Slope
1	1.49	0.09	1.54	0.14	4.16	0.37
2	2.22	0.07	1.88	0.08	4.32	0.42
3	2.72	0.03	2.85	0.03	1.17	0
4	1.89	0.2	1.74	0.17	3.75	0.53
5	1.08	0	1.13	0	1.06	0
6	3.71	0.16	3.47	0.19	2.34	0.23
7	1.09	0	1.25	0.03	1.91	0.11
8	3.79	0.18	3.57	0.13	4.1	0.49
9	1.29	0.1	1.47	0.15	6.85	0.45
10	1.17	0.02	1.31	0.07	1.94	0.21
11	1.14	0.01	1.3	0.06	2.24	0.08

Table 13: Disparity ratios and slopes for UHI indicators for the whole study area and for the urban agglomeration only.

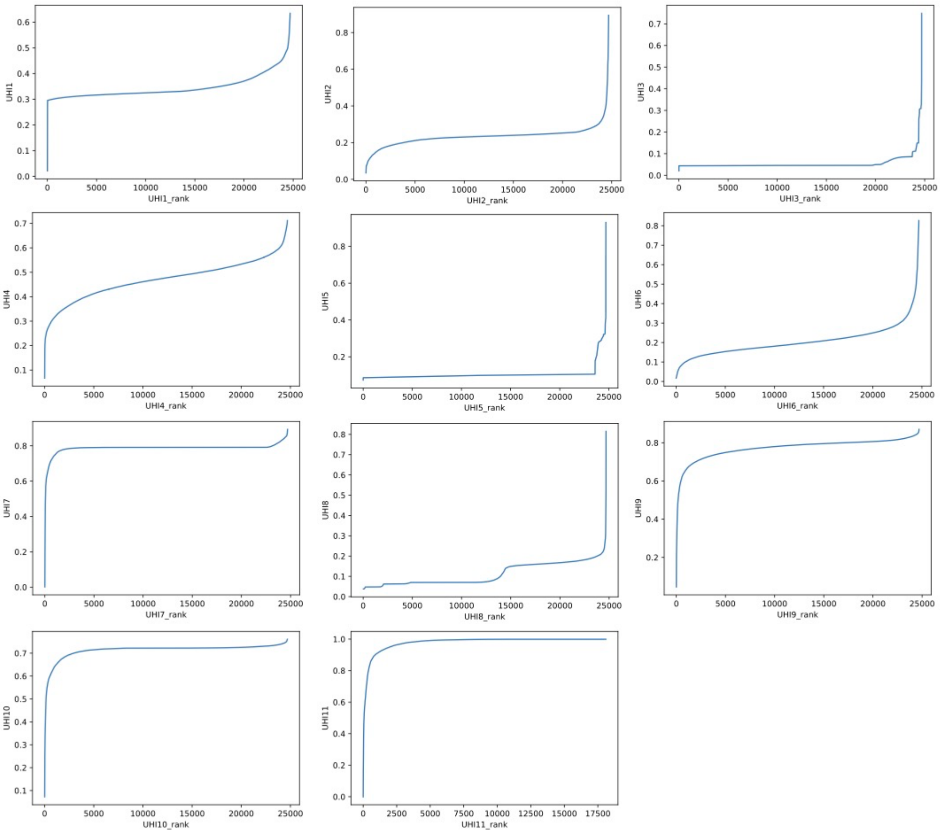


Figure 32: Rank distribution chart for each UHI indicator.

3.4 Discussion

Global approach

Multiple composite indicators were created using a global and a local statistical method to represent the HBE features within canton of Geneva following the UHI framework created in Chapter 2. The application of the statistical methods for dimensionality reduction, followed the spatial aggregation of HBE features at the scale of one-hectare SUs; with the intention of addressing issues such as the Modifiable Areal Unit Problem (MAUP) and the Uncertain Geographic Context Problem (UGCP). The use of PCA provided dimensionality preserving at least the 70% of variance in HBE features. The first component alone already provides a good insight into each UHI since it explained at least 34% of the variance, with an average of 48%, making it suitable for a general understanding of UHI (Table 8). The loadings of major components (Table 10) allow the interpretation of components for each UHI. The road network significantly contributes to multiple HBE features, for Air pollution, Noise pollution and Urban Heath Island. The first components of the latter explain principally the sources, whether environmental estimates were represented mainly by the second components or had smaller loadings. The Flooding components respectively described independently past events, water bodies, and modelled flooding areas. Similarly, the components of Contaminated land differently characterised contaminated sites depending on the source, the state, and the natural mean of contamination. Road injuries first components gather shared active mobility networks with road nodes number and injuries events. The latter suggest a higher prevalence of road accidents between different transportation modes, thus between when network host both motorised and cycling or pedestrian networks. The healthcare accessibility first component gathers different services: physician cabinets, pharmacies, hospitals, clinics, and ambulatories. The Indoor Environment first component merges different building quality proxies: residential building height, age, and energy consumption index. The Active Mobility components differently address the multimodal active transportation and thus commuting mobility; the exclusive active mobility network which may represent mobility for recreational purposes; and the exchange facilities for active mobility. The Community places components differently collect public services, commercial activities, and sports facilities. The Food environment UHI was described by one component, which concatenates all food facilities, so that its low values identify food deserts (Shannon, 2014). Healthcare accessibility and Community places identify controversial hot spots in the peri-urban area due to the negative correlation between HBE features. The negative correlation between HBE features creates the misconception that those locations have an adverse impact greater than rural areas where these services are absent. The HBE features contributing to those hot spots are social care facilities for healthcare accessibility and sports facilities for Community places, which are characterised by negative loadings (Table 10). This issue can be solved by merging HBE that we assume have similar impacts (either positive or negative) on health. However, this approach reduce the information carried by those HBE features.

In brief, the first components of the PCA (Figure 20) display three generic spatial patterns in representing the potential impact of HBE, which can be deduced by the discording correlations and by visualising the different spatial distributions:

1. **Centralised hotspots:** A centralised adverse impact for Air Pollution (UHI1), Noise Pollution (UHI2), Urban Heat Island (UHI4), Road injuries (UHI6) and Indoor Environment (UHI8).
2. **Centralised coldspots:** A centralised beneficial impact for healthcare accessibility (UHI7), Active Mobility (UHI9), Community places (UHI10), and Food Environment (UHI11). Second, the spatial patterns of those UHIs appear to be distributed throughout several small centres.
3. **Decentralised distribution:** A contextual distribution of adverse impacts for Flooding (UHI3) and Contaminated land (UHI5).

This spatial distribution is related to the monocentric pattern of the urban gradient widely observed in ecological research of urbanization (Alberti et al., 2001; Mieszkowski and Mills, 1993). Overall, this general spatial distribution is conserved by combining all principal components in UHI indicators (Figure 22) and combining the latter in the three domains (Figure 23). The first two spatial patterns are related to the urban advantage and penalty (Choi et al., 2015; Freudenberg et al., 2005) in the first components, UHI indicators and domains. The urban advantage is linked with the potential accessibility to services which contributes positively to health and wellbeing, while the urban penalty is linked with the secondary effect of higher density of impacts generally related to human activities and urbanisation (Choi et al., 2015). In the first components and indicators, UHI related with penalties are positively correlated between them and negatively correlated with UHI related to advantages (Figure 20 and Figure 21). The UHI related to more centralised services are the ones that are only partially regulated by planning or depends on market demands, such as in the case of the spatial distribution of pharmacies or the distribution of restaurants. The UHI, which display a contextual distribution of adverse impacts (UHI3 and UHI5), are related to natural risk and its management for Flooding and with the zoning of human activities that are located and were in different areas of the study area.

The outliers of UHI indicators identified by the Box function for eight UHI (Figure 24) are characterised by different threshold and covers different proportions of the study area. The thresholds values were narrow in the case of UHI7, UHI10 and UHI 11 due to the imbalanced distribution of data. In general, the other outliers are differently identified as cold or hot outliers, mainly located in the town centre of Geneva, due to the concentration of human activities, which brings both advantages and penalties. The representation of the rails by their density rather than its availability overweighted the hot spots of Noise Pollution in two areas, the train station, and the railway freight yard.

In the end, the contributes of services in terms of advantages and the adverse impacts of dense urban areas are summarised by a single indicator, the HBE index (Figure 23). The domains equally contribute to the HBE index regardless the number of issues, and we can observe how the advantage of services is predominant in the core of the city but quickly decay, moving further from the geographic centre of the canton of Geneva. The cold spots can be identified within the area of the urban agglomeration: the river areas on the west and south-east of the town centre, the area on both the lake banks. Those area are not accessible but creates a discontinuity in the urban texture within the urban agglomeration. The proximity to the waterbodies within the urban agglomeration display lower values in the HBE index, because HBE linked to of exposures suddenly drop while preserving the accessibility to services. However, this outcome does not provide a useful information to the spatial planning except in the case of great changes in the BE of the urban agglomeration.

The distribution of the HBE index against the residential population density display how dense SU are characterised around 0.6, while low-density SUs displays a more significant variation in the HBE index (Figure 25). Therefore, this distribution suggests that the denser residential areas are, higher are the adverse impacts of the HBE, and this relation tends to a horizontal asymptote. Then, less dense regions exhibit a wide range of potential HBE impacts, but they are concentrated around HBE index values below the asymptote for high density areas. The HBE index in function of the distance from the geographic centre of the canton displays how a small number of SUs (with non-null population) can profit from low values. Instead, HBE index values increase with distance until reaching a peak at approximately 1800m and after shows a gentle slope that tends to get flat at approximately 10 km. This distribution of values summarises the previous observed variation in urban health issues which trade-off between urban advantages and penalties.

In the end, the relationship between all indicators (the UHI indicators, the domains and the HBE index), town centre distance, population density, and median revenue is displayed by Figure 26. The latter shows how the two categories related to urban health advantage and penalty split into two different quadrants and line up on the same axis consequently the radial variation of HBE. Therefore, adverse impacts of exposures and injuries are higher in densely populated areas and closer to the town centre. Instead, adverse impacts related to the lack of services are further from the town centre and affect low-density areas. Also, the correlations with the median revenue (at the geographic level of sub-statistical units, Figure 12) decrease along the axis on which the points are aligned. The first and second domains, and respective UHI indicators, display adverse impacts where revenue is low, and the third domain displays adverse impacts where revenue is higher.

The UHI indicators are heterogeneously distributed as suggested by the decay of mean autocorrelation. The latter is low only for spatially scattered UHI (Flooding and Contaminated Land), and the Food Environment due to the high share of null value in SUs. Five UHI shows a steep drop in mean autocorrelation by increasing spatial lag (Figure 27 left), while six UHI display a peak between 200 and 300m, suggesting the presence of multiple homogenous centres (Figure 27, right). This finding is coherent with the smoothing effect of the spatial interpolation of discrete values, which assigns weights above 0.5 within 300 m of distance (Paragraph 3.2.2).

Local approach and heterogeneity

The results of PC allowed a global analysis of HBE within the study area, synthetising the HBE feature regardless the spatial context. Afterward, we adopted a local method, the GWPCA, which was performed by gathering the same HBE features to generate the same number of components per UHI calculated with PCA. Firstly, GWPCA outperform PCA in explaining data variability across all UHI by using the same number of components (Figure 29). Indeed, the average of cumulative local EV of GWPCA is 15% higher than the EV with PCA. Similarly, the average of the local EVs of the first components of GWPCA is 9% higher than the one of PCA. Also, GWPCA reaches cumulative local EVs above 95% in large areas and across multiple UHIs (Figure 29).

Then, we shown the maximum loadings of GWPCA (Figure 28) to display the heterogeneous distribution of how HBE contributes to the first principal component of GWPCA. The loadings of PCA are not coherent with the loadings of GWPCA within the urban agglomeration. For example, for the Air Pollution, the PCA identify road characteristics as the most relevant loading, which according to GWPCA is the major loading for rural areas. Instead, for Air pollution, GWPCA identifies NO^2 estimate and building characteristics as the main contributors to data variability in the first component. The map of maximum loadings allows the visual interpretation of maximum loading of GWPCA for all UHIs, showing how the local maximum loading concerns all variables contributing to the first component generation depending on the location. The PCA deliver a global interpretation of HBE, thus depending on values across all study areas, so that all SUs is compared together. Instead, GWPCA delivers a local interpretation of GWPCA, thus comparing differences in the HBE depending on the areas that are closer or accessible, whether the chosen bandwidth is representative of the activity space. The HBE can be considered heterogenous within the study area since all local maximum loadings, lists at least half the HBE features required to calculate that component. This finding is visually outlined by the complex patch-pattern of maximum local loadings. Also, the variability of loadings values is high across all loadings due to the observed high standard deviation (Figure 28). The improved performances of GWPCA compared to PCA and the understanding of spatial heterogeneity in data, are common findings in the application of GWPCA which outline the limits of spatial-unaware methods on spatial data (Benita et al., 2020; Chi et al., 2013; Harris et al., 2015; B Lu et al., 2021; Saib et al., 2015).

The measure of local discrepancy is mapped in Figure 30, providing the identification of the location of multivariate outliers (by using all components of GWPCA). The UHI3, UHI7, UHI8 and UHI11 displays low values (means below 1). To understand the directly nature of the multivariate outlier, the parallel coordinates plots display the standardised value of the HBE feature in a chosen location that displays a high value of discrepancy; for nine of the eleven UHI. The discrepancy identifies an area in which values are more variable in short distances, and the parallel coordinated describe which features are different for the selected location. For example, the multivariate outlier of UHI9 displayed in the zoomed map of Figure 30, is characterised by high values in multiple features: active mobility networks (both exclusive and shared), train station and taxi areas and carsharing services. These values are high since the multivariate outlier is located on the central train station of the canton of Geneva. However, the outliers are identified because of the local variation HBE features. In brief it tells also that the values observed in neighbouring area are significantly different. This example is coherent with the outliers of PCA, for UHI9 (Figure 24). The latter shows how the cold spot located on the train station is characterised by low values and those vary in short distances. The higher disparities founded at the local level, when linked to adverse impact can quickly profit from proximal areas. However, this solution does not consider differences in mobility between close areas. Indeed, the latter can be affected by physical constraints even regardless the short distances, such as rivers or road networks with higher hierarchy.

The PCA and GWPCA have different findings, both fundamental in capturing differences in the HBE within the study area at global and local level respectively. The relationship between findings is measured by the correlations (Pearson and Spearman) between the first components of PCA and GWPCA. The UHI4, 5, 6, 7, 10 and 11, reports a good agreement in both values and rank. Instead, other variables have either inconsistent or negative correlation, i.e., Indoor environment.

Disparities

Most rank distribution charts of UHI indicators for the study area predominately flat, so calculated slopes are below 0.21 (Figure 32). The highest discrepancy slope is indicated for Urban Heat Island, indicating that this is the issue most likely to cause health disparities throughout the entire population.In fact, the UHI also display a high mean value of discrepancy, meaning that its composing features display a high variability also at local level (Figure 30). The steeper slope is also related to the variety of contributors: in fact, Urban Heat Island features do not simply gather characteristics of urbanisation such as heat source (i.e., human activities) and heat storage (hard surfaces), but heat wells (i.e., water bodies and green areas), which are located within the urban agglomeration. Therefore, the proximity to these urban Heat Island antagonists affects how the population could be exposed to extreme temperatures. Similarly, the Road Injuries UHI display a non-null disparity slope, which is explained by the occurrence of injuries in different areas of the study area, rather than being spatially concentrated. This finding is coherent with the differences observed in loadings of the first two principal components of PCA. The first one is related to the coexistence of shared mobility, road nodes and the frequency of injuries, which are high in the inner part of the city (Table 10). In contrast, the second one, gathers both highway and low road hierarchy, which are in the more outer urban agglomeration (map not shown). In another case, the disparity slope is misleading after observing the rank distribution chart. The Indoor Environment displays a slope of 0.18, which is caused by the central "step" of the rank distribution. The latter is likely to be derived by including areas with null values, thus areas that are not built, mainly outside the urban agglomeration. This net difference is probably the product of the lack of spatial interpolation in aggregating spatial data for the Indoor Environment UHI.

The disparity ratio instead identifies inequality in extreme values, so that, for example, a value of 1.5 indicates that the upper decile of a UHI indicator is 50% greater than the lowest decile. The highest values are reported by Road Injuries (3.1), Noise Pollution (2.22), Urban Heat Island (1.89) and Air pollution (1.49). The disparity ratio displayed by these four UHI is likely to be generated by the HBE features related to the road network since they are the only UHI integrating them and since all share only those HBE features. However, the hot spots/outliers of this UHI are located slightly differently within the study area, depending on the other HBE features. The higher is disparity ratio, the higher are the inequities between the healthiest areas and least healthy ones. On one hand, a high disparity ratio suggests that limited areas might have lacked planning interventions capable of delivering healthier BEs. On the other hand, if inequality is displayed only by the disparity ratio, planning can act quickly by addressing priorities only in those limited areas. The unbalanced distribution of data causes the high values of disparity ratio displayed by UHI3 and UHI8. The latter present an unbalanced distribution due to the lack of interpolation and the choice of a small-scale SU.

While slope identifies disparities in the central distribution, the height of the same central distribution means that high values characterise most SUs, thus adverse impacts, such as for UHI7, 9, 10, and 11. That is the case of the HBE related to services, which are absent in many rural areas. To understand how it affects areas characterised by non-null values, we calculated disparity ratios and slopes for the area of the urban agglomeration only (Table 13). Overall, disparity slope was robust to the exclusion of rural areas. Instead, part of the disparity ratios increased, hence for Road Injuries (3.47), Air pollution (1.49) and Active Mobility (1.47). Instead, Noise pollution (1,88) and Urban Heat islands weakly decreased. In addition, we calculated the disparity slope and ration within the urban agglomeration by using the geometric mean of the GWPCA components. Since the GWPCA is a local method, it cannot account for the global inequities in the study area but allow the synthesis of the local inequities. After using a local approach to represent the HBE, such as GWPCA; disparities increase across the whole set of SUs, generating higher slopes than PCA on the urban agglomeration. Also, disparity ratios increased, displaying an average of 3.07 compared to 1.9 given by PCA. A significant increase is observed in both the Active Mobility disparity ratio and slope calculated with GWPCA, which rank the first and second values, respectively among the UHIs. Indeed, Active mobility previously displayed the highest mean discrepancy values for GWPCA components. The measure of disparity ratio and slope has been applied in few other studies characterised on different application. For example, the measure of disparity using seven health determinants in the urban area of Atlanta (USA), displayed a disparity ratio of 5.92 and a disparity slope of 0.54 (Rothenberg et al., 2014).

The study of Khan et Hussain about social and living standards in Pakistan at regional level, reported a disparity ratio of 16.95 and disparity slope of 0.38 (Khan and Hussain, 2020). Bortz et al. employed the same measurement to understand the change in health inequalities among eight indicators in Rio de Janeiro, identifying a decrease in in disparity ratio from 1.57 to 1.32, and in disparity slope from 0.23 to 0.16 between 2002 and 2010 (Bortz et al., 2015). To gain a thorough knowledge of the disparity ratio and slope, further empirical examples should be compared (Rothenberg et al., 2014).

Limitations, strengths and applications

The study presents various limitations and strengths.

The choice of small SUs was not compensated by the spatial interpolation for Indoor environment, Contaminated land and Flooding, which significantly affected the statistic calculations. These UHIs could be spatially interpolated even if the interpolation is meaningless; or they might be analysed directly using disaggregated geospatial data, if the direct comparison to other geospatial data is not needed (Verstraete, 2017).

The definition of neighbourhood, or more precisely of what is local or not; is defined by a chosen distance representative of the activity space defined by walking distance (Paragraph 3.2.2). The neighbourhood definition could be larger, i.e. in case of cycling mobility, either smaller, by accounting for physical constrains (i.e., rivers and main roads) or for reduced mobility. Additionally, this assumption defines a radial activity space (on the network) that ignores the way BE shapes activity space in terms of destination (Liu et al., 2020; Matthews and Yang, 2013).

Multiple limitations are related to the data employed in the study. The HBE representation was based on existing opensource data which are updated at different years, so the geospatial data may not be coherent in time. Then, most of geospatial data lacks qualitative representation of an HBE, which may be relevant to understand its relationship with individuals and their health. For example the aesthetics of BE is relevant in predicting physical activity (McCormack et al., 2004). The study use objectively measured HBE attributes, but it could be integrated with perceived or subjective data to better study the pathway to health (Roda et al., 2016), but also to integrate participation (Sallis et al., 2016).

In addition, the spatial analysis of qualitative dataset could be implemented using models of potential accessibility to services, which are widely used in the context of healthcare services (Apparicio et al., 2017; Kelly et al., 2016a). However, the latter have not been adapted yet for a multi-attribute problem. Overall, HBE dataset lacks information when related to private properties. In particular, the Indoor environment, describe housing characteristic through proxies rather than through the characteristics have a direct impact on health, i.e. dampness issues or thermic insulation (*WHO*, 2018b). Other UHI lacked the unavailability of geospatial data, such as noise level of aircraft transportation, which is reported to be relevant for the study area (Canton de Genève, 2020; Ville de Genève, 2017). Otherwise, air pollution environmental measures rely on geospatial data with a coarse geographic resolution, and which represent only one pollutant, which might be not sufficient to understand any spatial variation within the canton of Geneva.

The PCA deliver a misleading information when at least two HBE feature that are expected to contribute similarly to health, are negatively correlated because they occupy different locations (Demšar et al., 2013). Another intrinsic limitation of both PCA and GWPCA models, is that input data require to be aggregated for each observation, and thus are not implemented with spatial sampling method to deal directly with disaggregated data (Verstraete, 2017).

This study provided a representation of the HBE on fine geographic scale from disaggregated data for a broad range of attributes. We considered proximity of features by using a spatial interpolation weighted by network travel time or linear distance, so that the HBE feature density take into account all neighbouring features, rather than the nearest. These two approaches aim to tackle two issues related to spatial analysis, MAUP and UGCP.

The PCA methods is suitable for this study because it conserves the variability of data so that differences between observation can display inequities. Otherwise, different statistical methods could be used to consider for the cumulative effect of multiple attributes whether the latter represents different pathways of health impact. The methods used in this study can be retrieved with updated dataset, extended by additional data, and it is also suitable to be implemented in software package. The use of additional data can be implemented for specific UHIs that are considered a priority after a first screening analysis of the HBE. Explore difference at global and local level can drive intervention through spatial planning in many ways. Firstly, the spatial analysis identifies differences in HBE and their spatial patters, so that intervention can precisely address the identified priorities. Additionally, this approach enables comprehension of local variance in HBE by illustrating how HBE changes within the studied area. The local spatial analysis enables comprehension of how those changes take place within short distances, avoiding to compare geographic areas that are geographicly distant. In this instance, treatments may not be necessary if the locations exhibiting significant variations between them are mutually accessible. The measure of disparities allows to visualise how those inequities are distributed, therefore to understand when interventions need to address only limited areas where HBE are particularly unhealthy, or interventions need to be addressed in a wide range of locations. This approach also allows to compare how findings different across multiple issues of urban health, so that any relevant issue is forgotten a priori. This screening approach on multiple issues of urban health, is suitable for monitoring the HBE development, or even to understand the changes introduced by new projects and programs.

3.5 Conclusion

This study adopted local and global methods to represent the characteristics of the HBE in the canton of Geneva. The HBE has been represented adopting the framework previously created for a generic case study, and representing eleven UHIs related to hazardous exposures, healthy behaviours, and accidental injuries.

The application of both statistical methods, allowed to summarise the HBE by synthetic indicators by preserving the information of geospatial data, and the GWPCA provided a more accurate representation of HBE features compared to PCA. All components of PCA carry a useful information because they summarise different mechanisms related to each issue, i.e., the commuting or recreational active mobility. The spatial arrangement of components and the resulting indicators display the two sides of urbanisation which are negatively correlated and broadly monocentric: the advantages related to services and the penalties related with secondary effects of denser human activity. The potential beneficial effect of the first decreases moving further from the municipality of Geneva, while the adverse impact of the second decreases. Issues related to Flooding and Contaminated Land instead are contextual to specific sites within the study area.

The PCA allow the combination of components to merge principal components into UHI indicators, into three domains of UHIs, and into a single HBE index. The UHI indicators are not randomly distributed in space and tend to display high autocorrelation in short distances. The HBE index summarises the stratification of all UHIs, so that higher values represent unhealthy settings and lower values healthier settings. The HBE index spatial arrangement displays the most unhealthy areas are characterised by a higher residential population display unhealthier HBE compared to low-density areas. Also, the greatest values in the HBE index are located, in terms of radial distance from town centre, at approximately 1800m, and slowly decrease moving away from it. The UHI and respective domains display a relation with the median income of resident population, so that issues related to exposure to unhealthy environments, to accidental injuries and unhealthy housing are greater in low-income areas, while high-income areas lack the access to public service which can facilitate healthy behaviour. The geographic weighted method by using the same number of components showed how the variability of HBE is heterogeneous in the study area, so that more than half of HBE features significatively contributed to the local variation of principal components. The local differences in HBE provide suggest that the drivers of health inequity related to BE within the study area depends on the location and cannot be assumed to be stationary in space. This finding highlights the advantage of using multi-attribute approach rather than representative single measures of the HBE. Also, the magnitude of spatial variation of HBE is particularly high in determined location as displayed by the multivariate outliers.

In the end, the greatest inequalities are observed in Urban Heat Island and Road Injuries, Noise pollution and Air pollution across the whole area or within the urban agglomeration. The findings of GWPCA and PCA display a different complementary information, which differently correlated depending on the UHI. While GWPCA delivers better results, it also delivers a complex finding that is prone to be used for explorative purposes. Instead, the global approach allows the comparison of all locations between them. The analysis of the HBE would take advantage of a geographic weighted method that go beyond explorative purposes, and that do not require the spatial aggregation of environmental characteristics.

Furthermore, this study has been limited by the characteristics of opensource existing data, which specially affected housing characterization, and generally lacked information about the quality of the HBE. The spatial analysis of the HBE could be improved by incorporating two additional pieces of information: a time-series of the HBE to understand its evolution, a better knowledge activity space to model the HBE to which individuals are exposed, and geospatial health data to understand the relationship between them.

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Chapter 4 Viewpoints on urban health issues and healthy planning integration

Abstract : In this chapter, we studied perspectives on urban health in three groups of stakeholders: experts in urban health, planning practitioners and the local community (citizens of the canton of Geneva). Using a structured survey, stakeholders rated urban planning objectives, the importance of urban health and multiple urban health issues (previously developed in Chapter 2). After comparing responses among groups, we identified whether groups rated as relevant planning objectives related to health if the built environment is perceived as relevant in shaping health and in which issues are more critical. Urban health experts rated health-related objectives more important than the other groups, with the citizens mediating the response between the other groups. Overall, the built environment is considered a relevant factor in shaping human health, and air pollution, active mobility and community space are the most important issues for healthy urban planning. The ratings of urban health issues also weighted the indicators generated in Chapter 3 so that the built environment is assessed by merging viewpoints and measurements. The indicators' weighting was not relevant in generating significantly different indicators. Also, the most important urban health issues were mapped for local citizens across different postal codes. Air pollution and urban heath island indicators' values were positively correlated with the citizens' responses. The potential relevance of integrating multiple groups of stakeholders was discussed in this chapter and the inadequacies of using direct rating to weight spatial data.

4.1 Introduction

To integrate health in planning, research and practice need to integrate multiple disciplines gathered by the umbrella of urban health (Bird et al., 2018; D'Alessandro, 2020; Sallis et al., 2016). In the spatial planning and Healthy Urban Planning (HUP) subsector, decision-makers already identify priorities and compare alternatives on multiple issues that are not directly comparable (D'Alessandro, 2020). For example, increasing physical activity among the population may require intervention to reduce road safety and improve the active mobility networks (WHO, 2020). The challenge of decision making in those contexts already take advantage of the experts' viewpoint to provide an insight into complex challenges (Franz W. Gatzweiler, ; Lawrence and Gatzweiler, 2017). However, evidence and data are not widely used, and its integration is not widely implemented in HUP (de Leeuw et al., 2015; Grant, 2015). It can be argued that urban health studies have not delivered yet the adequate information that planners need to consolidate the role of health planning (Elsey et al., 2016; Friel, Vlahov, et al., 2011; Sallis et al., 2016).

The integration of stakeholders viewpoints, thus participation in the planning processes, is reputed to favour the translation of HUP into practice (Elsey et al., 2016; Freitas et al., 2020; Pineo, Zimmermann, et al., 2020; Sallis et al., 2016). Also, understanding the principles that drive decision-making can provide HUP research with precious information to deliver a compelling message and reduce resistance to research translation(Morais et al., 2021; Sallis et al., 2016). This method also has indirect effects, such as stakeholder formation (de Leeuw, 2013; Katz et al., 2015) and understanding grassroots engagement (Morais et al., 2021; WHO, 2020; Zhu, 2015). According to Pineo and Moore, after exploring the viewpoint of urban health experts through thematic analysis to understand challenges and potential for HUP integration, the necessity of forming stakeholders was not univocal across responses (Pineo and Moore, 2021). The understanding of stakeholder perspectives can also be integrated into the weighting process of data analysis (Freitas et al., 2020), such as composite indicators (WHO et al., 2014).

Pissourios et al. observed a decrease in the land-use survey for urban planning in the last half-century (Pissourios, 2019). They consider three mechanisms that could have driven this finding: the lack of new methodologies, the futility of land-uses in planning, or the replacement by data technologies. Also, Pineo and Moore reported how the study of stakeholders viewpoints in urban health is an under-researched topic (Pineo and Moore, 2021).

The study of stakeholders viewpoints is not a novel concept in HUP, which mainly involves decision-makers (Katz et al., 2015; Pineo and Moore, 2021) either communities (Morais et al., 2021; Thomson et al., 2019). Those two groups of stakeholders are usually not investigated jointly because methods are tailored to stakeholders' different knowledge and experience. A recent study considered experts in urban health, thus with the dual expertise in planning and public health fields, to understand challenges in HUP integration (Pineo and Moore, 2021). Katz et al. l. argue that the participation process in urban health is generally biased by many factors, such as the limitation of participation cross planning phases and consequently the conveners' responsibility, or the self-selection of participants, especially for community or public participation (Katz et al., 2015).

The study of stakeholder perspective can be based on an extensive range of methods, such as Multi-Criteria Decision Analysis, Simple Multi-Attribute Technique, or Analytic Hierarchic Process (Frazão et al., 2018; Ho et al., 2015; Schmidt et al., 2015). Despite the multiple analytical advantages, those methods are constrained by a limited number of objects due to pairwise comparisons or the need to instruct participants (Frazão et al., 2018). Instead, more simple approaches, i.e. direct rating, are widely used to collect public surveys and avoid issues related to cognitive load boost response rates (Bottomley et al., 2000; Lenzner et al., 2010).

This chapter aims to investigate the viewpoint about the role of health in planning and the relevance of multiple urban health issues (UHIs) in three stakeholders, thus including decision-makers and the communities. Stakeholders were recruited among international experts in urban health, planners in the French-speaking region of Switzerland, and residents in the canton of Geneva. Participants responded to an online survey based on direct weighting. Responses were statistically analysed and compared between groups to understand how relevant urban health is in planning objectives and which UHIs are more relevant. The survey employed the framework created in Chapter 2 as the structure to compare different urban health challenges. In addition, the study adopted experts rating of UHIs to weight UHIs indicators used to represent the Healthy Built Environment in the canton of Geneva (Chapter 3), and compare responses of the local community across the place of residence within the canton of Geneva.

4.2 Methodology

Groups of participants

To understand how different Urban Health Issues (UHIs) are prioritized and thus perceived, we gathered responses using a survey from three different groups of stakeholders:

- Group A; formed by international experts on urban health.
- Group B; formed by local experts in urban planning (in the French-speaking region of Switzerland).
- Group C; formed by the local population (in the study area).

The first two groups were selected actively, while the last group spontaneously participated in the survey. Also, "snowball sampling" allowed participants to expand each group (Goodman, 1961). Data were collected between September 2019, and May 2020 included.

The group (A) gathers international experts with a general background in urban health. Participants belonging to this group were selected among participants of the International Conference of Urban Health in 2018 and 2019. Participants accessed the online survey using a tablet in person by scanning a QR code or email contact. Participants who reported not general knowledge of urban health and specialized in urban planning or public health were discarded. The group (B) gathers experts whose practice expertise is in urban planning and operate in Switzerland's French-speaking area. The French-speaking area of Switzerland, also Romandie, includes the cantons of Bern, Fribourg, Neuchâtel, Genève, Jura, Valais, and Vaud. Participants of group B were contacted by email upon the identification of potential contacts by web-search. Contact information was gathered from planning services in cities with at least 5000 residents and from private urban planning studios. Group (C) collects participants who are reported to be residents in the canton of Geneva. Participants spontaneously accessed the online survey from social media (Twitter and Facebook). The survey was published on public local groups and pages referring to the canton of Geneva. Participants reported being adults and residents in the canton of Geneva for at least one year. Participants of group C were also geo-referenced by the postal code of residence.

Survey structure

After initiating contact, participants consented to anonymous data collection. Health was purposefully omitted from the survey's description to ensure that responses were not biased when participants were asked to rank various planning objectives (in the first section). Rather than that, the opening said unequivocally that the survey targets urban planning. Additionally, participants were advised that the survey was not unique to any location or setting but was rather generic and ideological. The length of the survey was deliberately short (five to ten minutes) to reduce the cognitive load for the participants and motivate participation (Crawford et al., 2001; Marcus et al., 2007; Revilla and Höhne, 2020).

The survey is composed of three main sections. The first section (I) discusses urban planning objectives, while the second section (II) discusses the relationship between health and urban planning. Then, the third section (III) gather individual demographic information. The survey collected 48 variables for groups A and B, and 43 variables for group C by answering 18 and 14 questions. Items' order was permutated in question rating four or more items, while sections and questions order were the same for all participants. The survey is based on direct rating using a Likert scale from 1 to 8. Therefore, participants were allowed to rate any survey items equally and visualize ratings of all items per question. Also, the survey included multiple-choice questions to determine the profile of participants and two open questions. In the first section (I), participants were asked to rate the importance of 16 urban planning objectives. The list of objectives was created to address urban planning generally. It was not designed to be exhaustive of the totality or representative of the complexity of urban planning subjects (Levy, 2016; UN-HABITAT, 2019). Planning objectives were coupled with a brief description enclosed in an additional information tooltip on the side of each item. This section aimed to understand how participants rated objectives related to health (and wellbeing) compared to other objectives. After rating the objectives, participants were allowed to suggest if there is an objective missing from the previous list that they would perceive as relevant to urban planning The second section (II) was composed of three parts. The first part generally addresses the relation of the BE with health. In this part, participants were asked to rate four core determinants of health: genetic, behaviour, environment, and wealth. Then, participants rated the impact (both positive and negative) of the BE on human health according to the framework of UHIs generated in Chapter 2. Similarly, to planning objectives, UHIs were accompanied by a brief description within an additional information tooltip adjacent to each item (Table 14).

In the third part (absent in group C survey), group A and B participants first evaluated their decision-power in spatial planning. They were asked if their contribution to planning is restricted to consultation, if they can make decisions on their work, or if they make decisions on the work of others and delegate tasks. Secondly, they rated how frequently it is included in planning practise: quality of life, health, and health as a primary goal. In the end, they were asked to classify their expertise. Participants of group A were asked if they were experts in public health, in urban planning, in both public health and urban planning, in a specific sub-sector of urban health or none of the previous. Also, participants of group A provided their country of origin and residence. Group B participants were asked whether they were specialists in urban planning, in a particular sub-sector of planning, or none of the above. Then, group B participants were asked if they actively work on the territory of Canton Geneva or others cantons of the French-speaking region of Switzerland. The last and third sections (III) collected individual information, such as age and gender, for all groups and the postal code of residence and the year of relocation in that postal code for group C.

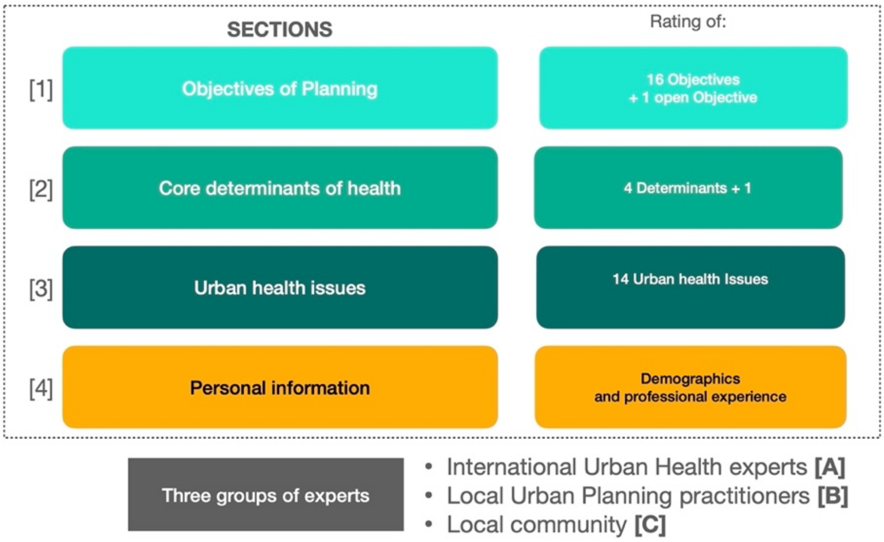

Figure 33: Survey structure and participants' groups.

Domains	*UHI: Urban Health Issues*	UHI descriptions
Outdoor environment	**Air pollution**	The air that individuals are exposed to daily should not be hazardous to them. Pollutant sources, such as transportation and heating systems that run on hydrocarbons, are regulated, minimizing their emissions.
	Noise pollution	The population is not subjected to noise levels that are likely to have detrimental consequences. Noise sources are minimized and separated from noise-sensitive areas.
	Hydro-geologic risk	The territory is managed to mitigate hydrogeologic hazards such as flooding, landslides and other hydrogeologic instability, seismic events, and avalanches. Adverse effects of climate change are mitigated.
	Extreme outdoor temperatures	The places where we live are managed to mitigate extreme outdoor temperatures, reducing the thermic storage of built areas, and mitigating the domestic thermic sources.
	Contaminated land	The population is not exposed to hazardous air, water, or soil due to productive activities, accidents, waste disposal and management. Hazards are reduced or isolated from the population.
	Road injuries	Transportation networks are managed and regulated to reduce and prevent transport accidents and the consequent injuries and deaths.
Indoor environment	**Thermo-hygrometric comfort**	Housing characteristics mitigate the impact of extreme outdoor climate and protect residents from dampness. The formation of mould is prevented, and indoor spaces are ventilated.
	Safe design and accessibility	Housing offers a solid structure and durable shelter, providing a liveable space for all residents. It is also free of hazards and accessible to people with reduced mobility.
	Sanitation & Safe Water	Housing is provided with a reliable source of safe water and an improved private sanitation facility to allow the safe disposal of human excreta.
	Household air pollution	Housing is free from sources of domestic pollution such as smoke, cooking and heating. Living indoor spaces are isolated from an external source of pollution.
Healthy lifestyle	**Active mobility**	Active transport networks (for walking, cycling and public transports) are available, accessible, and safe. Public transportation is affordable, accessible, and reliable.
	Healthcare (geographic) accessibility	Healthcare services are available via a variety of forms of transport. Primary care and other healthcare services are distributed geographically to accommodate the patient influx.
	Community spaces	Public spaces and services are available accessible. Public places are safe, clean, designed for social interaction, leisure and recreational activity, physical activity, and culture. Administrative, community and education services are sufficiently provided.
	Food environment	Food stores, particularly those selling healthy and local food, are available and affordable. The availability of unhealthy food activities is controlled. Areas for community gardens and urban agriculture are available.

Table 14:The UHIs framework and the brief descriptions of UHIs employed in the survey.

4.2.1 Survey analysis

The responses were coded, and ratings standardized. Overall findings can be summarised in five parts. Firstly, results are displayed for each group, including general descriptive statistics. Secondly, seven indicators are used to synthesize the survey results for the first and second sections. Initially, groups are generally described by demographic information and work expertise for groups A and B. Thirdly; we compared responses between groups. Then, the experts' groups (A and B) are grouped with K-means clustering to provide four profiles. Responses per cluster provide weightings of the UHI indicators created in Chapter 3. In the end, responses of group C are mapped by postal code and compared with the UHI indicators.

Indicator	*Definition*	*Description*
I_H	$r_h / \bar{r}_{obj.}$	The ratio of the health objective (Health and Wellbeing) rating (r_h) on the mean rating of all objectives ($\bar{r}_{obj.}$).
I_{HR}	$\bar{r}_{hr} / \bar{r}_{obj.}$	The ratio of the mean rating of health-related objectives (Health and Wellbeing, Public Transport and Active Mobility, Access to green areas, Improved building standards, social cohesion) ratings ($\bar{r}_{hr}$) on the mean rating of all objectives ($\bar{r}_{obj.}$).
I_{OB}	$\bar{r}_{obj.}$	The mean value of objectives ratings ($\bar{r}_{obj.}$).
I_{BE}	r_{BE}	*The rating of the question: "In your opinion, how important is the Built Environment in shaping our health?" (r_{BE}).*
I_{UHI}	$\bar{r}_{UHI}$	The mean of UHIs' ratings ($\bar{r}_{UHI}$).
I_{ENV}	$r_{env.} / \bar{r}_d$	The ratio of "Environment" rating ($r_{env.}$) on the mean rating of other core determinants of health (Environment, Genetics, Wealth, Behaviour) ($\bar{r}_d$).
I_P	$\bar{r}_P$	The mean of ratings of health integration frequency in planning practice ($\bar{r}_P$).

Table 15: Indicators of survey's ratings.

Survey indicators

The survey collects many data which seven indicators have summarised (**Error! Reference source not found.**). The latter have been g enerated by a set of responses, such as the objectives; or by selecting a single question. Three indicators address the first section of the survey (the rating of the planning objectives), while the other four address the second section (the ratings that deal with urban health). In the objectives' section, we wanted to understand how relevant is considered health among other objectives. Therefore, we measured two ratios. The first one (I_H) outline whether that the *Health and Wellbeing* object is relevant than the mean objectives' rating. Similarly, the second indicator (I_{HR}) outlines the health-related objectives' responses (Health and Wellbeing, Public Transport and Active Mobility, Access to green areas, Improved building standards, social cohesion) compared to the mean rating of all objectives. Thirdly, we directly used the mean rating of all objectives ($I_{OB)}$ to understand how responsibility is attributed to urban planning. In the second section, four indicators were used to understand the BE's relevance in shaping health. Firstly, we adopted a single question rating ("*How important is the Built Environment in shaping our health?"*) as an indicator (I_{BE}). Secondly, we wanted to understand how UHIs are overall perceived as relevant or not (I_{UHI}). In the end, the last indicator describes how participants rated the determinant "Environment" compared to all core determinants of health (I_{ENV}). For the groups of experts (HUP and UP), an additional indicator measures health integration in the decision-making process (I_P).

Statistical analysis

The ratings were rescaled so that Likert scales from 1 to 8 displayed a variation between 0 and 1. Descriptive statistics were used to characterize the ratings of each group, and the distributions of objectives' and UHIs' ratings are also represented with box-plots plots. In addition, for group A, we adjusted UHI ratings by using quantile regression for the country of residence and origin based on the UN human development index (D pogramme UN, 2020) and we compared adjusted values with un-adjusted ones. Descriptive statistics were used to describe indicators, and the latter were compared by correlation analysis within each group. The responses were also compared between groups by ANOVAs (one-way with unequal variances) and paired T-tests (Welch).

Clustering and weighting of UHI indicators

We used K-means clustering to identify profiles in the group of experts (group A and B) depending on the first two sections of the survey, thus excluding the demographic characterization and the membership to a survey's group. The optimal partition was obtained by employing the Elbow method so that an adequate number of clusters is chosen while the sum of squared error is minimized (Thorndike, 1953). Descriptive statistics for ratings and indicators were calculated as described before for groups. We used a set of mean ratings of UHI to weight the respective UHI indicators generated in Chapter 3 to compose weighted domains of UHI ($UHI_{d,w}$). We used seven different mean UHI ratings, provided by each of the three groups (A, B, C), and each of the profiles generated with K-means clustering. The generic framework was adapted on the case study using a single UHI to represent the second domain of *Indoor Environment* (Table 5). For the case study, the issues of *Sanitation and Safe Water*, and the *Household indoor pollution* were not considered relevant for the case study. Therefore, weighting to the domain of *Indoor Environment* was provided by the mean of the rating of the two left UHI of the second domain, *Thermo-hygrometric comfort* and *Safe design and Accessibility*. The seven weightings allowed the calculation of three domains of UHI and the single indicator for HBE by weighted geometric mean, as suggested by the sourcebook of urban health index of WHO (WHO et al., 2014). Each weighted UHI domain, $UHI_{d,w}$ was calculated with weighted geometric mean as follow:

$$UHI_{d,w} = \left(\prod_{i=1}^{j} UHI_i^{w_i} \right)^{\frac{1}{\sum_{i=1}^{j} w_i}}$$

Where UHI_i is a single indicator contributing to the domain d and j is their total number, and w is the weight which is equal to mean ratings. Unweighted domains and weighted domains by the seven sets of weights were compared by T-test.

Spatial analysis of group C responses

Group C was geographically defined by the postal code of residence, allowing comparisons of participant perspectives across different areas of the canton of Geneva. Firstly, since participants in the group C were not selected, we studied the geographic representativeness of the cohort compared to geographic population distribution a posteriori. Hence, we calculated the difference between participants' density and the population density per each postal code. Afterwards, we mapped the most and less frequent responses in rating objectives and UHIs and mapped the ratings of the indicators. The small number of postal codes was sufficient to calculate the correlations (Pearson) (Bonett and Wright, 2000) between the mean values of UHI ratings with the mean values of UHI per each postal code area calculated by PCA and GWPCA on the HBE features (Chapter 3). Similarly, we calculated the correlations for the domains of UHIs.

4.3 Results

We studied the viewpoints on urban planning and urban health issues in three groups of stakeholders: the international experts in urban health (group A), the local practitioners in urban planning (group B), and the local citizens (group C). A total of 510 people participated in the online survey, almost equally split between experts (group A and B) and citizens (group C), as shown in Table 16. In group A, 33% of participants declared to be experts in public health and urban planning, 41% in public health, 14% in urban planning, and 11% in sub-sectors of urban health. Instead, respondents who declared not to have place-based knowledge or formation in either public heal, urban planning and respective sub-sectors were excluded from the study. Participants in group A reported on average 11.8 years of experience in the field of urban health. The 83 international experts come from 31 different countries in origin or 29 different countries in terms of residence, from both developed and developing countries (Table 17). In group B the group, 57% is working on the territory of the canton of Geneva, 36% in the other cantons of the French-speaking region of Switzerland, and 7% generally works in the French-speaking region for Switzerland. 91% of the local practitioners are experts in urban planning, while 9% are experts in a sector related to urban planning. Instead, participants not belonging to these two categories were discarded. Participants in group B reported, on average, 17.9 years of experience in the field of urban health. The experts of groups A and B reported participating differently in the decision-making process, either working purely on commission (Passive), either taking decisions on their work subject (Limited), actively making decisions also on the work of other people (Active) (Table 18). Participants of group C, selected between participants who reported to be residents in the canton of Geneva, were differently distributed within the study area (Figure 38). The participants were residents in the canton of Geneva for a mean of 32 years (std: 20.8), with 10.8 % of participants reporting to have moved to canton Geneva within the last five years. The ratings of the survey in both sections have been normalised.

Groups	*A*	*B*	*C*
Participants number	87	161	266
Percentage of women	43%	38%	68%
Mean Age (std)	43.4 (12.4)	45.8 (11. 3)	40.7 (14.0)

Table 16: general demographics for each group of participants.

	Countries n.	*mean HDI*	*HDI range*
Country of origin	31	0.78	0.54-0.95
Country of residence	29	0.80	0.54-0.95

Table 17: Geographic origin and residence within group A and the respective HDI.

Decision power	*Passive*	*Limited*	*Active*
UP	53%	33%	21%
HUP	64%	13%	23%

Table 18:Decision power classes among experts (group A and B).

4.3.1 Planning objectives

In the first section of the survey, each group evaluated the importance of 16 objectives, which descriptive statistics are shown in Table 19, while the distributions are displayed in Figure 34. Groups differently ranked the objectives, generally agreeing on access to green areas and public transport and active mobility, tourism, and economic growth. However, the two latter were perceived as less important compared to other objectives. The high rating of Public Health and Wellbeing in group C is probably biased by the COVID-19 pandemic, which started during data collection. To address this potential bias, the introduction explicitly suggested not considering the current health crisis linked to the pandemic. Instead, the responses of group A were collected before February 2020. The objective that showed more uncertainty (in terms of standard deviation) within each group were respectively Tourism, Improved building standards, and Densification for groups A, B and C (Figure 34). Also, the mean of all objectives was similar between groups. In identifying a relevant objective missing from the previous list, participants addressed multiple subjects summarised in six classes (Table 20). Most of participants of Group A reported a missing objective (74.9%), a percentage which dropped in Group B (57.5%) and C (20%). Groups agreed in choosing sustainability and environmental protection as the missing objective.

Group	***A***		***B***		***C***	
Objectives	mean	rank	mean	std	mean	rank
Employment Opportunities	0.23	10	0.18	15	0.23	11
Improved Building Standards	0.24	8	0.18	12	0.23	10
Economic Growth	**0.22**	**13**	**0.18**	**13**	**0.16**	**15**
Dwelling offer	0.23	11	0.26	4	0.24	8
Improved Safety	0.26	6	0.18	14	0.21	13
Urban Regeneration	0.24	9	0.24	11	0.22	12
Public transport & Active Mobility	**0.28**	**2**	**0.28**	**1**	**0.27**	**3**
Access to Green Areas	**0.27**	**3**	**0.28**	**2**	**0.29**	**2**
Public Health & Wellbeing	0.29	1	0.26	6	0.29	1
Social Cohesion	0.26	7	0.27	3	0.26	4
Tourism	**0.17**	**16**	**0.17**	**16**	**0.15**	**16**
Socio-economic Equity	0.26	5	0.25	8	0.25	6
Service Accessibility	0.27	4	0.25	7	0.26	5
Densification	0.21	14	0.25	10	0.18	14
Heritage Conservation	0.21	15	0.25	9	0.24	9
Aesthetics & Landscape	0.22	12	0.26	5	0.25	7
Mean	**0.24**		**0.23**		**0.23**	

Table 19: Means and standard deviations (std) of the rated urban planning objectives across all groups. Coloured values display means that are significantly different from the mean rating of the objectives within each group (T-test p-value:<0.01). Red values are significantly lower, thus less important, while green is significantly higher than the mean rating and rated as more important than the mean. Bold values display UHIs which shows more agreement, thus ranks varying only between +1 and -1.

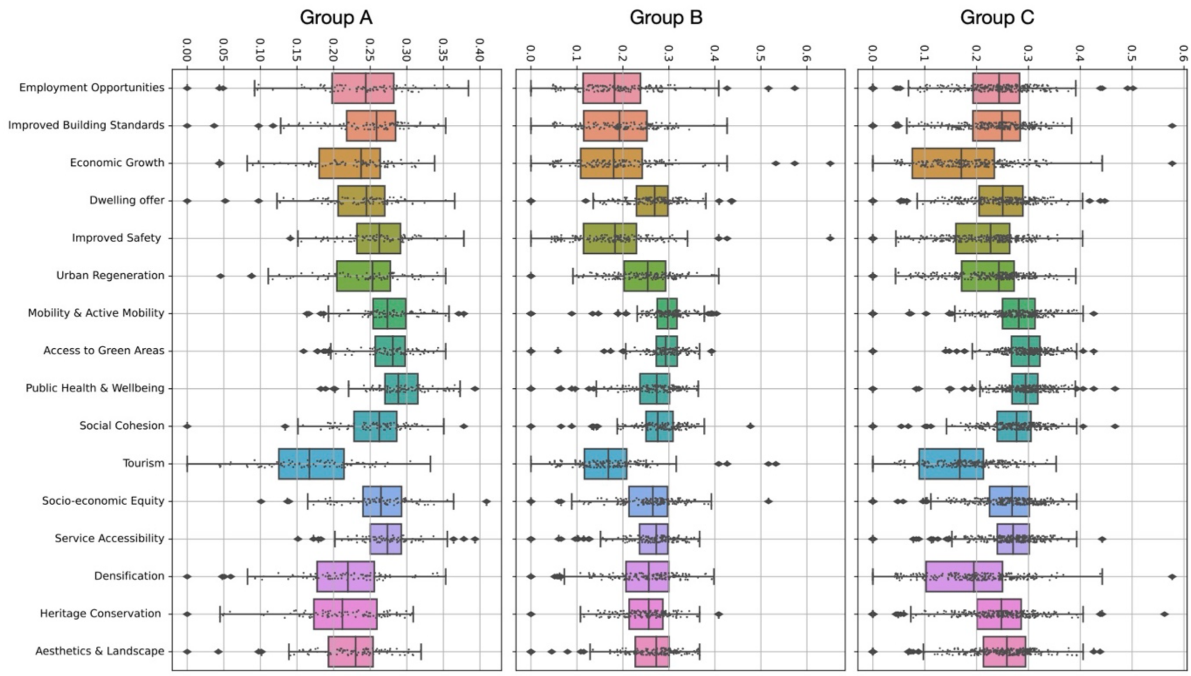

Figure 34:Boxplot of the objectives' ratings.

	Groups [%]		
Missing objective	A	B	C
Nature, environmental protection and sustainability, climate change, biodiversity and energy planning	44.9	27.3	9
Participation, democracy, spatial justice and segregation, community, cohesion, culture	20.6	13	6.6
Urban regeneration, Land Mix Use, Resilience	36	5.5	3.9
Active mobility, public transport, physical activity	14.3	3.7	3
Inter-regional planning, Politics interplay with planning, local necessity, intra-sectoral communication	1.8	5	0.7
Food environment, urban agriculture	4	1	0
No answer	15.1	44.5	80

Table 20: Reported missing planning objectives. The sum of percentages in group A exceeds 100% since participants reported more than one objective.

4.3.2 Built environment and health

All groups rated genetic factors as the least relevant core determinants of health (which was also the determinant displaying higher standard deviation). Instead, groups A (0.41 ± 0.02) and C (0.40 ± 0.02) identified the environmental factors as more important, while group B pointed to lifestyle factors important (0.39 ± 0.03). Groups displayed high agreement in seven UHIs on eleven, in top-ranked ones, i.e., Air pollution, and bottom-ranked, i.e., hydro-geologic risk. The higher variation (in terms of standard deviation) across all groups are Road Injuries. Most of the UHIs perceived as more critical belong to the third domain of UHI, which gathers characteristics of the BE related to behaviour. The environmental issues identified by the missing objectives (Table 20) and the high importance attributed to the environment determinant of health; correspond only to the higher rating of Air pollution among UHI. Instead, UHI is related to climate change (Hydro-geologic risk and extreme outdoor temperatures) and other forms of exposure (Noise pollution and Contaminated land).

Under the assumption that the personal experience linked with the place where we lived and where we live now may influence the perception of UHIs, we adjusted the ratings of UHIs in group A for the Human Development Index. Adjusted and unadjusted normalised ratings of UHI were not significantly different (T-test p-value <0.05). Experts (group A and B) characterised my more decision power (classed as Active), reported integrating health and wellbeing more frequently than experts with less decision power (Figure 37). In planning practice, experts also addressed quality of life or wellbeing more frequently than health, while both groups reported similar frequency in integrating health and wellbeing (Figure 37). We compared groups responses by testing whether objectives and UHIs display different means with T-tests between pairs of groups (Welch) (Table 22). Three objectives display similar means for all pairs. Overall, the higher similarity is displayed between groups A and C. Instead, two UHIs, Air Pollution and Thermo-hygrometric comfort, show similar means for all pairs. For the UHIs, the count of similar means is higher between groups B and C.

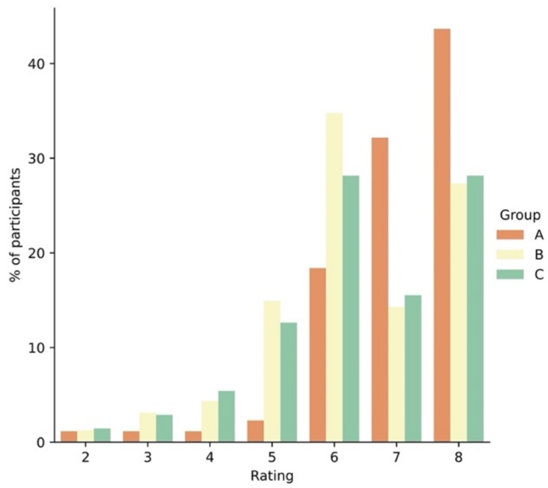

Figure 35: Rating of indicator I_{BE}: the contribution of the BE in shaping health with both positive and negative impacts.

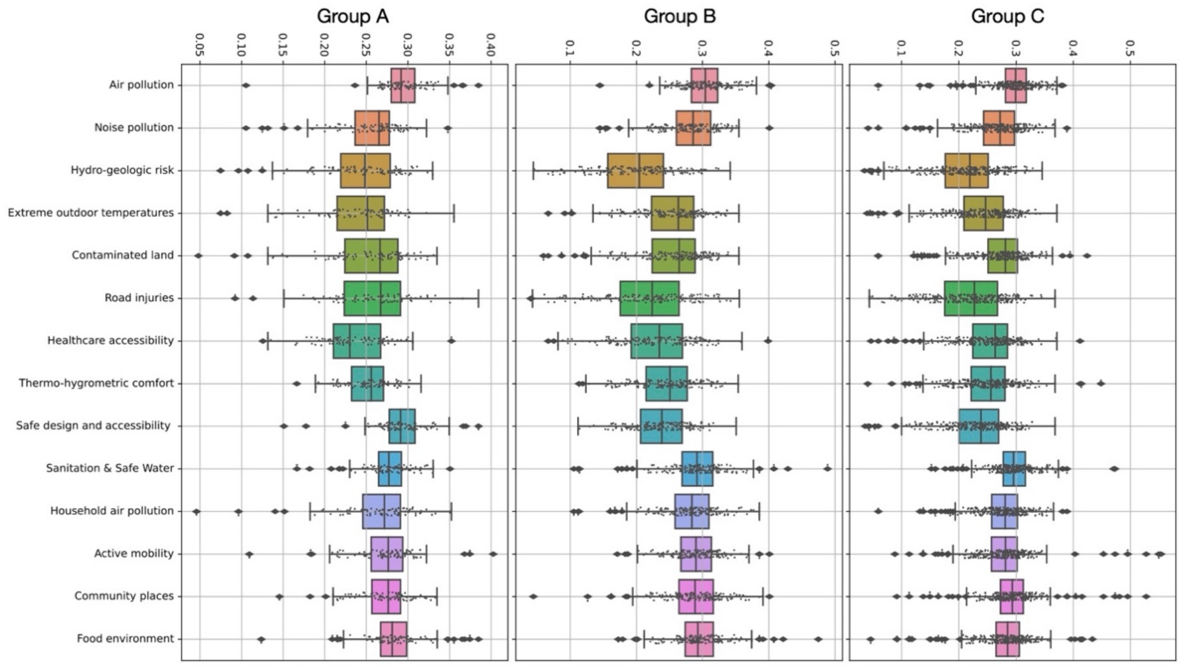

Figure 36: Boxplots of UHIs ratings.

Groups	***A***		***B***		***C***	
UHI	mean	rank	mean	rank	mean	rank
Air pollution	**0.29**	**1**	**0.30**	**1**	**0.30**	**1**
Noise pollution	0.25	10	0.28	6	0.27	8
Hydro-geologic risk	**0.24**	**12**	**0.20**	**14**	**0.21**	**14**
Extreme outdoor temperatures	0.24	13	0.25	9	0.24	11
Contaminated land	0.25	11	0.25	8	0.27	7
Road injuries	0.26	8	0.21	13	0.22	13
Healthcare accessibility	0.23	14	0.23	12	0.25	9
Thermo-hygrometric comfort	**0.25**	**9**	**0.24**	**10**	**0.25**	**10**
Safe design and accessibility	0.29	2	0.24	11	0.23	12
Sanitation & Safe Water	**0.28**	**4**	**0.29**	**3**	**0.30**	**2**
Household air pollution	**0.26**	**7**	**0.28**	**7**	**0.28**	**6**
Active mobility	**0.27**	**5**	**0.29**	**4**	**0.28**	**5**
Community places	0.27	6	0.29	5	0.29	3
Food environment	**0.28**	**3**	**0.29**	**2**	**0.28**	**4**
Mean	**0.26**		**0.26**		**0.26**	

Table 21: Means and rankings of the rated UHIs ratings across all groups. Coloured values display means significantly different from the mean rating of the UHIs within each group (T-test p-value:0.01). Red values are significantly lower, thus less important, while green is significantly higher than the mean rating and rated as more important than the mean. Bold values display UHIs which shows more agreement, thus ranks varying only between +1 and -1.

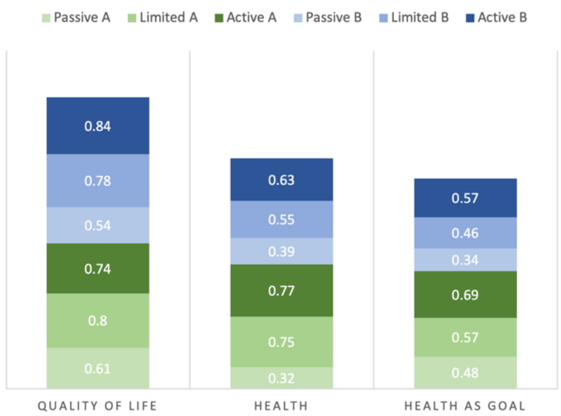

Figure 37:Ratings of health integration in practice between groups A and B and for different levels of decision-power.

GROUPS	A:B		A:C		B:C	
OBJECTIVES	**T**	**pv**	**T**	**pv**	**T**	**pv**
Employment Opportunities	5.31	0.00	**0.33**	**0.75**	-5.88	0.00
Improved Building Standards	5.91	0.00	**1.48**	**0.14**	-5.45	0.00
Economic Growth	3.41	0.00	6.03	0.00	**1.84**	**0.07**
Dwelling offer	-3.55	0.00	**-0.95**	**0.34**	3.12	0.00
Improved Safety	9.13	0.00	6.75	0.00	-3.99	0.00
Urban Regeneration,	**-0.60**	**0.55**	2.29	0.02	3.35	0.00
Public Transport & Active Mobility	-1.83	0.07	**0.11**	**0.91**	2.04	0.04
Access to Green Areas	**-1.49**	**0.14**	-3.43	0.00	**-1.47**	**0.14**
Public Health & Wellbeing,	4.81	0.00	**-0.18**	**0.86**	-5.67	0.00
Social Cohesion	-2.33	0.02	-1.95	0.05	**0.67**	**0.50**
Tourism	**-0.47**	**0.64**	**1.01**	**0.31**	**1.64**	**0.10**
Socio-economic Equity	**0.57**	**0.57**	**0.35**	**0.73**	**-0.29**	**0.77**
Service Accessibility	**1.89**	**0.06**	**1.36**	**0.18**	**-0.77**	**0.44**
Densification	-4.10	0.00	3.39	0.00	8.44	0.00
Heritage Conservation	-5.05	0.00	-3.74	0.00	**1.62**	**0.11**
Aesthetics & Landscape	-5.16	0.00	-4.10	0.00	1.64	0.10
Agreements' count	**5**/16		**8**/16		**7**/16	
UHI	**T**	**pv**	**T**	**pv**	**T**	**pv**
Air pollution	**-1.82**	**0.07**	**-0.51**	**0.61**	**1.63**	**0.10**
Noise pollution	-4.95	0.00	-2.28	0.02	3.54	0.00
Hydro-geologic risk	6.07	0.00	5.00	0.00	**-1.88**	**0.06**
Extreme outdoor temperatures	**-1.59**	**0.11**	**0.32**	**0.75**	2.42	0.02
Contaminated land	**-0.05**	**0.96**	-3.11	0.00	-3.73	0.00
Road injuries	5.86	0.00	6.55	0.00	**-0.14**	**0.89**
Healthcare accessibility	**0.57**	**0.57**	-3.36	0.00	-3.93	0.00
Thermo-hygrometric comfort	**1.80**	**0.07**	**0.69**	**0.49**	**-1.17**	**0.24**
Safe design and accessibility	11.40	0.00	12.98	0.00	**1.42**	**0.16**
Sanitation & Safe Water	-2.48	0.01	-4.81	0.00	**-1.46**	**0.15**
Household air pollution	-2.63	0.01	-2.11	0.04	**0.98**	**0.33**
Active mobility	-2.98	0.00	**-1.08**	**0.28**	2.19	0.03
Community places	-2.76	0.01	-4.61	0.00	**-1.43**	**0.15**
Food environment	-2.28	0.02	**0.49**	**0.63**	3.25	0.00
Agreements' count	**5**/14		**5**/14		**8**/14	

Table 22: T-tests (Welch) between pairs of groups for urban planning objectives and UHIs. The counts display the number of items with similar means for objectives and UHIs. Items characterised by p-values above 0.05 are displayed in bold, meaning that a pair of groups have similar means.

4.3.3 Indicators, participants clustering and weighting of the HBE

Indicators

The seven indicators are not significantly different between groups since the T-test (Welch) test between values showed p-values above 0.05 for all indicators and all pairs of groups. Overall, I_H and I_{HR} are greater than 1, meaning that the objective that included health and wellbeing was more important than the others (Table 23). Similarly, among core determinants of health, the environment was perceived as more relevant than the mean of core determinates (Table 23). The correlations (Pearson) between indicators, for all participants together and within each group, were weak (smaller than 0.20). The correlations between dependent indicators, such as I_H and $I_{obj.}$, and the correlations between the mean rating of objectives and UHIs were not weak. However, the first it's given by the equation's formulation, and the second means that participants assigned similar ratings to objectives and UHIs.

Group	A	B	C
I_H	1.17(0.16)	1.08(0.22)	1.2(0.21)
I_{HR}	1.08(0.08)	1(0.11)	1.06(0.09)
$I_{obj.}$	0.24(0.01)	0.24(0.01)	0.24(0.01)
I_{ENV}	1.78(0.2)	1.76(0.24)	1.71(0.23)
I_{BE}	0.88(0.16)	0.8(0.19)	0.75(0.27)
I_{UHI}	0.26(0.01)	0.26(0.01)	0.26(0.02)
I_P	0.36(0.28)	0.51(0.13)	

Table 23: Mean and standard deviations of indicators per each group.

Clusters and weighting of the HBE

One of the aims of this study was to provide a weighting of the UHI indicators generated in Chapter 3 by employing the viewpoint of experts, the international experts in urban health and the local practitioners in urban planning. Since those two groups of experts displayed a partial agreement in weighting the UHIs (Table 22) and no significant difference among indicators, an alternative partition of experts have been studied. The totality of experts (N= 248) has been split into three groups by K-mean clustering using ratings of UHIs. By observing the indicators calculated per each cluster, the indicator that displays the only significant dissimilarity between clusters is the I_P, thus representing the frequency of integration of health and wellbeing in planning practice (Table 24). The third cluster is also different from the others for four Indicators, three indicators calculated from the objectives (I_H, I_{HR}, $I_{obj.}$) and I_{ENV}. The domains of UHI calculated with a weighted geometric mean (WHO et al., 2014) on UHI indicators obtained with PCA; were not significantly different. The comparison of the unweighted with each weighted domain by T-tests were never rejected (Welch, p<0.01). Indeed, the correlation (Pearson) between the unweighted and weighted domains sets ranged from 0.95 and 0.99.

CLUSTER	GROUP	NUMBER	GROUP %
1	A	69	80.2
	B	62	38.9
2	A	10	11.6
	B	71	44.6
3	A	7	8.1
	B	26	16.4

Table 24: Partition of groups in the cluster by groups' membership.

Cluster	1	2	3
I_H	1.15(0.14)	1.18(0.18)	**0.96(0.31)**
I_{HR}	1.04(0.06)	1.07(0.09)	**0.93(0.11)**
$I_{obj.}$	0.27(0.00)	0.28(0.01)	**0.21(0.02)**
I_{ENV}	1.72(0.2)	1.76(0.24)	**1.80(0.23)**
I_{BE}	0.86(0.16)	0.83(0.19)	0.85(0.27)
I_{UHI}	0.26(0.05)	0.27(0.01)	0.26(0.05)
I_P	**0.81(0.14)**	**0.05(0.08)**	**0.51(0.12)**

Table 25: Mean and standard deviation of indicators per each cluster. Bold values are significantly different from the other two clusters in terms of mean (Welch T-test with p-value <0.01).

UHI	1	2	3
AIR POLLUTION	0.31	0.29	0.31
NOISE POLLUTION	0.26	0.27	0.29
HYDRO-GEOLOGIC RISK	0.16	0.25	0.16
EXTREME OUTDOOR TEMPERATURES	0.23	0.26	0.23
CONTAMINATED LAND	0.22	0.27	0.23
ROAD INJURIES	0.3	0.25	0.16
HEALTHCARE ACCESSIBILITY	0.2	0.24	0.22
THERMO-HYGROMETRIC COMFORT	0.22	0.25	0.25
SAFE DESIGN AND ACCESSIBILITY	0.25	0.26	0.24
SANITATION & SAFE WATER	0.27	0.28	0.31
HOUSEHOLD AIR POLLUTION	0.25	0.27	0.3
ACTIVE MOBILITY	0.3	0.27	0.3
COMMUNITY PLACES	0.29	0.27	0.3
FOOD ENVIRONMENT	0.33	0.28	0.3

Table 26: weightings of UHIs per each cluster.

4.3.4 Spatial analysis of citizens' perspectives

The spatial representativeness of participants was like the distribution of the resident population by postal code of residence, with differences between densities ranging between -3.7% and 8.4% (Figure 38). The 13 postal codes lacking participants were mainly located in areas characterised by low density. They caused a loss inferior to the 2.6% difference between participants and population density (Figure 38). The objective "Employment Opportunities" is a more frequently addressed objective (12 postal codes), followed by Public Transport and Active Mobility (10 postal codes) (Figure 39). Instead, Economic growth is the least rated objective in 15 postal codes. Group C's high air pollution ratings (Table 21) correspond to 33 postal codes rating it as the most important UHI (Figure 40, top left). Therefore, the majority of most rated UHI target the domain of the Outdoor Environment, followed by Healthy places and Indoor Environment (Figure 40, bottom left). The least rated UHI are Hydro-geologic risk (26 postal codes) and Road injuries (13 postal codes) (Figure 40, top right). The set of six indicators used to characterize the survey response does not display any specific spatial pattern. The ratings of UHIs were compared with the UHI indicators calculated with PCA and GWPCA (chapter 3). Overall correlations are very weak (<0.2), with both sets of UHI values calculated with PCA and GWPCA (Table 27). The higher correlations of *Contaminated land* (0.26 and 0.20) may be explained by the low risk from contaminated sites in the study area, which in turn is likely to be perceived as a minor determinant of health. Instead, *Air Pollution* and *Urban Heat Island* both show a weak but positive correlation (>0.20) with PCA indicators and Air Pollution for GWPCA. Instead, a weak negative correlation (<-0.20) is displayed for Food Environment UHI. This result was robust to the use of weightings to generate domains of UHIs so that UHI rating by group C showed similar correlations (ranging from -0.16 and 0.14) (Welch T-test, p-value>0.05).

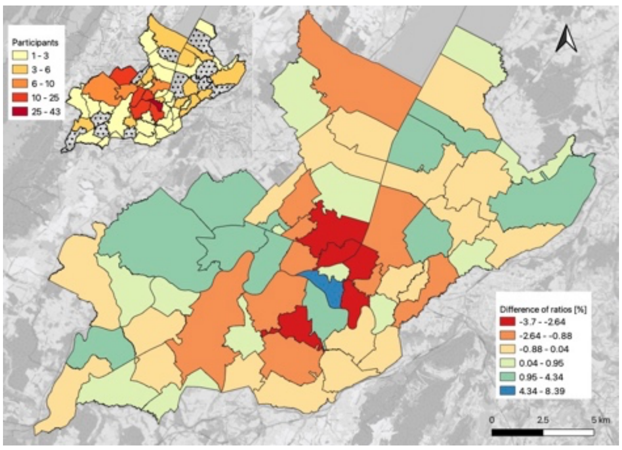

Figure 38: Spatial representativeness of the group C participants about residential population density. The map in the top left corner shows the density of participants within each postal-code area. Positive values imply that participants over-represented a postal-code area compared to population density, while negative represents under-represented areas.

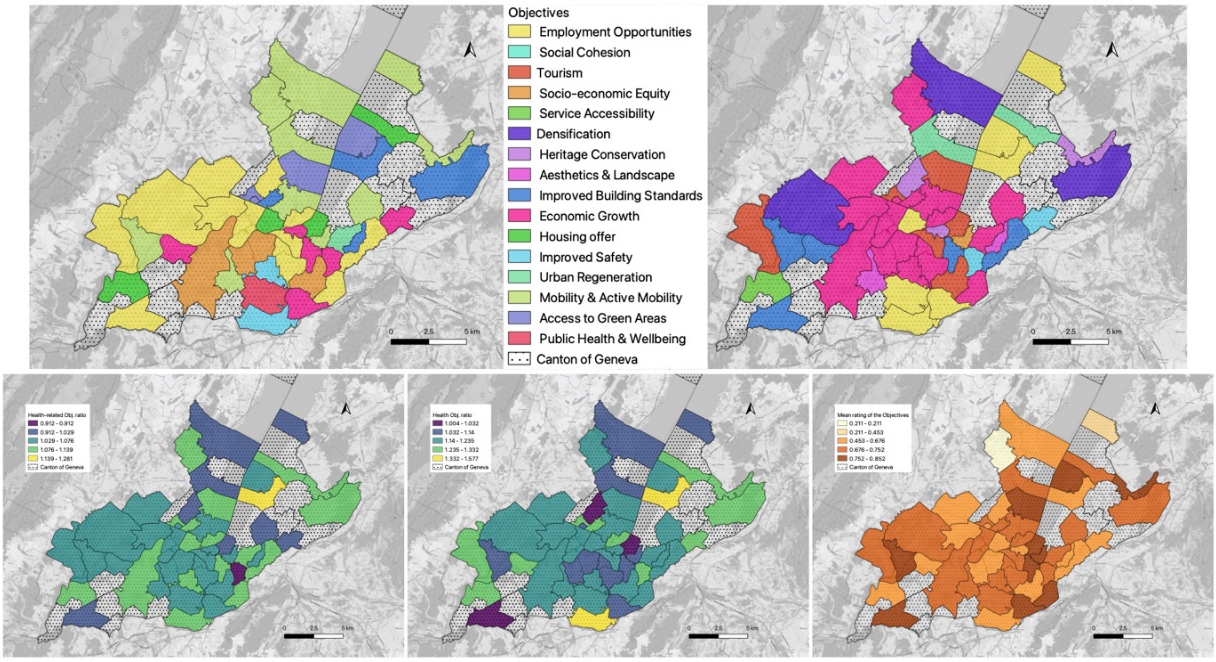

Figure 39: Maps of planning objectives ratings: most rated objectives (top left) and least rated objectives (top right). The three maps on the bottom display the mean values of three indicators: I_{HR}, I_{H} and $I_{obj.}$. Colours are assigned by Natural Breaks partition in four classes.

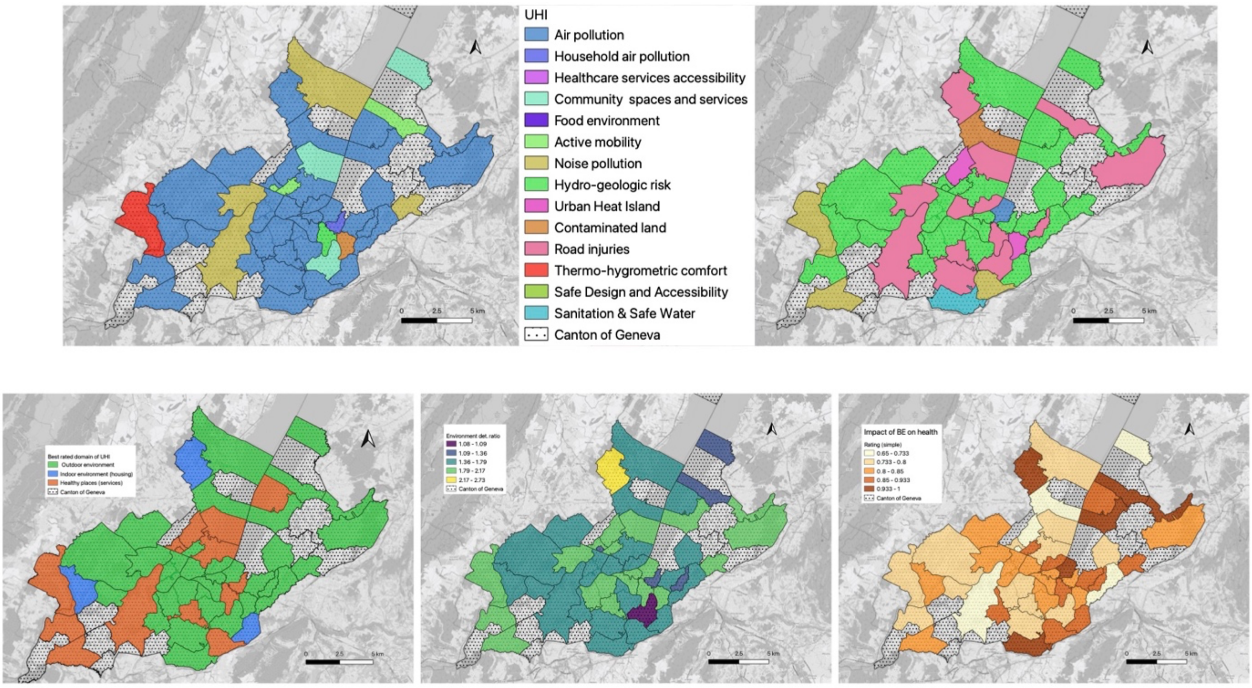

Figure 40:Maps of UHIs' ratings: most rated UHIs (top left) and the least rated UHIs (top right). The three maps on the bottom show from the left: the most rated UHI domain, the I_{ENV} and the I_{BE} indicators.

UHI	PCA	GWPCA
AIR POLLUTION	**0.19**	**0.24**
NOISE POLLUTION	0.1	-0.02
FLOODINGS	-0.09	-0.10
URBAN HEATH ISLAND	**0.27**	0.11
CONTAMINATED LAND	**0.26**	**0.20**
ROAD INJURIES	0.06	0.03
HEALTHCARE ACCESSIBILITY	-0.2	-0.15
INDOOR ENVIRONMENT	0.04	0.08
ACTIVE MOBILITY	-0.06	-0.24
COMMUNITY PLACES	-0.01	0.14
FOOD ENVIRONMENT	**-0.21**	-0.05

Table 27: Correlations between UHI ratings and UHI indicators calculated with PCA and GWPCA (Pearson).

4.4 Discussion

The participants in the survey were generally heterogeneous in terms of age, gender, years of experience, country (group A), and decision power (group A and B). Participants characterized the group of local experts generally specialized in urban planning, while among international experts, only 33% declared to be specialists in urban planning and public health.

In rating planning objectives, groups agreed in ranking as more critical access to green areas, public transport, and active mobility, and in ranking as less relevant economic growth and tourism. International experts and local citizens ranked as first public health and wellbeing and generally perceived more relevant health-related objectives than the mean rating of objectives. The rank was relatively high in the group of international experts due to their involvement in urban health. At the same time, citizens' response was probably biased by the COVID-19 pandemic during the data collection. Group A and B are the groups that display more differences in rating objectives, where the international experts privilege safety, employment, building standards and health, and local planners privilege aesthetics, landscape and heritage conservation compared to other groups. This finding is coherent with the formation of respective experts, and it may display the trade-off between utility or beauty in urban planning (Freestone, 2011; Levy, 2016). In rating planning objectives, international experts and local practitioners display more odds, with citizen ratings mediating the responses of the other two groups. Overall, participants identified as missing relevant objectives, subjects related to sustainability and nature, and secondly to participation and inclusion. Group A also frequently identify land-use mix, urban regeneration and urban resilience as conceptual objectives of planning missing from the proposed list.

All groups generally attribute high importance to the role of the BE in shaping health, with international experts attributing greater importance than local experts and citizens. Also, experts and citizens privileged the environmental factors compared to other core determinants of health, while local practitioners ranked first lifestyle factors. The tendency to assign more responsibility to individuals in terms of health is still a contemporary debate in urban health, which is often instrumentalized to justify inaction (Resnik, 2007; Wikler, 1987; Williams and Fullagar, 2019). Air pollution was distinctly the most relevant UHI across groups. Groups also agreed to rate more relevant sanitation and safe water, food environment, active mobility, and household air pollution. Three issues related to lifestyle, behaviour; hence active mobility, food environment and community places are relevant compared to the mean rating of UHI despite showing different ranks among groups. The agreement in attributing less importance to UHIs was found in hydro-geologic risk and thermo-hygrometric wellbeing. The latter is related to the increasing environmental pressure of climate change on health (Fagliano and Roux, 2018; Friel, Hancock, et al., 2011; UN, 2020). This divergence may be related to the way individuals still perceive as distal the effects of climate change on health through the BE (Fagliano and Roux, 2018; Friel, Hancock, et al., 2011; Morris et al., 2017) because sustainability was previously identified as a relevant objective of urban planning across all groups. Also, the local practitioners and citizens perceived relevant issues of sanitation, safe water, and household air pollution, which are relevant worldwide but have a low impact in the context of Switzerland (Paragraph 3.2.1). Contrarily two other issues of housing, the thermo-hygrometric comfort, safe design, and accessibility, were low ranked by local practitioners and citizens.

In terms of mean values of UHI ratings, the international experts disagree more frequently with other groups, with higher ratings in safety design and accessibility, hydrogeologic-risk, road injuries, and lower ratings in noise pollution (Table 22). The frequencies of integration health and wellbeing in the planning of local practitioners are weakly higher than international experts, which was expected the selective process of two groups of experts consequently. The 41% of international experts are mainly specialized in public health, meaning that their participation in spatial planning is more likely to be occasional and limited since they may work exclusively on public health (Bond et al., 2013; Carmichael et al., 2012). Also, differences in integration health and wellbeing frequencies in planning are not associated with significant differences in rating planning objectives and UHIs.

Afterwards, we employed the rating of each group, and the rating of three alternative clusters, to weight the composite UHI indicators generated in Chapter 3 from the BE attributes in the canton of Geneva. The weighting of UHIs indicators did not generate a significant difference regardless of the subset of weighting used. The WHO's sourcebook of the Urban health index displayed how the rank of weighted and unweighted indicators was robust to weightings (WHO et al., 2014). In our case, both rank and values were robust to weighting, despite the difference between groups (9 UHI on 14 displayed significantly different ratings), because of the low variability among UHIs ratings (standard deviations <0.02). The scale used for the rating is itself a constrain to the variability in weights. However, it's not recommended to use a non-linear scale in surveys (Friedman and Amoo, 1999; Lipkus et al., 2001), which could significantly weight indicators. Instead, the weighting could benefit from a different method of amalgamation, which rewards extreme values which also carries risks. Also, Pineo and Moore reported findings robust to the weighting of experts employing a different method(Pineo and Moore, 2021). Therefore, we suggest integrating stakeholder viewpoints differently during the planning process, i.e., choosing alternatives, providing an alternative source of data, such as self-reported data, perceptions, or behaviours, or building models or eliciting inputs.

The spatial analysis of citizen responses in the local area is characterized by a low spatial resolution and lack of participants in part of the postal codes, even if the latter are sparsely populated. The representativeness of postal codes can be considered reasonable since it is not excessively disproportionate. The most rated objectives of planning generally separate northern areas on the lake shores, which perceive as more important public transportation, active mobility, access to green areas, and improved building standards; from the urban agglomeration and the periphery, which rated as more important objectives related with employment and economy. Also, two central area rates as relevant the housing offer, coherently with their geographic location.

About UHIs, citizens rated as most important Air pollution. Three areas located on the axe of the airport are instead rated as more important noise pollution. Furthermore, the rating of UHIs was positively correlated with three UHIs. Two of them, Air pollution and Urban heat island, displayed more considerable disparities in the UHI indicator values, which were frequent and extended in terms of surface within the canton of Geneva. Among the whole group of citizens, air pollution was ranked as the most important issue regardless of the postal code. Instead, urban heath island was less relevant in citizens ratings, ranking 11 on 14 UHIs, contrarily to the high values and rank observed in the spatial analysis of the BE (Paragraph 3.3).

Multiple factors limit the study. The selective process of groups was necessarily different, and each selection can be affected by different biases. In particular, the recruitment of citizens was self-selective and was limited to users of social media. Direct rating methods do not force participants to rank objects or rate them to display a normal distribution but allow participants to rank objects freely. If participants freely rate objects, they are also allowed to assign equal ratings. Indeed, the findings of this study display a low variability in ratings across participants. The rating of objectives could profit from continuous scales rather than discrete ones (Treiblmaier and Filzmoser, 2011). The list of planning objectives was not designed to be exhaustive and representative of the planning itself because its objective was limited to health compared to other objectives. Also, we did not identify an exhaustive list that included health among the goals of planning. The survey offers a preliminary insight into planning objectives and urban health issues. This choice was made to boost response rates and recruit more participants at the expense of the quality of the information collected by the survey. The study of the role of BE in shaping our health can be integrated from participatory process and survey, also building community contribution to HUP, such as in the protocol created by Black et al. (Black et al., 2021). This study could be further developed to represent the BE by decision-makers and the community in a determined small-scale spatial context, completing the information of objectively measured BE. At the time of the redaction of this thesis, the authors did not find other studies that explore the compare responses between decision-makers and participants recruited from the community.

4.5 Conclusion

This study compared differences in perspective about planning objectives and UHIs across three groups of participants, which represented international urban health experts, planning practitioners of the French-speaking region of Switzerland, and citizens of the canton of Geneva. Significant differences in ratings' values were more frequent than similarities in both objectives and UHIs. International experts reported the most independent responses, regardless the adjustment for the geographic origin, while the local citizens mediated the most responses of other groups. The study allowed the identification of agreements and differences among ratings' rank. Groups generally identified as priorities planning objectives such as greenness, public transportation, and active mobility, or UHIs such as air pollution. The differences between international urban health experts and local planners displayed how the first favour utility in planning compared to planners who cope with aesthetics and culture. With less agreement in ranks, groups prioritized urban health challenges related to services, i.e., active mobility, community places and food environment, and housing, i.e., sanitation, safe water and household air pollution. Also, all groups jointly identified matters of sustainability and climate change as missing planning objectives but later perceived as less important the respective effect of the latter, thus the consequences of extreme climate events. The potential of BE in shaping health was considered important across all groups. Still, international experts in urban health provided the highest ratings and planners with the lowest by summarising ratings with multiple indicators. The weighting of UHI's indicators created in the previous Chapter 3 did not provide a significantly different result due to the low variability across UHIs ratings and methodological constrain of the scale. However, further understanding is necessary to determine whether a stakeholder perspective can successfully be used to compare the many disciplines of urban health. In the end, citizen responses displayed different geographic patterns in planning objectives and UHIs related to the actual BE in the study area, in limited areas for noise pollution, and across the whole study area for air pollution and urban heat island. Also, participants who lived in northern locations along each lake coast prioritized public services and housing quality, while those who lived in urban and suburban areas placed a premium on jobs, economy, and equity. This study enables us to comprehend how health is relevant in planning for stakeholders belonging to different groups with different decision-making power, formations, and roles in the planning process. The findings provide an initial insight into the role that perspectives can play in planning healthier cities depending on the involvement of communities, planning practitioners and urban health expertes.

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Chapter 5 Spatial clustering of geospatial health data and spatial association with the Healthy Built Environment: the case study of Cardiovascular risk factors in the canton of Geneva

Abstract : In this chapter, we conducted a spatial analysis of the healthy built environment in the canton of Geneva, Switzerland. The conceptual framework of urban health issues is employed as the guiding structure after adapting it to the case study. Initially we collected a broad range of geospatial data providing a spatial aggregation of datasets in small-scale spatial and taking into account accessibility. Afterward we employ two statistical methods to summarise the global spatial variation of the healthy built environment (principal componenent analysis), and and the local one (geographic weighted principal component analysis). The global approach enables the comparison of urban health indicators and the quantification of disparities in the distribution of a healthy built environment. Rather than that, the local approach enables comprehension of the heterogeneity of the research area's healthy built environment, as well as the limitations of the global approach in interpreting geographical data as independent. This chapter provides an overview of the canton of Geneva's healthy built environement, allowing for a better understanding of the priorities and areas to examine in order to improve health by shaping the built environment.

5.1 Introduction

The built environment (BE), or the human-made space in which we live, has a significant role in determining our health and well-being (Barton and Grant, 2006; Roof and Oleru, 2008). Indeed, non-communicable diseases (NCDs) prevention requires a multidisciplinary strategy that extends beyond the healthcare sector, not least through urban planning (Barton and Grant, 2013; Leeuw and Simos, 2017a; Rydin, Bleahu, Davies, Dávila, Friel, De Grandis, Groce, Hallal, Hamilton, Howden-Chapman, Lai, CJ Lim, et al., 2012). Numerous studies indicate that multiple characteristics of the BE are associated with cardiovascular diseases (CVD) (Chandrabose et al., 2019; Malambo et al., 2016), which are a leading cause of death worldwide, accounting for 17.9 million deaths in 2019 (WHO, 2021); and in Switzerland, accounting for 67 thousand deaths in 2017 (OFS, 2019). Attributes of the BE, such as residential density, recreational facilities, transportation networks, food environment, have been related to cardiovascular risk factors (CVRF) and outcomes (Diez Roux, 2003; Malambo et al., 2016). The CVRFs include hypertension, obesity and overweight, hypercholesterolemia, blood glucose, and heart rate (Anderson et al., 1991; WHO, 2021).

When comparing BE qualities and CVRFs, several issues related to the relationship's complexity should be addressed, including the spatiotemporal contextualization of persons in space, their heterogeneous responses, and the plethora of BE traits to consider (Koohsari et al., 2020). Therefore in the field of non-communicable diseases (NCDs), the extent to which the BE affects population health has been a matter of contention in the literature, even though its effects and direct causes are well recognized (Eid et al., 2008; Koohsari et al., 2020; Pearce et al., 2015; Rydin, Bleahu, Davies, Dávila, Friel, De Grandis, Groce, Hallal, Hamilton, Howden-Chapman, Lai, CJ Lim, et al., 2012; Walls et al., 2016). Indeed, despite the relevance of the BE where we live, most research does not deal with the geographical context of this relationship (Hills et al., 2019). Research on BE characteristics incorporates geospatial health data infrequently (Kirby et al., 2017; Simpson and Novak, 2013; Yang et al., 2013a), and when it does, spatial analysis is based on aggregated data at district or city spatial scales, which do not allow for a more specific understanding of the relationships between BE and health outcomes (Blangiardo et al., 2020; Rothenberg et al., 2015; Wang et al., 2020). The use of disaggregated data or data aggregated at small spatial scales is crucial to identifying inequities in the distribution of the healthy built environment at individual level (Costa et al., 2019; Elsey et al., 2016; Organization and WHO Centre for Health Development (Kobe, 2010).

In the spatial analysis of health data, numerous studies displayed how CVD and CVRF are spatially dependent and thus contribute to clustering (Auchincloss et al., 2012b; Bergquist, 2011; Charreire et al., 2010; Chen et al., 2014; Drewnowski et al., 2007; Guessous et al., 2014a; Huang et al., 2015; Joost et al., 2016; Mena et al., 2018; Michimi and Wimberly, 2010; Pouliou and Elliott, 2009; Valson et al., 2019; Yin et al., 2020). In particular, the spatial clustering of body mass index in the canton of Geneva has already been discussed by Guessous et al. in both adults and children (Guessous et al., 2014a). Instead, few studies explored the spatial clustering of multiple CVDs and CVRFs (Darikwa and Manda, 2020; Mena et al., 2018). The clustering of CVRF suggests that the BE attributes of its geographic location should be investigated to determine whether an individual's health is related to the geographic context in which they live (Charreire et al., 2012; Frank et al., 2019). Moreover, while evidence linking a broad range of BE qualities to CVRFs has been established(Lovasi et al., 2012; Sallis et al., 2012), research assessing several aspects of the BE and linking them to CVRFs is still scarce(Chum and O'Campo, 2015; Kwan et al., 2021). The CVRFs appear to be prone to form spatial clusters and show spatial dependency depending on the location of residence (Auchincloss et al., 2012b; Bergquist, 2011; Charreire et al., 2010; Mena et al., 2018).

In connecting individuals' health with BE characteristics, few studies recently employed techniques to improve regression performance to account for the non-linearity of the link between BE and health (Kamel Boulos et al., 2019) and to account for the spatial heterogeneity of the latter (Chi et al., 2013; Mansour et al., 2021; Ndiath et al., 2015; Oshan et al., 2020; Saib et al., 2015; Wei et al., 2016). In the first case, methods employing algorithms, such as machine learning, are expected to improve the regression performance parameters (Kamel Boulos et al., 2019; Weng et al., 2017). In the second case, local approaches, which locally implement regression analysis, such as geographically weighted regression (Harris et al., 2011), are expected to understand how the relationship between health and BE vary within the study area (Chi et al., 2013; Oshan et al., 2020).

Research in spatial epidemiology and health geography overlooked the association of spatial dependent covariates, such as socioeconomic status and deprivation (Clark et al., 2009; Koohsari et al., 2021; Winkleby et al., 1992), which findings do not deliver a direct instruction on how to intervene through spatial planning (Elsey et al., 2016; Friel, Vlahov, et al., 2011; Sallis et al., 2016; Walls et al., 2016). Instead, the multi-attribute investigation of BE is suggested as an approach to detangle the multiple determinants of CVDs and deliver an appropriate massage to advocate healthier BE for CVDs (Huang et al., 2015; Sallis et al., 2020).

The representation of the attributes of the BE in the canton of Geneva employs the geospatial data generated in Chapter 3. This chapter is organized into two parts: the spatial analysis of geospatial health data and its relationship with the BE. In the first part, we determined the spatial dependence of six measured CVRFs adjusted for demographic factors in the canton of Geneva (Switzerland). The goal of this part was to determine whether CVRFs measured during medical visits cluster spatially according to the geographic location of the residence. Afterwards, in the second part, using regression analysis, we examined the link between CVRF and BE characteristics across multiple dimensions: different techniques (global and local), neighbourhood sizes, sets of BE independent variables and spatial clusters of CVRFs. Firstly, we studied the performance of the Regression analysis across all dimensions and then its interpretation. Finally, we demonstrated with two examples whether model estimates enable the location of CVRF clusters to be identified.

5.1 Methodology

5.1.1 Analysis of geospatial health data

This study's geospatial health data have been extracted from the Bus Santé study cohort (Guessous et al., 2014b). The Bus Santé is a cross-sectional study on cardiovascular diseases, and cardiovascular risk factors started in 1993 in the canton of Geneva (Guessous et al., 2014b)(de Abreu et al., 2014). The cohort is a stratified sample representative of the demographic distribution of the source population in the study area in terms of age groups, gender within postal codes. Every year, one thousand participants were recruited among non-institutionalised adult (18 -74 years old) residents by mail and telephone. A yearly residence list compiled by the local government is used to identify eligible individuals among all residents in the canton of Geneva. The sampled respondents are contacted initially by mail, and further seven recruitment attempts are made by phone call. Non-reachable subjects are replaced using the same selection process, unlike those who refuse who are not replaced. Individuals who agree to participate fill out a questionnaire then were interviewed and examined by a trained group of four medical collaborators in two hospitals or a mobile station visiting three urban areas. As a result, health data were acquired via an interview and a survey or measurements during a medical visit. Individual data are geographically referenced using the postal address of the participants (Guessous et al., 2014b)(de Abreu et al., 2014). Before entering the study, each participant signed an informed consent form. The Bus Santé cohort has been used to study the spatial distribution of health determinants (Guessous et al., 2014b), the relation between risk factors and socioeconomic status (Galobardes et al., 2003; Stringhini et al., 2017), or the relation between lifestyle and health outcomes (De Ridder, Belle, et al., 2021; Joost et al., 2019). The cohort of Bus Santé participants has also been recently used to study the SARS COVID-19 pandemic (De Ridder, Sandoval, et al., 2021; Stringhini et al., 2017).

We used data from collected between 2005 and 2014, corresponding to more than 9500 participants, employing health measures rather than surveyed data. They provide a continuous appraisal with a numerical value rather than a binary state of illness-healthiness or a definite factor measure. Multiple health measures allowed the calculation of six cardiovascular risk factors (CVRF): body mass index, waist-hips ratio, mean arterial pressure, low-density cholesterol, heart rate, and blood sugar. Also, we excluded older data, which would have introduced a larger bias in linking health with a different geographic context than the one represented in Chapter 3.

Body Mass Index (BMI) (Khosla and Lowe, 1967) was determined using weight w[kg] and height h[m], both of which were measured in light clothing, without shoes and using a medical scale and a medical gauge:

$$BMI = \frac{w}{h^2}$$

Waist-Hips Ratio (WHR) (WHO, 2008) was calculated from the physical measure of waist circumference w_c [m], the hips circumference hc [m] in light clothing:

$$WHR = {}^{w_c}/_{h_c}$$

The Mean Arterial Pressure (MAP) (Zheng Liqiang et al., 2008) was calculated from the systolic blood pressure (SBP) and the Diastolic Blood Pressure (DBP) [mm HG] measured via tensiometer test:

$$MAP = \frac{SBP + 2 * DBP}{3}$$

The Low-Density-Cholesterol (LDL) was calculated according to the Friedwald equation (Vujovic et al., 2010) [mmol/L] using the total cholesterol tot_{chol} , the high-density cholesterol HDL, and the Triglyceride measured with a non-invasive (finger) blood test:

$$LDL = tot_{chol} - \frac{Triglyceride}{5} - HDL$$

A tensiometer test directly measured the Heart Rate (HR) [bpm] and Blood Sugar (or blood glucose) [mmol/L] by a non-invasive (finger) blood test.

Furthermore, health data were adjusted for age, gender and education level (years of formation). We did not consider household economic status because approximately 66% of participants preferred not to report it. The median revenue per administrative subsector in 2009 (OFS, 2009) might have been used instead. Still, its low spatial resolution introduces an excessive amount of inaccuracy at the individual level, which we have chosen to avoid.

STATISTICAL ANALYSIS

Firstly, we calculated summary statistics of the dataset. We used multivariate linear regression to adjust health measures by age, gender, and education level. We employed the Moran's I statistic to calculate the Local Indicators of Spatial Autocorrelation (LISA) (Anselin, 1995) to investigate whether health measures were randomly distributed in space or displayed spatial dependency by using the geographic locations of the participants' postal addresses. The Moran's I statistics are intended to evaluate if the spatial randomness is rejected, favouring clustering, which does not indicate the clusters' location. Instead, the LISA allow the calculation of a statistic (and a pseudo-p-value) per each point. Also, it classifies points in local clusters or local outliers depending on the relationship between the sum of local statistics and the sum of global statistics. The measure of what is defined as local depends on the spatial lag and the weighting method. Therefore, the relationship between each participant's standardised health measure and the local weighted mean of the same standardised health measure was calculated for each participant. By plotting standardised health measures and lagged (local) counterparts on the Moran scatterplot, each participant is assigned to one of four distinct classes or considered randomly distributed. Consequently, participants are categorised as follow depending on their postal address and the value of their health measures:

- High-High (HH) cluster (red points): high individual value in a neighbour (spatial lag) predominantly characterised by high values.

- Low-Low (LL) cluster (blue points): low individual value in a neighbour (spatial lag) predominantly characterised by low values.
- Low-High (LH) outlier (pink points): low individual value in a neighbour (spatial lag) characterised by predominantly high values.
- High-Low (HL) outlier (purple points): high individual value in a neighbour (spatial lag) predominantly characterised by low values.
- Not-Significant (NS) relationship (white points): individual value that is not spatially dependent, so that it may be considered randomly distributed in space.

The statistical significance test used to assign an individual to one of the previous classes uses a conditional permutation method on all other local values, delivering a pseudo-p-value for everyone. This study used a binary weighting approach using a spatial lag of 800m, and clusters were generated using 999 permutations and a pseudo-p-value of 0.05.

To understand how the choice of spatial lag influence LISA, we studied the weighting characteristics of multiple spatial lags ranging from 400m to 1600m at intervals of 200m (Appendix). The spatial lag of 800m has been chosen as the minimum spatial lag so that the 99.9% of points have at least 1 neighbour. Therefore, the most geographically isolated points (n=6), namely “islands” (the 0.01%) are considered as not significant in forming spatial clusters a priori. Also, the spatial lag allows the 99% of the participants display at least 10 neighbours (Figure 41).

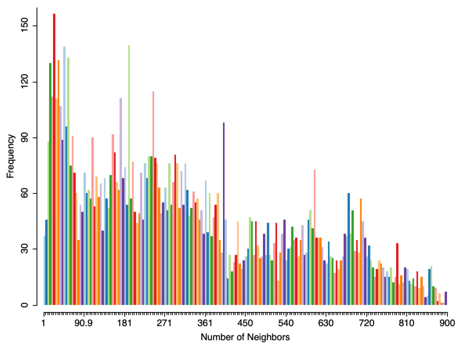

Figure 41: Connectivity histogram of geospatial health data with the spatial lag of 800m.

To understand the robustness of the significance level; 99, 999, 99999 permutations were tested to calculate LISA. By comparing the LISA sizes calculated with different number of permutations, 999 was chosen since clusters sizes display a small variation (SD ± 2.0%) compared to the 99999 permutation LISA clustering. To understand if sub-sets belonging to different periods (2005-2009, and 2010-2014) could be merged, we tested if Moran's Is were significantly different from the Kolmogorov-Smirnov test means were significantly different with T-Test (Welch). The p-values for Moran's I were greater than 0.01 for both sub-period for all health measures, ranging from 0.69 to 0.81 for 2005-2009, and from 0.72- 0.79 for the sub-period 2010-2014 compared to the whole period 2005-2014. Also, the p-values for means of health measures were greater than 0.01 for both sub-periods, ranging from 0.09 to 0.19 for 2005-2009, and from 0.07- 0.20 for the sub-period 2010-2014 compared to the whole period 2005-2014. Therefore, we deduced that subperiods could be merged. Furthermore, the linear regression of health measures shows a null to weak decrease (coefficients ranging between -0.01 and -0.31, R^2 between 0.01 and 0.02) across years for all health variables. Maps of LISA clusters (and the respective significance level) of both unadjusted and adjusted health measures are presented (Figure 43 and Figure 44). Maps of the values of health measures are not shown because they visually display a salt-and-pepper pattern, thus appears randomly distributed in space (Li et al., 2020). In the end, to explore the relationship between health measures, we performed a correlation analysis (Pearson) among them, and to compare clusters we calculated the colocation of high-high (HH) and low-low (LL) relationship. The strong correlation between health measures was a prerequisite for creating a synthetic indicator to merge multiple variables. Therefore, similarly to HBE features in chapter 3, health measures were combined using Principal Component Analysis (PCA) and Geographic Weighted Principal Component Analysis (GWPCA). The approach followed precisely the same procedure described in chapter 3, applying it on standardized values of the adjusted health measures. Then, we calculated the LISA statistics of the resulting health indicator of CVRF as already done for health measures.

5.1.2 Regression analysis

We performed a regression analysis to estimate health measures of CVRF extracted from the Bus Santé cross-sectional study by using as explanatory variables the characteristics of the HBE in the canton of Geneva. The performance of the regression analysis was explored across multiple directions, thus by varying inputs (both dependent and independent variables), employing different spatial aggregations, and using either aspatial (global) methods or spatial (local) methods of analysis (Figure 42).

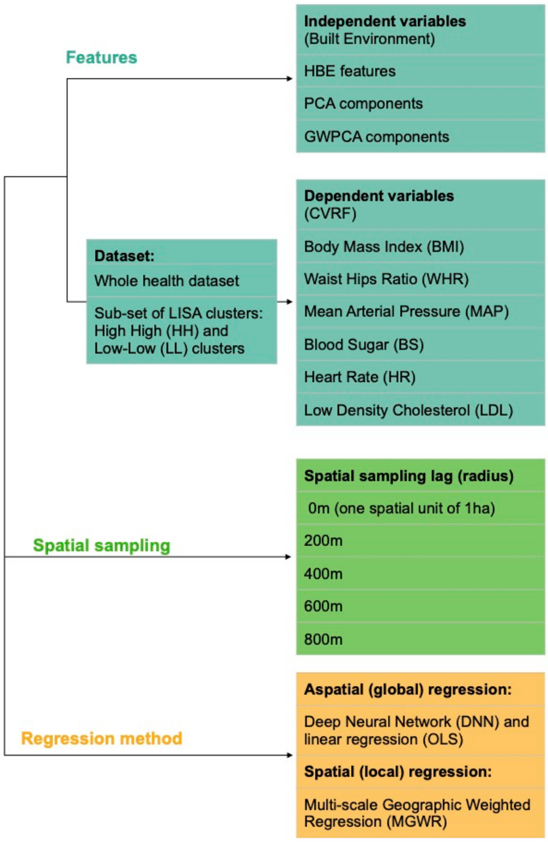

Figure 42: Dimension of the regression analysis.

Datasets

The independent variables were selected from the HBE geospatial data generated in chapter 3. The HBE geospatial data are characterised by the same set of 24690 hexagonal spatial units (SUs) (chapter 2). We used three groups of HBE variables to estimate health measures:

- the HBE features; thus, the raw variables that directly represent the HBE, i.e., road network length.
- the principal components obtained with PCA by decomposing HBE features.
- the principal components generated with GWPCA by decomposing HBE features.

We excluded Flooding and Contaminated Land UHIs and the respective HBE features within each group. The latter are not considered significant risk factors for CVD in the scientific literature and were excluded from the analysis.

The regression analysis was performed on each of the six health measures of CVRF as dependent variables: body mass index (BMI), waist-hips ratio (WHR), mean arterial pressure (MAP), heart rate (HR), blood sugar (BS), low-density cholesterol (LDL). Secondly, the regression analysis was tested on the sub-set of LISA clusters of high-high relationship (HH) and low-low relationship (LL). Therefore, we tested the hypothesis that individuals who show significant spatial (positive) spatial dependence are more likely to show a spatial association with HBE characteristics than the whole dataset. In brief, regression analysis was performed for each health measure, the whole dataset, and the respective sub-set of HH and LL LISA clusters of each health measure.

Spatial aggregation

The geospatial health dataset of CVRF has been used to sample HBE characteristics in two ways:

- By sampling the HBE characteristic from the SU on which a point of the health dataset, consequentially to each participant is attributed an HBE defined only by the SU in which the postal address is located.
- Or by attributing the mean values of HBE characteristic sampled by a buffer around a point of the health dataset, thus to each participant is attributed a mean value of the HBE from multiple neighbours SUs.

In the second case, we tested four radii for the sampling buffer around postal address location: 200m, 400m, 600m and 800m. Adopting a single SU provides a sampling buffer whose area is slightly larger than a circle of 100m since a hexagonal SU of one hectare circumscribes a circle of 107m. The single SU corresponds to an area of 1 ha, the radius of 200m to an area of 12.5 ha, the radius of 400m to an area of 50.3 ha, the radius of 600m to an area of 113.1 ha, and the radius of 800m to an area of 201.6 ha. When spatial sampling is performed at the level of the single SU, all individuals whose postal address is located within the same SU is assigned the same set of HBE characteristics defined by that SU. In the second case, the different locations within a SU can bring differences with points located in the same SU.

5.1.2.1 Regression methods

After that, regression analysis was tested using aspatial and spatial methods, thus by a global approach that considers the whole dataset regardless of the spatial arrangement of features or a local approach that weighs more closer features than the further ones. In the first case, we adopted a Deep Neural Network (DNN) model and an ordinary least square regression (OLS), and in the second case, we used Geographic Weighted Regression (GWR).

Deep Neural Network

Neural Networks is a machine learning method based on a hierarchic network of neurons organised in layers. Each neuron, namely a perceptron (Rosenblatt, 1958), by using an activation function calculates an estimate from training subset of input data, which is used as input in the following cascading layer of neurons. Then the error related to the estimate of the last layer allow in turn the adjustment of the weighs of each neurons' function backward or forward. Upon the adjustment the model is run again multiple times (epochs) until the error is minimised and converge for the training and test subsets. A Deep Neural Network (DNN) is basically a neural network with multiple layers, so that there is at least one hidden layer beside the input and output layers (Gulli and Pal, 2017).

The regression between the dependent and the independent variables by Deep Neural Network was performed on Python employing the TensorFlow package (Mart´ın Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, et al.,). The regression between one standardised dependent variable and multiple standardised n independent variables was performed on a random sample of 10% of the dataset (test size 0.1) pre-processing data with the package Scikit-learn (Pedregosa et al., 2011). We used a sequential model based on multiple dense layers characterised by a decreasing number of neurons. The number of layers was variable, with a minimum of 2 hidden layers. The number of layers depended on n, so that each following layer halved the number of neurons of the previous layer (rounded down), and the output layer has one neuron. For example, a model employed on one output and n=12 is characterised by four layers with 12, 6, 3, and 1 neuron. The input and the hidden layers are characterised by a decreasing random dropout of neurons, ranging from 0.5 in the first layer to 0.1 in the last hidden layer. Those layers were based on "relu" activation function. The output layer was characterised by one neuron based on the "relu" activation function and mean absolute error as loss parameter. The model was compiled based on "adam" optimiser (Liu and Grana, 2019), used accuracy as a metric and performed a maximum of 500 epochs. Also, model fitting was characterised by "Early Stopping" based on value loss with the patience of 50 epochs.

The model was tested on HBE characteristics to understand its performance compared to Linear regression and Random Forest (Tin Kam Ho, 1995). Therefore, we calculated R_2 using the DNN model previously described, Random Forest and Linear regression, to estimate two environmental HBE features, noise level and physiologic equivalent temperature (PET). We used as independent variables road and railway network characteristics for noise level, and building characteristics, green areas, water bodies, and road networks characteristics for PET. The noise level and PET, provided by SonBase (FOEN, 2018c) and SITG (SITG, 2021), are based on physical models that use as input the independent variables and other variables such as traffic counts for noise level or wind speed for PET. For noise level, the DNN model (R^2=0.33) performed better than Random Forest (R^2=0.27) and Linear regression (R^2=0.25). For PET, the DNN model (R^2=0.27) performed similarly to Random Forest (R^2=0.28) and better than Linear regression (R^2=0.21). Thus, we concluded that the model could be applied to another dataset, such as the health measures of CVRF. The architecture used in this study prevented overfitting, which was qualitatively evaluated by plotting value losses with losses of the model and checking its convergence. Early stopping reduced computational time by delivering prediction with a mean number of epochs of 189 (SD:

±71.6). The performance of the DNN model was measured in terms of errors by mean percentage error (MAPE), and about the correctness of the model, by R^2 score and explained variance (EV).

To grasp the independent variables' contributions to OLS, it is required to extrapolate weights, and hence coefficients, for each feature. Instead, non-linear models such as neural network, can be interpretated a posteriori using the estimates of the model (Lundberg and Lee, 2017). We used Shapely Additive explanation (SHAP) values to understand the contribution of feature values. The SHAP is based on a coalitional game theory model in which a pay-out is assigned to each player depending on the contribution on the total pay-out (Shapley, 1953), which make it suitable for cases of multicollinearity (Lundberg and Lee, 2017). The SHAP calculates for each feature value the average marginal contribution of that feature value across all possible "coalition", thus all possible sub-sets of features, meaning that it varies all possible withheld features. In brief, it retrains the model by giving a weight to each feature, for example, the length of the road network, reflecting the effect of including that feature on the model estimate of the dependent variable, i.e., mean arterial pressure. The Shapley values can be positive or negative so that it explains how a feature shift values from baseline values to be higher or lower per each feature value. Therefore, a feature, usually shows both positive and negative shapely values. As a result, if the sum of the squares of the Shapley values in a feature is larger than the sum of the squares of the Shapley values in a second feature, the first one is more significant. However, the Shapley values' distribution is needed to understand whether how features contribution is concentrated and whether contributions are positive or negative.

Multi-scale Geographic Weighted Regression:

Geographically weighted regression (GWR) is a variation of ordinary least square regression (OLS) whose parameters that describe the relationship between dependent and independent variables vary locally, thus can be sensitive to geographic contextual factors (A. Stewart Fotheringham et al., 2002; Oshan et al., 2019). The GWR is mainly used as explorative tool to understand complex spatial relationship, i.e. dose-effect or stimulus-response, which may vary depending on the location, rather than provide a prediction for inferring spatial processes (Páez and Wheeler, 2009). Shortly, GWR perform OLS regression for each point weighting parameters depending on their location, so nearer points are given greater weights than observation further away. The measure to which weights affect neighbouring observation in the GWR, is related with the bandwidth and the model that calculate weights. The GWR which was initially developed to perform at fixed bandwidth (A. Stewart Fotheringham et al., 2002), was implemented by a statistical method based on cross-validation to identify an optimal bandwidth that fit the model (Guo et al., 2008). However, identification or the choice of a bandwidth imply the assumption that the observed relationship operates at the same spatial scale. To overcome this assumption, GWR has been implemented by Oshan et al. to identify an optimal local bandwidth per each feature value thus per each point through the Multi-scale Geographic Weighted Regression (MGWR) (Oshan et al., 2019).

We used Multi-scale Geographic Weighted Regression (MGWR) to compute a regression that is spatially-aware, thus it takes into account the non-stationary relationship between variables in the geographic space. We performed MGWR employing the python package mgwr (Oshan et al., 2019), using gaussian model based on Akaike optimization criterium (Akaike, H., 1973), searching the adaptive multi-scale bandwidth, and weighting by bisquare spatial kernel. We evaluated the performance by calculating R^2 score and sum of squares (SS). Moreover, the MGWR allows the visualization of local estimators of the regression, thus local coefficients and local R^2. Then, contributions of variables have been studied by observing the summary statistics of estimated coefficients.

Statistical analysis of two representative examples and clusters subdivision:

After evaluating the performance and contribution of BE characteristics across all regression dimensions, we chosen an example whose combination of dimension performed the best and was most representative of the spatial distribution of CVRFs. Following the findings of spatial clustering of CVRFs values, we displayed the full set of estimators of the OLS, DNN, and MGWR regression about all sets of BE independent variables for two health measures.

Afterwards, to directly understand the HBE profile of LISA location, we directly compared the value of HBE features of LISA cluster's locations of high-high relationship with the rest of the dataset. We focused on HH clusters rather than LL clusters because we are interested in understanding what is associated with illness rather than healthiness. A consequence of the heterogeneity of the HBE is that the characteristics of HBE depend on the location. While this issue is solved theoretically by MGWR, two barriers affect a complete understanding of relevant information in different locations. Firstly, the MGWR produces a different set of coefficients per point, meaning we can summarise the contribution of coefficients by picking extreme values. However, the features so sampled might be discordant to the expected association between HBE and health. For example, a cluster of individuals with a high body mass index can be in an area well served by public transport. The maximum local coefficient consequently displays a positive association with better public transportation. This information can still suggest which intervention could be avoided to support healthy living through planning. However, in this way, secondary adverse HBE features may be missed. Secondly, the MGWR coefficients can be affected by multicollinearity in the input variables so that two strongly correlated features can generate discording signs in coefficients more significant than other variables. In this way, the joint contribution of correlated variables is almost null even though they display high values. After that, to avoid these two issues and provide a direct interpretation of how different the HBE in different cluster areas is, we proceeded by two steps:

- Identify contiguous points of HH clusters.
- Study the statistical differences that those locations display in terms of HBE features compared to the rest of the study area.

Initially, we identified separated clusters in multiple areas by setting a minimum distance between points and a minimum number of points per location. Therefore, isolated points, namely “islands”, were excluded.

Afterwards, we tested whether means or distributions of HBE features in those locations significantly differ from the rest of the study area with a non-null residential population. The difference between means was tested with Welch T-Test, and the difference between distributions was tested with the Kolmogorov-Smirnov test. Consequently, the different locations identified by LISA clustering across health measures, we tested the difference in HBE for HH LISA clusters of body mass index (adjusted), which is the health measure that displays the greater positive correlation with the others health measures; and for HH LISA clusters of heart rate (adjusted), which displayed a negative correlation with all other health measures. Indeed, LISA clusters of waist-hips ratio, low-density cholesterol and blood sugar mainly overlapped with the BMI clusters and were not investigated.

5.1.2.2 Reconstitution of clusters by regression estimates

In the end, we tested how regression estimates formed LISA clusters and compared them to the clustering of health measures. We have chosen a representative health measure and spatial sampling lag rather than verifying it for all health measures and spatial lags. For this example, we have chosen BMI (adjusted) as a health measure since it’s one of the most studied CVRF in literature and since it has already been studied by Guessous et al. on the same case study (Guessous et al., 2014a). Also, the other health measures, except HR, are highly correlated with BMI (Pearson correlation > 0.8). We used 200m as the spatial lag of sampling because it produced the best estimates (in terms of EV and across different methods in describing variance of the dependent variables. Regarding independent variables, we examined both PCA and GWPCA principal components and DNN and MGWR in terms of regression techniques. Clustering methods followed the same procedure described in paragraph 5.1.1 (Univariate Local Moran’s I, 800m spatial lag for distance weighting, 0.05 significance level, 999 permutations). Then we compared the locations of LISA clusters of BMI (adjusted) with the location of LISA clusters of BMI estimates according to two methods and two sets of independent variables. Depending on the method and the independent variables set, we calculated the percentage of HH, and LL clusters point identified by estimates and compared the size of clusters obtained from estimates and health measures.

5.2 Results

5.2.1 Spatial analysis of geospatial health data

By eliminating participants with missing data, a total of 6835 participants were chosen. Participants were evenly split between genders (49.6 % Men, 50.4% Women), the mean age among participants is 50 years (SD±12.8), and 38.3% of them had a tertiary degree. The mean BMI adjusted by covariates was 25 kg/m2 (SD ±2.6), with 47% of participants (n=3215) being classed as overweight (BMI> 25 kg/m), 13% (n=891) classed as obese (BMI> 30 kg/m). The mean MAP adjusted by covariates was 90 mm HG (SD ±5.4), so that for the 19.7% (n=1351) of values hypertension could be diagnosed (MAP> 100 mm HG). The mean WHR adjusted by covariates is 0.86 (SD ±0.07), and women above the heathy threshold of WHR (0.86) are 26.7% (n= 911), while men above the threshold (1.0) are 18.8% (n=645) (WHO, 2008). The mean adjusted HR was of 68.9 bpm (SD ±1.6), with 0.4% (n= 34) of values above 100 bpm, and 19.3% (n= 1321) of values below 60 bpm. The mean adjusted LDL was 3.74 mmol/L (SD ±0.22), with 30% (n= 2052) of values considered high, thus above 4.2 mmol/L. The mean SB adjusted by covariates is 5.07 mmol/L (SD ±0.33), and the 19.8% (n= 1357) have high levels of SB (5.6 mmol/L) (GHO WHO, 2021). Also, the prevalence of CVRF in the Bus Santé dataset is coherent with the federal and cantonal reports (Canton de Genève, 2020; OBSAN,).

Variable	N (%)
Men	3391 (49.6%)
Women	3444 (50.4%)
Tertiary education	2618(38.3%)
Secondary education	6090 (89.1%)
	Mean (SD)
Age [years]	50.0 (12.8)
Body Mass Index (BMI) [kg/m²]	25.16 (2.6)
Waist-Hips Ratio (WHR)	0.86 (0.07)
Mean Arterial pressure (MAP) [mm HG]	90.0 (5.4)
Hearth Rate (HR) [bpm]	68.9 (1.6)
Blood Sugar (BS) [mmol/L]	5.07 (0.33)
Low Density Cholesterol (LDL) [mmol/L]	3.74 (0.22)

Table 28: Summary characteristics of the health dataset), Bus Santé (2005-2014), n=6835.

Additionally, the health measurements were consistent with the health data collected during the interview. For example, participants who reported receiving a diagnosis of hypertension had a considerably higher MAP than those who did not. The participants of the Bus Santé study are mainly located in the urban area, so that urban agglomeration collects 90% of the participants, while the same area collects 82% of the total residential population in the canton of Geneva. The percentage of participants that belongs to a LISA cluster, hence, display spatial dependency, ranges from 9.2 to 26.6% (Table 29). The spatial arrangement of health variables delivers a global Moran's I range from 0.01 to 0.05 (Table 29). As a result, most participants exhibit little spatial dependence and appear randomly distributed, indicating that they do not belong to any LISA cluster. Indeed, health measurement shows a percentage of individuals belonging to a LISA cluster ranging from 9.2% of BS to 26.6 % of MAP. The values of health measures belonging to different clusters show significant differences (two-way ANOVA, p-value <0.01). Indeed, clusters of High values (HH and HL), clusters of low values (LL and LH), and non-significant individuals' groups are significantly different (Welch T-test, p-value <0.01) (Table 30). This finding was reported for both adjusted and unadjusted variables. All health measures display LL cluster sizes larger than the respective HH clusters size, but the HR.

	UNADJUSTED		**ADJUSTED**	
VARIABLE	size (%)	Moran's I	size (%)	Moran's I
BMI	2467 (36.1)	0.013	2958 (43.3)	0.028
WHR	1366 (20.0)	0.003	2240 (32.8)	0.013
MAP	2828 (41.4)	0.011	2745 (40.1)	0.020
HR	1760 (25.7)	0.008	1948 (28.5)	0.004
LDL	1513 (22.1)	0.001	2896 (42.4)	0.022
BS	1307 (19.1)	0.007	2851 (41.7)	0.022

Table 29: Participants belonging to LISA clusters: counts and percentages per each health measure.

	HH mean	HH count	LL mean	LL count	Difference HH LL [%]	T	F
BMI	29.2	647 (9.5%)	22.1	736 (10.8%)	32.1	45.8*	522.6*
WHR	0.95	358 (5.2%)	0.79	372 (5.4%)	20.3	41.4*	281.3*
MAP	101.3	515 (7.5%)	80.9	1052 (15.4%)	25.3	46.1*	659.3*
HR	77.1	652 (9.5%)	61.2	320 (4.7%)	25.9	42.2*	320.0*
Sugar blood	6.0	245 (3.6%)	4.64	456 (6.7%)	29.3	13.0*	125.3*
Ldl	4.53	123 (1.8%)	3.0	711 (10.4%)	51	27.1*	298.1*
Adjusted:							
BMI (adj)	26.6	585 (8.5%)	23.9	1078 (15.8%)	10.9	55.8*	829.4*
WHR (adj)	0.94	350 (5.1%)	0.8	846 (12.4%)	17.5	61.1*	647.6*
MAP (adj)	95.3	480 (7%)	85.4	1021 (14.9%)	11.6	52.8*	700.3*
HR (adj)	70.5	546 (8%)	67.4	413 (6%)	4.6	70.2*	514.9*
Sugar blood (adj)	5.5	531 (7.7%)	4.89	1057 (15.5%)	12.5	54.7*	742.4*
Ldl (adj)	3.96	547 (8%)	3.55	1112 (16.2%)	11.6	57.1*	763.4*

Table 30: mean values of health measures (unadjusted and adjusted) in High-High (HH) and Low-Low (LL) clusters, respective count, F statistics between all clusters and T statistics between HH and LL clusters. (*) The p-value for both ANOVA and T-test (Welch) was always below 0.01.

The location of the LISA cluster, the significance level, and the cluster sizes are displayed in Figure 43 per each health measure and Figure 44 per each adjusted health measure. All raw health measures except for HR visually display similar locations:

- HH (red) points are located in multiple suburban areas east of the urban agglomeration and west.
- LL (blue) points are located in the urban agglomeration's core area and a few minor sites in the north-western rural area.

In HR, HH locations are placed generally in the west area of the urban agglomeration. In contrast, LL locations occupy the west urban agglomeration area and multiple locations on the lake shores and rural areas.

As shown in Figure 43 and Figure 44, clusters location is resistant to adjustment for age, gender, and education for all health variables. The adjustment affected extreme health measures so that HH and LL mean values display differences from 4.6% to 12.5% when unadjusted values differences were between 20.3% and 51%. The adjustment decreased the HH cluster sizes for all health measures, except for the SB and LDL, respectively increasing by 4.1% and 6.2% (Table 30). The adjustment also increased the LL cluster sizes for all health measures, except for the MAP and HR, which weakly decreased (Table 30).

Overall, the adjustment reduces the number of individuals who are classed in HH and LL clusters. Still, it increases the number of participants who belong to multiple clusters of different health measures since it increases the correlation between health measures (Figure 45). Therefore, the number of participants who belong to only one or two HH or LL decreases, increasing the number of participants who belong to more than two clusters (Figure 45). After the adjustment, 51.2% of LISA clustering is conserved for BMI, 71.1% for WHR, 61.4% for MAP, the % for LDL, the 51.6r BS, and the % for HR. In Appendix, we show the clustering with LISA clusters and joint counts (clustering for binary variables) of additional geospatial health data collected during interviews.

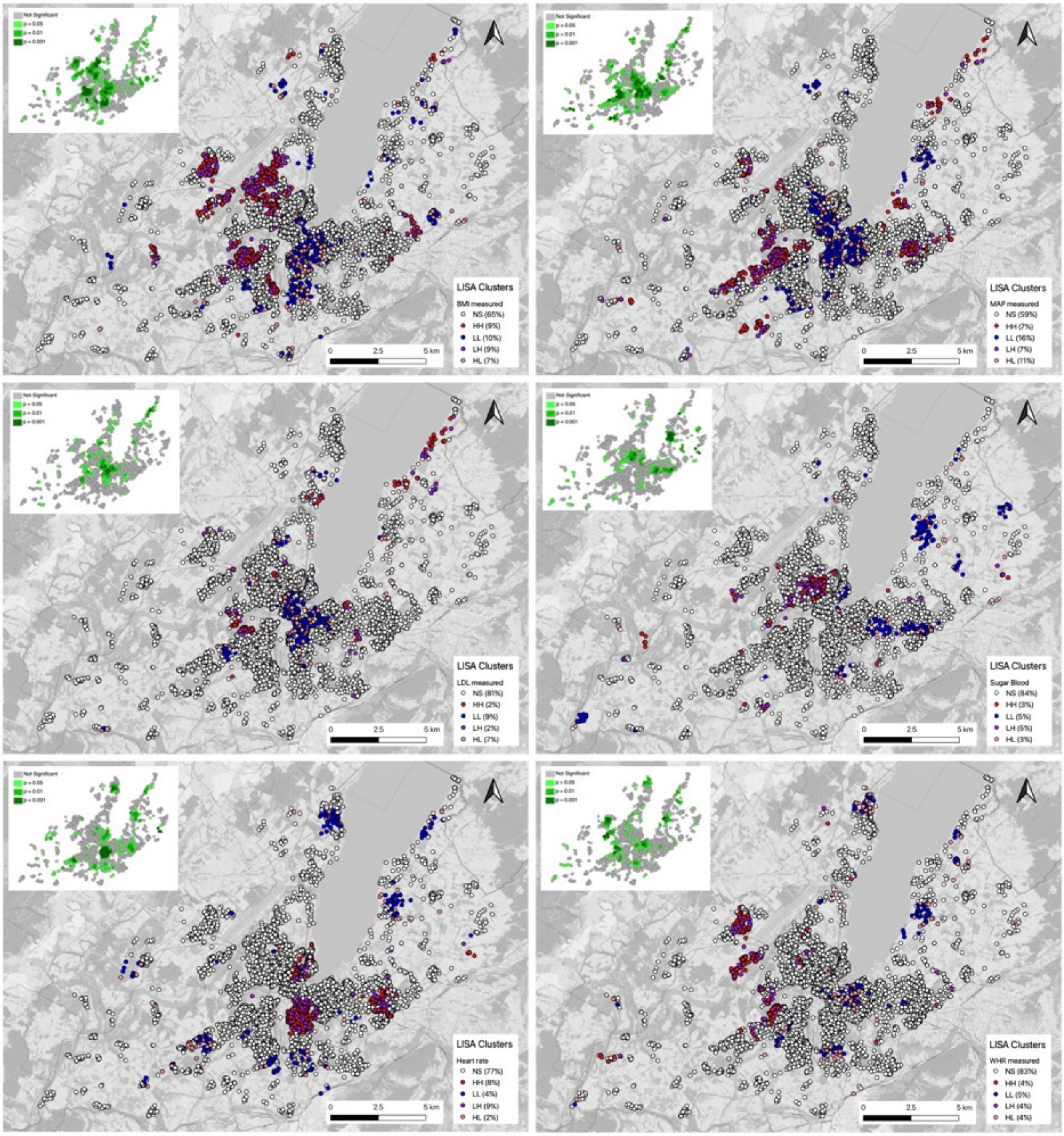

Figure 43: The maps of LISA cluster of health measures (raw). Each map of the LISA cluster is coupled with the map of pseudo-p-values in the top-left corner. White dots (NS) represent individuals who do not exhibit a substantial spatial dependence on the standardised value of a particular health parameter. Red dots (HH) show individuals characterised by significant high z-score in a neighbouring area of high z-scores. Blue dots (LL) show individuals characterised by significant low z-score in a neighbouring area (spatial lag) of low z-scores. Purple (LH) and pink (HL) dots represent individuals that show a significant z-score discordant from the z-scores in the neighbouring area (spatial lag).

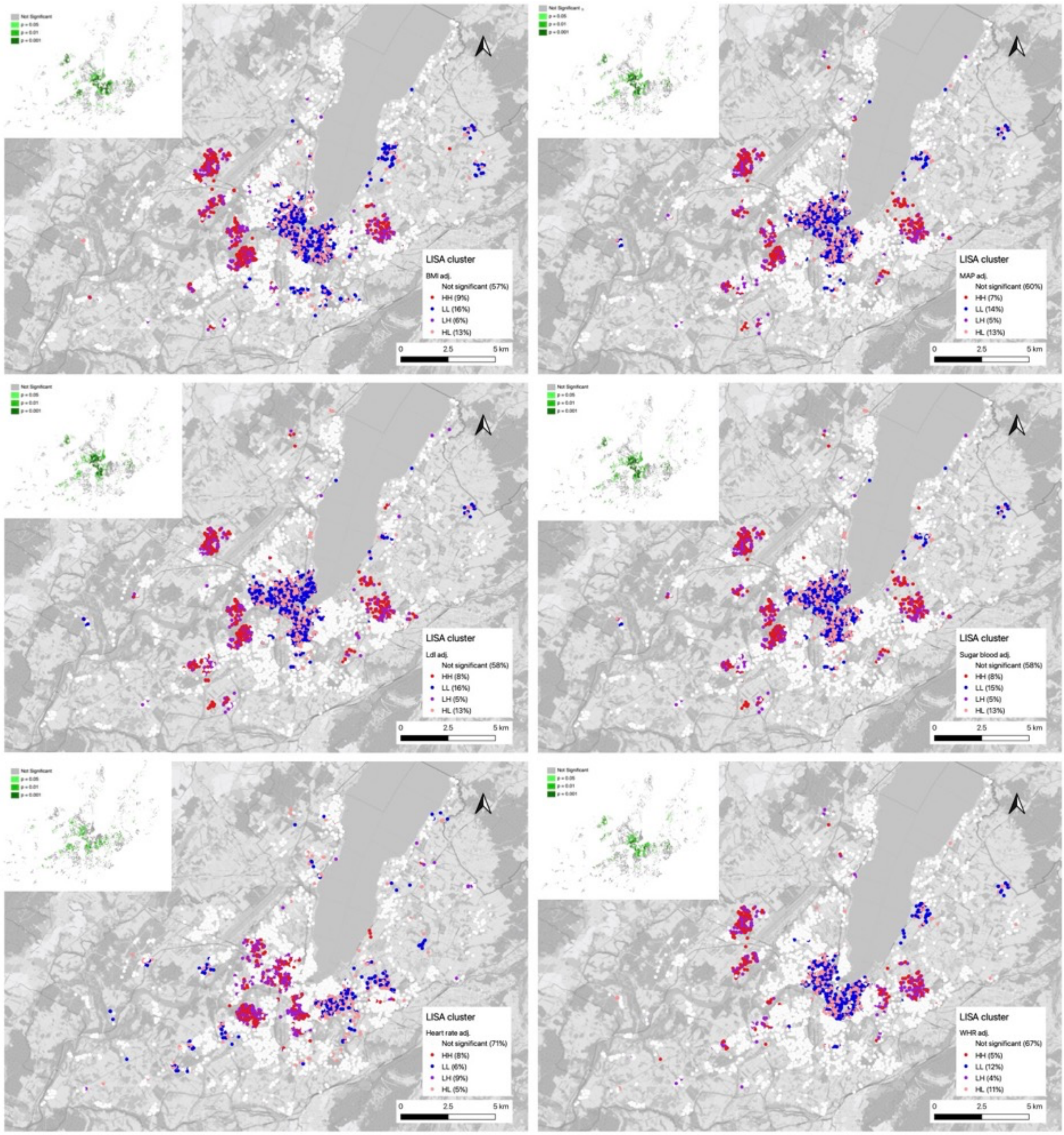

Figure 44: The maps of LISA cluster of health measures (adjusted). Each map of the LISA cluster is coupled with the map of pseudo-p-values in the top-left corner. White dots represent individuals who do not exhibit a substantial spatial dependence on the standardised value of a particular health parameter. Red (HH) shows individuals characterised by significant high z-score in a neighbouring area of high z-scores. Blue dots (LL) show individuals characterised by significant low z-score in a neighbouring area (spatial lag) of low z-scores. Purple (LH) and pink (HL) dots represent individuals that show a significant z-score discordant from the z-scores in the neighbouring area (spatial lag).

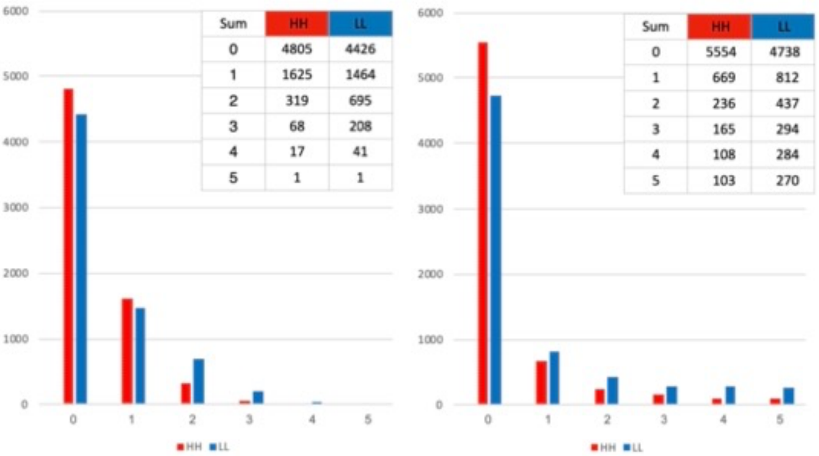

Figure 45: Counts of cumulative membership to HH and LL clusters among participants for all health measures, unadjusted (left) and adjusted (right.

Health measures were combined into a CVRF indicator using PCA and GWPCA, adopting only the first principal component, which could explain 86.2% of the total variance by using PCA or GWPCA. The loadings calculated with PCA of health measures were similar, ranging between 0.42 and 0.44 for BMI, WHR, MAP, BS, and LDL, except for -0.31 loading of HR. Similarly, GWPCA local loadings displayed means ranging between 0.40 and 0.47 for all health measures except for HR (-0.36). The maximum local loading attained with GWPCA is primarily MAP, as displayed in (Figure 47) although BMI and WHR are slightly lower. Afterwards, we calculated LISA clusters for the CVRF indicator adopting the same procedures of health measures (Figure 46). The clustering delivers a visually comparable result to the clustering of health measures (Figure 46), except HR, which delivered a negative loading. Also, clusters obtained with PCA and GWPCA are not significantly different (Chi-squared test, p-value: 0.85). The better performance of GWPCA compared to PCA in terms of explained variance (Figure 47) do not affect the identification of LISA cluster locations (Figure 46).

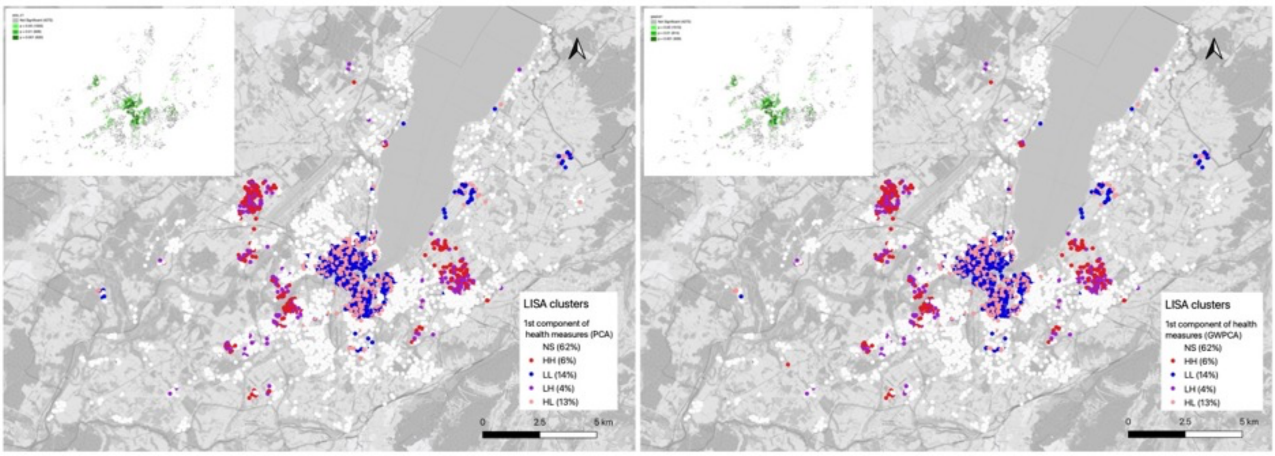

Figure 46: LISA cluster of the CVRF indicator calculated with PCA (left) and GWPCA (right). The maps in the top right corners display the pseudo-p-values of LISA clusters.

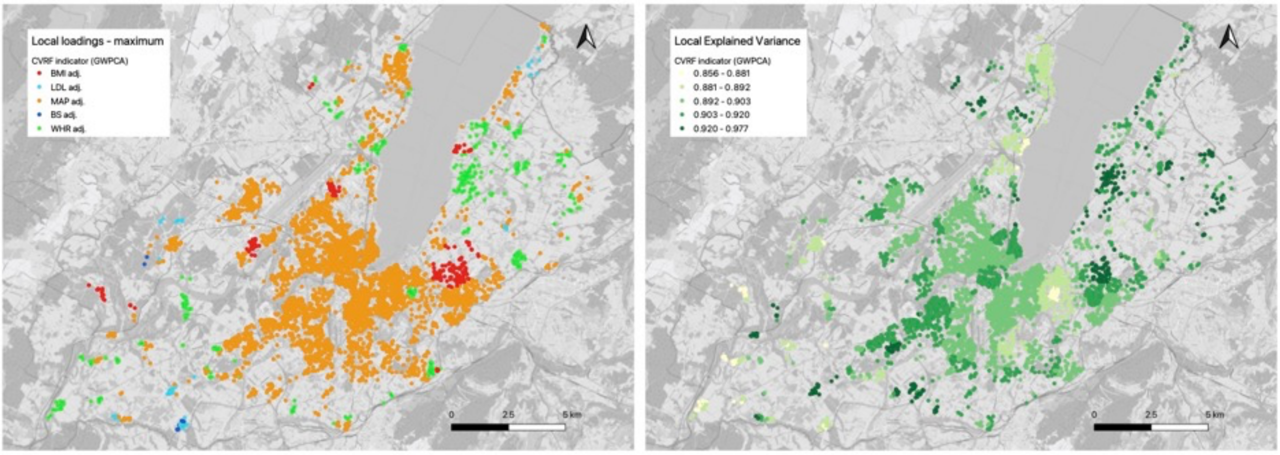

Figure 47: GWPCA results on health measures: maximum local loadings (left) and local explained variance (right) of the first principal component.

5.2.2 Regression analysis

The regression analysis between health measures and HBE characteristics was performed by testing each combination of independent variables, dependent variables, spatial sampling lags, and regression methods, resulting in 540 regressions. Firstly we show the findings of performance parameters for the whole dataset of health measures, and after for the sub-set of HH and LL LISA clusters of the health dataset.

5.2.2.1 Regression on the complete health dataset

We performed the regression analysis employing the aspatial models, thus DNN model and OLS, on the whole dataset of health measures. Figure 48 displays multiple charts of performance parameters (R^2, EV, MAPE) resulting from regression with DNN and OLS, obtained with different buffer radii of spatial sampling, and using HBE features as independent variables. Primarily, since both EV and R^2 show almost null values (<0.01) across all spatial sampling radii across all measurements, the regression model's ability to estimate health measures can be considered null by using BE features as independent variables. The mean absolute percentage error (MAPE) can be considered acceptable since it ranges between 0.7% and 6.6% across all health measures. Also, MAPE is stationary for OLS and higher compared to DNN.

Since HBE features cannot provide a reliable estimate of health measures, the principal components calculated with PCA and GWPCA from the same HBE feature are expected to present similar findings. Indeed, mean R^2 and EV parameters calculated with PCA and GWPCA do not differ from the ineffective estimate of HBE features (Figure 49). Overall, EV and R^2 calculated using PCA and GWPCA components can be considered null (EV<0.03 and R^2<0.02), hence we show only mean results of performance parameter (Figure 49). The null values of EV and R^2 make irrelevant further investigations, such as the contributions of features, of the aspatial regression on the whole health datasets. For the DNN model, the three sets of independent variables have a similar mean sum of squares (SS), which are respectively 6803 (SD ±23) for HBE feature, 6789 (SD ±33) for PCA components, and 6791 (SD ±49) for GWPCA components (Table 31). The powerless estimate by the global regression models could have been alleged from the weak to null correlations (Pearson correlation <0.05) between independent and dependent variables. Afterwards, we performed the regression analysis employing MGWR to estimate the whole dataset of health measures. The MGWR did not sufficiently estimate the dataset so that R^2 is always inferior to 0.1 regardless of the health measure, the spatial sampling lag, and the set of the independent variable describing the HBE (Figure 50). The mean R^2 across health measures displays a weak decay with increasing spatial lags, and the GWPCA component shows a slightly higher R^2 than PCA components and HBE features (Figure 51).

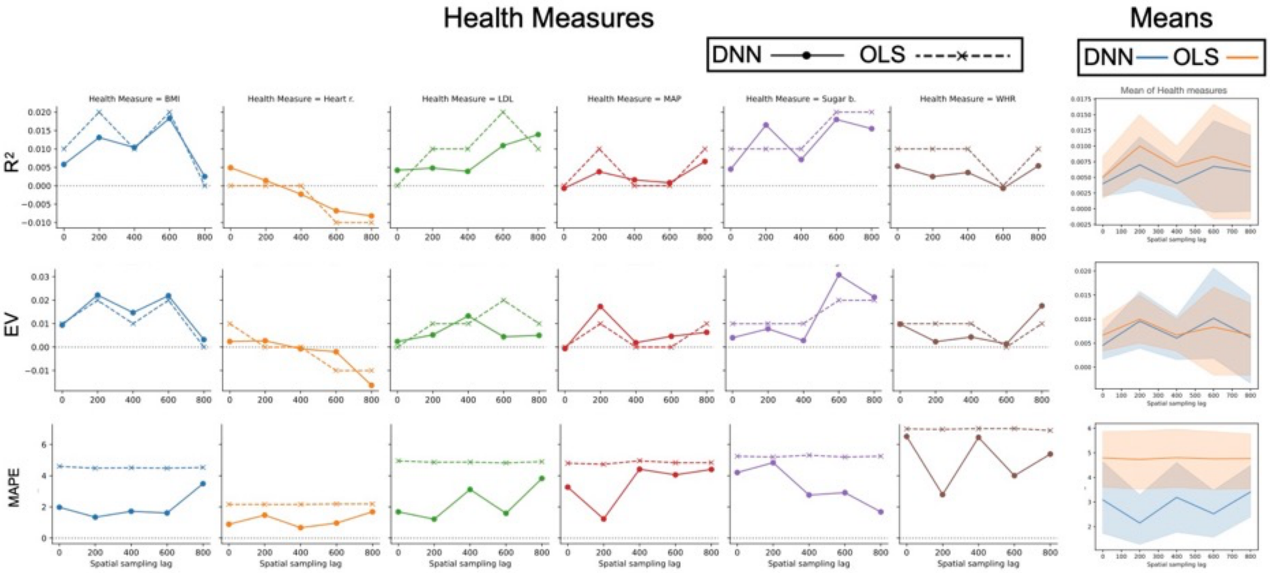

Figure 48: Aspatial regression on the whole health dataset: performance parameters by varying spatial sampling by DNN and OLS using BE features as independent variables. Each column represents a different health measure, and the last column on the right displays the mean performance parameters with a 95% confidence interval. The dashed line represents parameters calculated with OLS, and the solid line the parameters obtained with DNN. Each plotline represents a different parameter: R2 score explained variance (EV) and the mean absolute percentage error (MAPE).

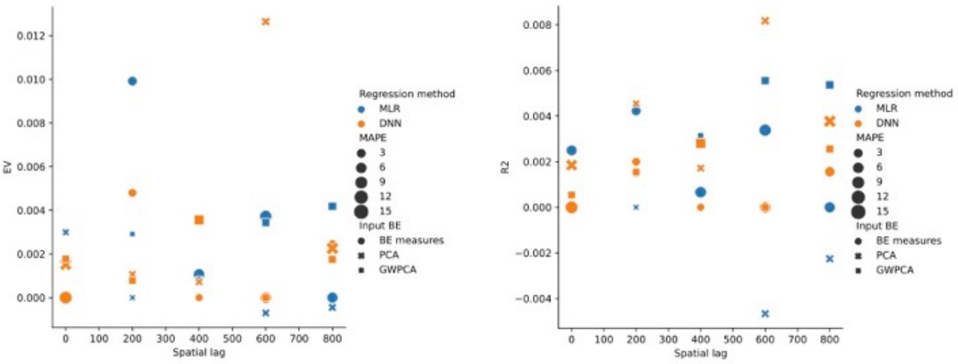

Figure 49:Aspatial regression on the whole health dataset: mean R2 and EV of health measures calculated with DNN and OLS across spatial sampling lags. Different symbols identify the set used as independent variables. The symbol size is in proportion to MAPE.

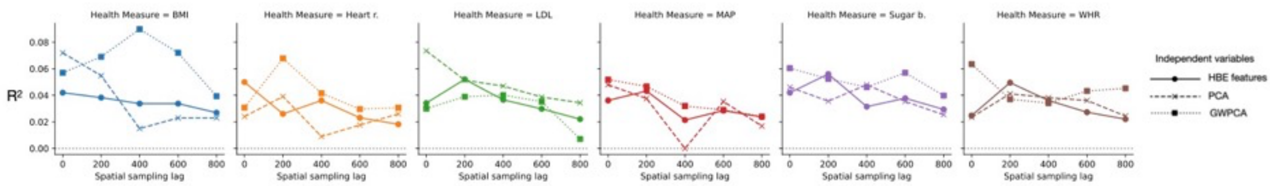

Figure 50: Spatially weighted regression(MGWR) on the whole health dataset: R^2 by varying spatial sampling lag using HBE features, PCA components and GWPCA components as independent variables. Each column represents a different health measure. The dashed line represents parameters calculated with PCA components, the dotted line with GWPCA components, and the solid with HBE features.

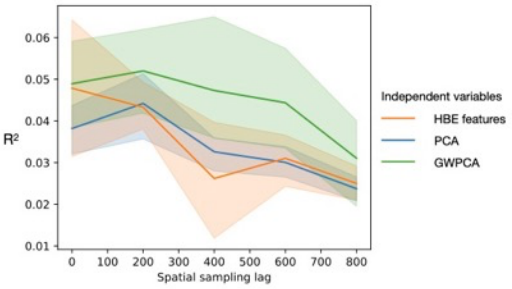

Figure 51: Spatially weighted regression (MGWR) on the whole health dataset: mean R^2 score with 95% confidence interval, across health measures by varying spatial sampling lag using BE features, PCA components and GWPCA components as independent variables.

Therefore, both global and local approaches were not valuable because they could not explain the variance in the dataset (EV <10%) (Table 31). Indeed, the mean R^2 across all health variables and spatial sampling lag display values below 0.05 for MGWR estimates and below 0.007 for DNN estimates (Table 31). MGWR has a lower mean SS than DNN, with the lowest value observed for HBE features (6763) (Table 31). About the regression analysis on the complete health dataset of CVRF, despite relative differences in findings between local and global approaches, between spatial sampling lags and between independent variables datasets, we cannot conclude which regression configuration better performs the powerless estimate of variance across all possible configurations consequently. According to this finding, feature contributions are ineffective and hence are not reported. Furthermore, this finding was expected since independent and dependent variables showed weak to null correlations (Pearson) 8results are not shown). Also, this result is coherent with the LISA clustering of health measures because most participants did not show a significant spatial dependence (Table 29). Indeed, because most health measure datasets are randomly distributed in space, any geographic dataset that is not randomly distributed in space, such as the HBE described in Chapter 3, is an implausible estimate.

REGRESSION METHOD	INDEPENDENT VARIABLES DATASET	MEAN R^2 (SD)	MEAN SS (SD)
DNN	HBE features	0.006 (0.010)	6803 (23)
	PCA components	0.006 (0.012)	6789 (33)
	GWPCA components	0.005 (0.014)	6791 (49)
MGWR	HBE features	0.037(0.006)	6763 (20)
	PCA components	0.038(0.010)	6781 (36)
	GWPCA components	0.045(0.011)	6775 (38)

Table 31: Regression analysis on the complete health dataset: mean R^2 and sum of squares (SS) for DNN and GWR and each set of independent variables (n=6835).

5.2.2.2 Regression on the sub-set of spatial clusters

Afterwards, we performed the same regression analysis varying the health dataset. We created a subset per each health measure, extracting the respective LISA clusters that showed a positive spatial dependence, thus selecting individuals belonging to high-high (HH) and low-low (LL) clusters. The LISA allows understanding the cluster location and discern between positive and negative spatial dependence and, consequently, differentiate clusters from outliers. The extraction of HH and LL LISA clusters, which we shall refer to as LISA clusters, significantly decreased the dataset, as seen in Table 29 and Figure 43. In brief, the LISA clusters of BMI collect 1383 individuals (20.2%), WHR LISA clusters 730 individuals (10.7%), MAP LISA clusters 1567 individuals (22.9%), HR LISA clusters 972 individuals (14.2%), BS LISA clusters 701 individuals (10.2%), and LDL LISA clusters 834 individuals (12.2%).

The regressions with DNN and OLS on LISA clusters of health measures generally performed better than the respective regressions on the complete dataset of health measures. The R^2 score was above 0.37 using HBE features, above 0.3 using PCA components and above 0.29 using GWPCA components. Similarly, EV was above 0.28 using HBE features, above 0.27 using PCA components and above 0.21 using GWPCA components. The ability to explain the variance in health measures overcame the regression performances on the whole health dataset, below 0.1 for both R^2 and EV (Figure 48). Both R^2 and EV display a stationary increase when OLS's spatial sampling lag increases (Figure 52). Instead, R^2 and EV calculated with DNN shows more fluctuations.

Generally, the MAPE displays a slight decrease across spatial sampling lags and can be considered stationary and more negligible for heart rate (HR) than other health measures. Also, DNN produces in all regression a smaller MAPE than OLS (Figure 52), which is also observed in terms of means by averaging across health measure and spatial lags (Table 32) or by averaging across health measure and independent variables (Table 33). By averaging performance parameters across health measures and spatial lags (Table 32), mean R^2 and mean EV are similar when the regression employs HBE features or GWPCA components, greater than the regressions employing PCA components. After averaging performance parameters across health measures and independent variables sets (Table 33), the mean R^2 and mean EV increase with increasing spatial lag for OLS regression. Instead of DNN regression, the mean R^2 and mean EV are higher for 200m lag and 800m lag. The values R^2 and EV indicates the global regression models provide a good fit for health measures.

Regression Method	***Independent Variables***	*mean* ***R2***	*mean* ***EV***	*mean* ***MAPE***
OLS	**HBE features**	0.60	0.61	3.14
	PCA comp.	0.46	0.47	3.59
	GWPCA comp.	0.62	0.62	3.10
DNN	**HBE features**	0.63	0.56	2.68
	PCA comp.	0.49	0.47	2.98
	GWPCA comp.	0.58	0.57	2.36

Table 32: Regression performance parameters by averaging across health measures and spatial lags.

Regression Method	***Spatial sampling lag***	*mean* ***R2***	*mean* ***EV***	*mean* ***MAPE***
OLS	**0 (1 SU)**	0.46	0.47	3.54
	200	0.54	0.54	3.37
	400	0.58	0.58	3.24
	600	0.62	0.62	3.16
	800	0.63	0.63	3.07
DNN	**0 (1 SU)**	0.50	0.43	2.78
	200	0.61	0.56	2.77
	400	0.58	0.53	2.65
	600	0.57	0.58	2.58
	800	0.57	0.55	2.57

Table 33: Regression performance parameters by averaging across health measures and independent variables.

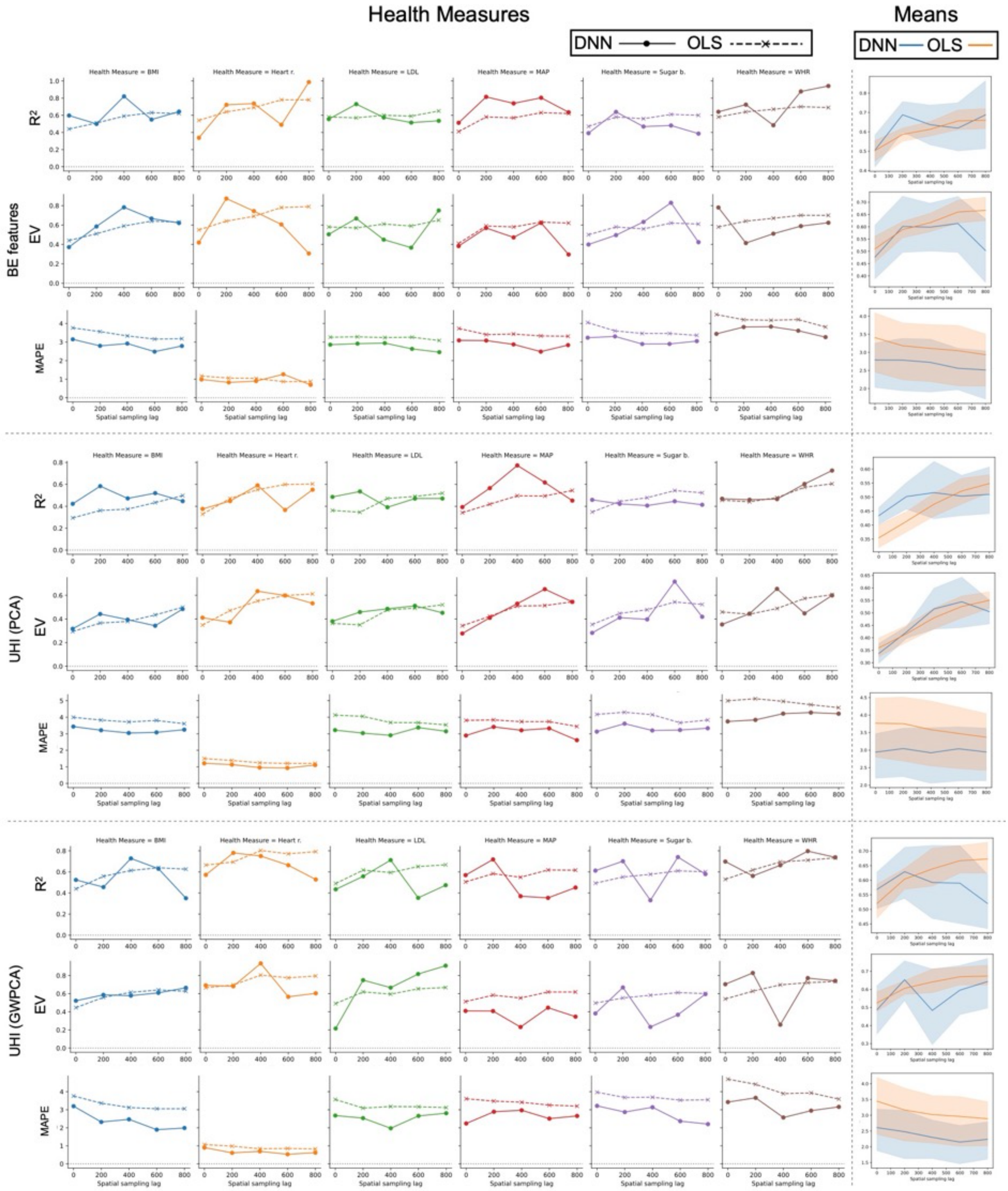

Figure 52: Aspatial regression on the LISA clusters (HH and LL): performance parameters by varying spatial sampling by DNN and OLS using different sets of independent variables. Each column represents a different health measure, and the last column on the right displays the mean performance parameters with a 95% confidence interval. The dashed line represents parameters calculated with OLS, and the solid line the parameters obtained with DNN. Each plotline represents a different parameter, R2 score, explained variance (EV) and mean absolute percentage error (MAPE).

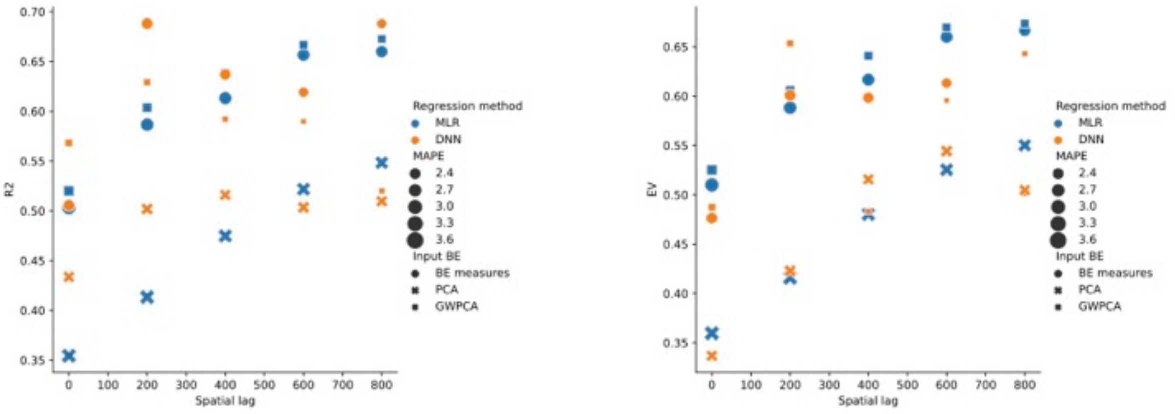

Figure 53: Aspatial regression of the LISA clusters (HH and LL): mean R2 and mean EV of health measures calculated with DNN and OLS across spatial sampling lags. Different symbols identify the set used as independent variables. The symbol size is in proportion to MAPE.

The significant contributors to OLS regression are the maximum and minimum OLS coefficients depending on independent variables. Coefficients obtained by HBE features deals mainly with mobility networks; firstly, with the pedestrian and cycling network shared with motorised vehicle transportation, and secondly, with the road network characteristics (Table 34). Those characteristics display both maximum and minimum values, i.e. Active mobility shared network (nodes) has a maximum mean coefficient of 2.9 and a minimum mean coefficient of -0.9; because one of the health measures, the heart rate, is negatively correlated with all other health measures, which generates OLS coefficients with opposite signs (Table 34). However, we cannot exclude that this outcome could be explained by the heterogeneity of the HBE described in Chapter 3. This outcome is also shared in the other sets of independent variables. Coefficients obtained with PCA components are related to urban penalties, thus with issues of Air pollution, Urban health island and noise pollution (Table 34). Also, PCA components identified by minimum and maximum coefficients are all first principal components, except for one (UHI 1.2). Coefficients obtained with GWPCA components are related to a broader range of UHI, which includes services, i.e., community places, indoor environment and exposure issues, i.e. air pollution (Table 34). Contrarily to PCA components, GWPCA components are more varied and include principal secondary components beyond the first one. The variety of main contributors obtained with GWPCA depends on the local nature of GWPCA, which describe the local variability of HBE rather than the global one.

The interpretation of DNN regression is based on the shap values' distribution using the interquartile range (IQR) for the magnitude and τ for the directionality of the relationship. To understand the contributions of DNN regression, we identified the features that displayed the maximum IQR and counted how frequently features displayed the maximum value. The directionality of the relationship is represented by the Kendall τ correlation coefficient between a health measure and the respective feature. Leading contributors of the DNN model generated with HBE features were mobility network characteristics, temperature estimates (PET) and noise levels, like OLS regression (Table 35). Also, PCA and GWPCA components identified features like the OLS regression (Table 35). In addition, DNN regression recognised additional features related to services among the least frequent contributors, which generally concerning the food environment and the healthcare services (Table 35).

Dataset	*Independent variables*	*Counts*	*Mean coefficient*
HBE features	Active mobility shared network (length)	17	-1.9
	Active mobility shared network (nodes)	12	2.9
	Active mobility shared network (nodes)	7	-0.9
	Road network (length)	6	4.1
	Active mobility shared network (length)	5	1.8
	Road network (nodes)	3	2.5
	PET (2020)	2	1.1
	Night-time noise level (road and rail)	2	-3.6
	Rail (counts)	1	2.4
	Day-time noise level (road and rail)	1	7.3
PCA components	Air pollution (UHI 1.1)	19	2.3
	Urban heat island (UHI 4.1)	13	-0.9
	Urban heat island (UHI 4.1)	8	1.9
	Air pollution (UHI 1.2)	7	-1.7
	Noise pollution (UHI 2.1)	5	-2.3
	Noise pollution (UHI 1.1)	5	-0.6
	Active mobility (UHI 9.1)	3	3.8
GWPCA components	Community places (UHI 10.1)	15	0.5
	Noise pollution (UHI 2.1)	8	-0.2
	Indoor environment (UHI 8.1)	6	-0.5
	Air pollution (UHI 1.1)	5	0.8
	Indoor environment (UHI 8.2)	5	-0.6
	Food environment (UHI 11.1)	5	-0.9
	Noise pollution (UHI 2.2)	4	1.2
	Urban heat island (UHI 4.1)	4	-0.2
	Road injuries (UHI 6.1)	2	0.3
	Active mobility (UHI 9.2)	1	1.6
	Indoor environment (UHI 8.3)	1	0.7
	Active mobility (UHI 9.1)	1	1.3
	Air pollution (UHI 1.2)	1	1.6
	Food environment (UHI 11.2)	1	-0.6
	Air pollution (UHI 1.1)	1	-0.8

Table 34: Regression analysis contributions: OLS maximum and minimum coefficients for LISA clusters. Per each regression performed to estimate health measures, we sampled the independent variable that displayed the maximum and the minimum coefficient.

Datasets	*Independent variables*	*Counts*	*IQR*	*τ*
HBE features	Active mobility shared network (length)	3	5.89	-0.32
	Active mobility shared network (nodes)	3	5.5	0.32
	Road network (length)	3	6.11	0.59
	Road network (nodes)	3	7.78	0.43
	PET (2020)	2	2.78	-0.39
	Night-time noise level (road and rail)	1	7.68	-0.46
	Rail (counts)	2	6.37	0.53
	Day-time noise level (road and rail)	1	3.07	-0.31
	Rural green	3	6.98	0.52
	Restaurants	2	7.87	0.21
	Urban green	2	2.72	0.28
	Hospital clinics and ambulatories	1	2.37	0.39
	Supermarkets	2	2.24	0.26
	Active mobility shared network (nodes)	2	3.19	-0.25
PCA components	Noise pollution (UHI 2.1)	7	3.68	-0.23
	Air pollution (UHI 1.1)	5	5.7	0.31
	Active mobility (UHI 9.1)	4	3.49	0.19
	Noise pollution (UHI 1.1)	3	7.39	0.32
	Health care accessibility (UHI 7.1)	4	1.2	0.45
	Indoor environment (UHI 8.1)	3	7.3	0.6
	Urban heat island (UHI 4.1)	2	1.5	-0.56
	Air pollution (UHI 1.1)	2	2.3	-0.25
GWPCA components	Noise pollution (UHI 2.1)	4	3.02	-0.21
	Indoor environment (UHI 8.2)	4	2.72	-0.24
	Indoor environment (UHI 8.3)	2	7.33	0.41
	Noise pollution (UHI 2.2)	4	6.4	0.35
	Air pollution (UHI 1.2)	2	0.96	-0.26
	Community places (UHI 10.1)	3	6.05	0.27
	Active mobility (UHI 9.3)	3	7.26	-0.35
	Food environment (UHI 11.1)	1	0.64	0.35
	Urban heat island (UHI 4.1)	2	3.17	0.08
	Health care accessibility (UHI 7.2)	2	6.85	-0.65

Table 35: Regression analysis contributions: DNN maximum and minimum shap values for LISA clusters. Per each regression performed to estimate health measures, we sampled the independent variable that displayed the maximum interquartile range (IQR). The IQR of shap values is larger in features that contribute more to the estimate but do not provide the relationship's direction. To understand the direction of the relationship, concordant features with dependent variables show a positive τ (Kendall correlation coefficient), and discordant features show a negative relation.

Afterwards, the local regression approach, which employed MGWR on LISA clusters of health, was able to explain the variability of the dependent variables. Indeed, the R^2 score was above 0.41 using HBE features and above 0.43 using both PCA components and GWPCA components (Figure 54). The capacity to explain variance in health measures outweighs the previous regression's performance on the entire health dataset, which was less than 0.1 for the R^2 score (Figure 50).

The R^2 generally display a decrease when spatial sampling lag increases (Figure 55 and Table 36).), which on average show the minimum value for the spatial lag of 600m. The MAPE generated by the MGWR method is constant across all combinations of the regression analysis for the LISA cluster of health measures, and it displays a mean value of 2.35 % (SD ± 0.11). By averaging performance parameters across health measures and spatial lags, the mean R^2 is 0.63 for HBE features, 0.68 for PCA components and 0.69 for GWPCA components (Table 36). Overall, the values R^2, which range between 0.38 and 0.90 (Figure 54), indicates that the MGWR regression models provide a good fit of health measures.

Similarly, to OLS, the MGWR is interpreted by the mean local coefficients. Since MGWR provides a different set of coefficients per observation, we used the mean coefficient for every single regression with MGWR. We determined each regression's highest and minimum coefficients and calculated their frequency and mean values throughout the extreme values observed. The mean coefficients derived from HBE features are principally concerned with mobility networks, the shared pedestrian and cycling network, and the road network's characteristics (Table 37). Likewise, with the aspatial regression, some features display both maximum and minimum values, i.e. Active mobility shared network (nodes) (Table 37). This outcome is related to the negative correlation of heart rate values with all other health measures, which can cause coefficients to show opposite signs. The mean coefficients calculated with PCA components deal mainly with exposure to air pollution, extreme temperatures, noise, and the Indoor environment and Community places USIs (Table 37).

Similar OLS regression (Table 34), PCA components identified by minimum and maximum coefficients are all first principal components, except for one (UHI 1.2) (Table 37). The mean coefficients from GWPCA components are associated with a broader range of features (15) compared to PCA components (12) and HBE features (9). The features of the significant contributors of GWPCA list more features but counts are higher for Air pollution and Noise pollution, identified in more than one-third of the maximum and minimum mean coefficients, thus precisely 11 and 12 times on 30 (Table 37). Furthermore, the mean of absolute values of coefficients is lower in GWPCA (0.35) and PCA (0.63) components than in HBE features (2.34).

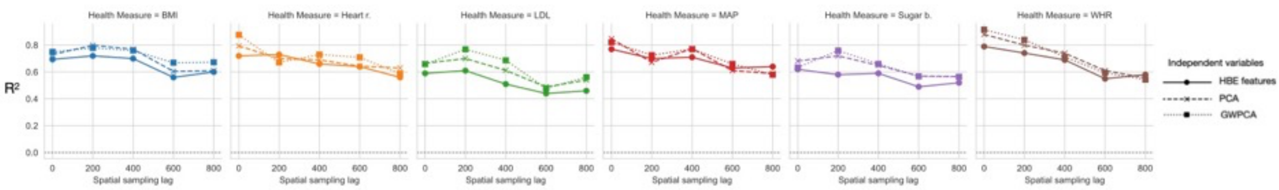

Figure 54: Spatial regression (MGWR) on the LISA clusters (HH and LL): R^2 by varying spatial sampling lag using different sets of independent variables. Each column represents a different health measure. Each column presents a different health measure. The dashed line represents parameters calculated with PCA components, the dotted line with GWPCA components, and the solid with HBE features.

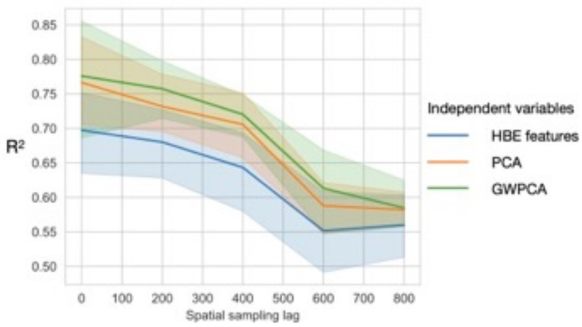

Figure 55: Spatially weighted regression (MGWR) on the whole health dataset: mean R^2 score with 95% confidence interval, across health measures by varying spatial sampling lag using BE features, PCA components and GWPCA components as independent variables.

Independent variables set	*Mean R^2*	*Mean MAPE*
HBE features	0.63	2.85
PCA components	0.68	2.79
GWPCA components	0.69	2.81
Spatial sampling lag		
0 (1 SU)	0.75	2.91
200	0.72	2.75
400	0.69	2.76
600	0.58	2.82
800	0.58	2.85

Table 36: Mean R^2 (MGWR) by averaging across health measures and spatial lags (top), and Mean R^2 (MGWR) by averaging across health measures and independent variables (bottom).

Table 37: Regression analysis contributions: MGWR maximum and minimum mean coefficients for LISA clusters. Per each regression performed to estimate health measures, we sampled the independent variable that displayed the maximum and the minimum mean coefficient.

Dataset	*Independent variables*	*Counts*	*Mean*
HBE features	Active mobility shared network (length)	20	-2.1
	Road network (length)	10	0.78
	Road network (nodes)	8	4.5
	Active mobility shared network (nodes)	6	-3.1
	Active mobility shared network (nodes)	6	2.8
	Night-time noise level (road and rail)	4	-1.5
	Active mobility shared network (length)	2	4.5
	PET (2020)	2	0.9
	Active mobility exclusive network (nodes)	2	0.9
PCA comp	Urban heat island (UHI 4.1)	8	0.4
	Air pollution (UHI 1.1)	8	0.9
	Noise pollution (UHI 2.1)	8	-1
	Indoor environment (UHI 8.1)	6	0.5
	Urban heat island (UHI 4.1)	6	-0.7
	Air pollution (UHI 1.1)	6	-0.4
	Community places (UHI 10.1)	3	0.9
	Active mobility (UHI 9.1)	3	0.5
	Noise pollution (UHI 2.1)	3	-0.9
	Air pollution (UHI 1.2)	2	-0.2
	Active mobility (UHI 9.1)	2	-0.5

Dataset	*Independent variables*	*Counts*	*Mean*
GWPCA components	Noise pollution (UHI 2.1)	12	-0.4
	Air pollution (UHI 1.1)	8	0.5
	Indoor environment (UHI 8.2)	7	-0.4
	Community places (UHI 10.1)	4	0.4
	Indoor environment (UHI 8.1)	4	0.4
	Noise pollution (UHI 2.2)	4	0.3
	Community places (UHI 10.1)	3	-0.3
	Road injuries (UHI 7.1)	3	+0.1
	Air pollution (UHI 1.1)	3	-0.2
	Food environment (UHI 11.1)	2	-0.1
	Urban heat island (UHI 4.1)	2	-0.2
	Air pollution (UHI 1.2)	2	0.3
	Active mobility (UHI 9.2)	1	0.2
	Indoor environment (UHI 8.3)	1	0.4
	Urban heat island (UHI 4.1)	1	+0.2
	Active mobility (UHI 9.1)	1	0.3
	Air pollution (UHI 1.1)	1	-0.8

5.2.2.3 A representative example of regression analysis

To provide a deeper insight on the variation of contribution between BE attributes, we displayed the complete set of estimators in a configuration of regression that performed the best and was also representative of the different locations of CVRFs clusters. Therefore, we showed the estimators of regressions on the high and low-values clusters (HH and LL) and using a spatial sampling lag of 200m (therefore sampling values from SUs in a radius of 200m). Both BMI (adjusted) and HR (adjusted) were chosen. The first represents other CVRFs because it displays significant association with the latter in values and cluster locations. Instead, HR was chosen because it is the most independent among CVRFs regarding values and cluster locations. Estimators are represented per each set of independent variables: for HBE features (Table 38), for PCA components (Table 39) and GWPCA components (Table 40). The set of HBE features was slightly reduced, excluding part of features to address the issues with multicollinearity among some variables, i.e., night-time noise and day-time noise level. Also, we excluded HBE features that displayed a spatial concentration from a single location of the study area (airport proximity, train station proximity, and lake proximity). The removal of those features allowed the regression to increase R^2 so that the latter ranged between 0.63 and 0.89 regardless of the different configurations of the regression analysis. Contrary to principal components, HBE features are not scaled and directly indicate the spatial density of a BE property, regardless of the expected adverse or beneficial relation with health.

Contributions are significant for at least 50% of features concerning the significance of OLS regression (p-value<0.05) regardless of the set of independent variables. This finding highlights the relevancy of studying the whole set of estimators rather than relying on extreme values. Overall, the proportion between MGWR means coefficient and the respective standard error display how the generation of local estimate generates highly variable local coefficients that reflect the BE's heterogeneity showed in Chapter 3. This finding suggests that the clusters' locations of BMI and HR are related with different BE attributes depending on the location, which suggests that the subdivision of clusters by their location would provide a better insight into the link of clustered health values with the HBE. This analysis has been performed in the following paragraph for the HH clusters. In terms of the sum of squares of estimators, the larger values are observed using the set of PCA components for BMI and the HBE features for HR. In contrast, GWPCA components always produce the smallest estimators regardless of the regression method (the sum of squares is not shown). Also, the variation between estimators that employ GWPCA components is a maximum of one order of magnitude regardless of the BE feature and the health measure. Those estimators display the least agreement in signs between global and local regression approaches. Similarly, using a local method of regression (MGWR) also delivers smaller differences among BE attributes, smoothing differences between them and increasing the significance of the singular independent variables. Indeed, the share of significant OLS coefficients is the highest, and the standard error of the mean MGWR coefficients are the smallest. In terms of the directionality of the relationship, the global methods, OLS and DNN, generate concordant estimators in terms of the sign. At the same time, concordance with MGWR is observed mainly for significant features of the OLS regression. Despite the difference in model interpretation, which valorises variability of features in OLS and MGWR or valorises cooperation between features in DNN regression, estimates display more agreement than disagreements for both health measures.

The leading and positive contribution for BMI across all methods for BMI estimate is the road length, followed by a network of active mobility shared with motorised vehicles. The latter has the opposite contribution for HR. This finding is confirmed by the estimators that employ principal components since UHI such as air pollution, noise pollution, road injuries and active mobility were generated from those characteristics of transportation networks. We observe a discording relationship between interconnectivity (nodes) and lengths in both road and active mobility network characteristics. The interconnectivity is expected to promote active mobility and its positive effect on health (Banavar et al., 1999; Frank et al., 2010), but it did not forcibly improve the adverse impact of motorised transportation (Jacobsen et al., 2009). We excluded that this discording relationship can be caused by multicollinearity between nodes and length of networks since estimators were robust after removing one of them. Instead, characteristics of public transportation, whose relationship with CVDs is frequently studied in the literature, are inversely related to BMI, and not significantly associate with HR. Another unexpected relationship is observed for noise level (by road and rail transportation) with BMI and HR values. The disagreements in estimators between the two health measures, BMI, and HR, were expected since the clusters of positive spatial dependence used for these regression examples occupy different locations within the study area, meaning that it is likely that HBE is different between those locations.

	BMI			HR		
HBE feature	**Est. (pv)**	**IQR**	**Mean Est. (se)**	**Est. (pv)**	**IQR**	**Mean Est. (se)**
Active mobility (exclusive, length)	0.63**	1.62(+)	0.82(2.46)	0.02	0.60(+)	-0.11(0.23)
Active mobility (exclusive, nodes)	-0.48*	1.04(-)	-0.61(1.22)	0.11	1.12(-)	0.03(0.05)
Active mobility (shared, nodes)	0.19	1.22(+)	0.49(0.98)	-0.66**	4.48(-)	-1.13(3.38)
Active mobility (shared, lenght)	-0.68	2.77(-)	-1.26(2.5)	0.4	6.52(+)	0.50(1.49)
Administrative services	0.16***	0.22(+)	0.10(0.20)	0.09**	0.05(+)	-0.04(0.07)
Bars and pubs	0.20	0.48(+)	0.20(0.61)	-0.10	0.07(-)	0.19(0.57)
Bike parkings	-0.03	0.13(-)	0.01(0.02)	-0.07**	0.06(+)	-0.01(0.02)
Building (age)	0.14***	0.22(+)	0.12(0.36)	-0.03	0.05(+)	-0.02(0.07)
Building (surface)	-0.69***	1.77(-)	-0.22(0.67)	-0.27**	0.23(-)	-0.10(0.30)
Collective facilities	-0.19*	0.45(-)	-0.15(0.30)	0.27***	0.90(+)	0.10(0.20)
Commercial activities	0.15**	0.17(+)	0.10(0.21)	0.00	0.28(+)	-0.08(0.17)
Education facilities	-0.08	0.08(-)	-0.00(0.01)	-0.28***	0.55(-)	-0.14(0.42)
Energy consumption index	0.39***	1.26(+)	-0.27(0.59)	0.11**	0.68(-)	0.01(0.02)
Entertainment facilities	-0.02	0.00(+)	-0.08(0.17)	0.01	0.04(+)	0.04(0.09)
Fast foods	0.16*	0.17(+)	-0.02(0.04)	0.16**	0.19(+)	-0.08(0.16)
Hospital clinincs and ambulatories	0.09	0.08(+)	0.15(0.44)	-0.04	0.06(-)	-0.08(0.24)
NO2 estimate	0.07	0.02(+)	-0.08(0.24)	-0.02	0.06(+)	0.08(0.17)
Noise level (nigh-time)	-0.50***	1.51(-)	-0.27(0.81)	-0.38***	0.21(+)	-0.05(0.14)
Noise protection area	0.23***	0.65(+)	0.07(0.21)	0.09*	0.00(-)	0.09(0.18)
Pharmacies	-0.05	0.00(-)	0.09(0.18)	-0.28***	0.54(-)	-0.21(0.66)
Physicians	-0.14**	0.26(-)	-0.20(0.40)	-0.22***	0.41(-)	0.10(0.28)
Public transport quality	0.35***	0.24(+)	0.13(0.27)	0.01	0.15(+)	0.08(0.15)
Public transport stops	0.20***	0.40(+)	0.05(0.14)	-0.08	0.00(-)	-0.14(0.43)
Rail (lenght)	-0.41***	0.55(-)	-0.21(0.62)	-0.34	1.10(-)	0.90(2.69)
Residential population	-0.24**	0.55(-)	0.09(0.27)	0.05	0.97(+)	0.02(0.05)
Restourant	-0.17	0.48(-)	-0.00(0.01)	0.01	0.06(+)	0.13(0.27)
Road (hierarchy)	0.10	0.49(+)	0.27(0.82)	0.45***	0.41(-)	0.28(0.85)
Road (lenght)	1.22***	3.27(+)	1.20(2.38)	1.97***	1.57(-)	-0.14(0.28)
Road (nodes)	-0.87	2.18(-)	-0.50(1.01)	-0.79	1.55(+)	2.13(6.39)

Road injuries index	-0.10	0.31(-)	-0.02(0.06)	0.15**	0.07(+)	0.15(0.29)
Road speed limit	-0.05	0.10(-)	-0.02(0.07)	0.12**	0.00(-)	0.05(0.15)
Rural green	0.12***	0.12(+)	0.18(0.534)	0.02	0.12(-)	-0.00(0.00)
Social care services	0.10**	0.19(+)	-0.00(0.01)	-0.01	0.00(+)	0.03(0.10)
Specialised groceries	-0.15**	0.50(-)	-0.03(0.06)	-0.20***	0.20(-)	-0.16(0.48)
Sport facilities	-0.00	0.00(-)	-0.02(0.05)	0.13***	0.39(+)	0.12(0.24)
Supermarkets	-0.03	0.00(-)	0.01(0.03)	0.15*	0.00(+)	0.27(0.80)
Taxi and car sharing	-0.05	0.02(-)	-0.03(0.08)	0.30***	0.00(+)	0.06(0.13)
Temperature (PET 2020)	0.30***	0.68(+)	0.03(0.05)	0.02	0.41(+)	-0.00(0.01)
uilding (higth)	-0.01	0.07(-)	-0.00(0.01)	0.15***	0.97(-)	0.13(0.40)
Urban green	-0.07	0.21(-)	0.10(0.30)	-0.08**	1.05(+)	-0.02(0.03)
Waterbody (river)	-0.11***	0.18(-)	-0.11(0.23)	-0.52***	0.11(+)	-0.24(0.47)

Table 38:Estimators of BMI (adj.) and HR (adj.) employing HBE features and a spatial sampling lag of 200m. Estimators are showed for OLS regression (Estimator and respective p-value), for DNN regression (Interquartile range and the sign of Kendall rank correlation) and MGWR (mean of local estimators and standard error). The values in the OLS coefficient (Est.) indicates the average change in a health measure by modifying the respective BE attribute, while the p-value expresses the significance of the coefficient: * for 0.05, ** for 0.01 and *** for 0.001. Similarly, the mean of MGWR coefficients (Mean Est.) displays the mean change since each measure owns a local coefficient. The variability of local coefficients is expressed by the standard error (se). The Interquartile range (IQR) displays the variability of BE attributes' shap values so that larger IQR are interpreted as more relevant contributors. The direction of the shap values contribution is displayed by the sign on Kendall rank correlation between shap values and the respective BE attribute: positive signs imply that a BE attribute contributes to an increasing the shap value. In contrast, negative signs imply that a BE attribute contributes to a decrease in the shap value.

	BMI			***HR***		
Principal component (PCA)	**Est. (pv)**	**IQR**	**Mean Est. (se)**	**Est. (pv)**	**IQR**	**Mean Est. (se)**
Air pollution (UHI1.1)	0.75	1.83(+)	2.61(3.54)	-1.12	2.62(-)	0.74(2.71)
Air pollution (UHI1.2)	-0.31	0.51(-)	-0.72(0.73)	0.15	0.34(+)	-0.45(0.86)
Air pollution (UHI1.3)	-0.51***	1.05(-)	-0.14(0.63)	0.34**	1.09(+)	-0.32(0.75)
Noise pollution (UHI2.1)	-1.08***	2.67(-)	-0.69(1.98)	0.30	0.95(+)	-0.29(0.98)
Noise pollution (UHI2.2)	0.12*	0.08(+)	0.01(0.22)	0.05	0.05(+)	0.00(0.21)
Noise pollution (UHI2.3)	0.27***	0.61(+)	0.05(0.60)	-0.42***	0.74(-)	0.34(0.58)
Urban heat island (UHI4.1)	-1.05	2.29(-)	-2.23(3.27)	-0.35	0.44(-)	-0.16(2.90)
Urban heath island (UHI4.2)	-0.23*	0.40(-)	-0.35(0.58)	-0.11	0.14(-)	0.01(0.46)
Urban heath island (UHI4.3)	0.09	0.07(+)	0.18(0.55)	0.10	0.11(+)	0.08(0.66)
Urban heath island (UHI4.4)	-0.03	0.02(-)	0.27(0.78)	0.20*	0.24(+)	0.06(0.96)
Road injuries (UHI6.1)	-0.49**	1.17(-)	-0.57(0.92)	0.25*	0.51(+)	-0.35(0.51)
Road injuries (UHI6.2)	-0.90***	1.76(-)	-0.84(1.62)	-0.27**	0.44(-)	-0.25(1.35)
Healthcare accessibility (UHI7.1)	-0.47***	1.02(-)	-0.04(0.27)	-0.30***	0.72(-)	-0.02(0.25)
Healthcare accessibility (UHI7.2)	0.04	0.03(+)	-0.06(0.30)	0.04	0.00(+)	0.10(0.18)
Indoor Environment (UHI8.1)	0.58***	1.17(+)	-0.00(0.38)	0.19*	0.36(+)	-0.00(0.31)
Indoor Environment (UHI8.2)	-0.00	0.00(-)	-0.27(1.57)	0.42***	1.31(+)	0.15(1.83)
Indoor Environment (UHI8.3)	0.37***	1.02(+)	0.18(0.24)	0.03	0.00(+)	0.19(0.27)
Active mobility (UHI9.1)	1.81***	3.74(+)	1.17(2.57)	0.71***	1.72(+)	0.55(1.83)
Active mobility (UHI9.2)	0.1	0.18(+)	0.49(0.88)	-0.09	0.25(-)	0.15(0.75)
Active mobility (UHI9.3)	-0.25***	0.24(-)	-0.04(0.45)	-0.13***	0.15(-)	-0.04(0.31)
Community places (UHI10.1)	0.03	0.05(+)	0.12(0.18)	0.28***	0.52(+)	-0.01(0.36)
Community places (UHI10.2)	0.15***	0.23(+)	0.11(0.23)	-0.05	0.08(-)	-0.19(0.19)
Community places (UHI10.3)	0.02	0.00(+)	-0.05(0.13)	0.021	0.00(+)	-0.01(0.08)
Food Environment (UHI11.1)	0.06	0.13(+)	-0.18(0.62)	0.14**	0.30(+)	0.24(0.47)

Table 39: Estimators of BMI (adj.) and HR (adj.) employing PCA components and a spatial sampling lag of 200m. Estimators are showed for OLS regression (Estimator and respective p-value), for DNN regression (Interquartile range and the sign of Kendall rank correlation) and MGWR (mean of local estimators and standard error). The values in the OLS coefficient (Est.) indicates the average change in a health measure by modifying the respective BE attribute, while the p-value expresses the significance of the coefficient: * for 0.05, ** for 0.01 and *** for 0.001. Similarly, the mean of MGWR coefficients (Mean Est.) displays the mean change since each measure owns a local coefficient. The variability of local coefficients is expressed by the standard error (se). The Interquartile range (IQR) displays the variability of BE attributes' shap values so that larger IQR are interpreted as more relevant contributors. The direction of the shap values contribution is displayed by the sign on Kendall rank correlation between shap values and the respective BE attribute: positive signs imply that a BE attribute contributes to increasing the estimation value. In contrast, negative signs imply that a BE attribute contributes to a decrease in the estimation value.

	BMI			*HR*		
Principal component (GWPCA)	**Est. (pv)**	**IQR**	**Mean Est. (std)**	**Est. (pv)**	**IQR**	**Mean Est. (std)**
Air pollution(UHI1.1)	-0.19***	0.31(-)	0.07(0.17)	0.38***	0.76(+)	-0.01(0.34)
Air pollution(UHI1.2)	0.14***	0.28(+)	0.02(0.08)	0.13***	0.16(+)	0.10(0.15)
Air pollution(UHI1.3)	0.03	0.07(+)	0.01(0.06)	0.11***	0.34(+)	0.03(0.22)
Noise pollution (UHI2.1)	-0.28***	0.78(-)	-0.18(0.27)	0.15***	0.36(+)	-0.04(0.214)
Noise pollution (UHI2.2)	0.09**	0.19(+)	0.09(0.11)	-0.21***	0.50(-)	-0.16(0.22)
Noise pollution (UHI2.3)	0.03	0.09(+)	0.00(0.09)	0.19***	0.36(+)	0.06(0.13)
Urban heath island(UHI4.1)	-0.06*	0.12(-)	-0.08(0.17)	-0.03	0.10(-)	0.20(0.29)
Urban heath island(UHI4.2)	-0.03	0.07(-)	-0.02(0.09)	0.01	0.00(+)	-0.08(0.12)
Urban heath island(UHI4.3)	-0.11***	0.11(-)	0.04(0.13)	-0.21***	0.28(-)	-0.09(0.14)
Urban heath island(UHI4.4)	-0.15***	0.23(-)	-0.03(0.15)	-0.04	0.09(-)	-0.06(0.14)
Road injuries(UHI6.1)	0.23***	0.46(+)	0.17(0.14)	0.13**	0.32(+)	0.05(0.51)
Road injuries(UHI6.2)	-0.15***	0.27(-)	-0.03(0.15)	-0.08**	0.16(-)	-0.02(0.11)
Healthcare accessibility(UHI7.1)	0.06	0.19(+)	0.02(0.09)	-0.07**	0.17(-)	-0.07(0.17)
Healthcare accessibility(UHI7.2)	0.09**	0.13(+)	0.03(0.05)	-0.25***	0.36(-)	-0.04(0.15)
Indoor Environment(UHI8.1)	-0.32***	0.56(-)	-0.05(0.13)	-0.11**	0.17(-)	0.08(0.24)
Indoor Environment(UHI8.2)	-0.20***	0.28(-)	-0.01(0.09)	-0.39***	0.81(-)	-0.28(0.32)
Indoor Environment(UHI8.3)	0.07**	0.14(+)	0.04(0.10)	0.04	0.07(+)	0.00(0.17)
Active mobility(UHI9.1)	0.11**	0.33(+)	-0.05(0.14)	0.02	0.04(+)	-0.02(0.25)
Active mobility(UHI9.2)	0.04*	0.07(+)	-0.01(0.06)	-0.13***	0.18(-)	-0.03(0.12)
Active mobility(UHI9.3)	-0.11***	0.21(-)	0.03(0.05)	0.03	0.07(+)	0.02(0.12)
Community places(UHI10.1)	0.18***	0.36(+)	0.04(0.07)	0.22***	0.45(+)	0.07(0.23)
Community places(UHI10.2)	-0.00	0.02(+)	0.00(0.08)	-0.07*	0.06(-)	-0.05(0.11)
Community places(UHI10.3)	0.05*	0.05(+)	0.04(0.06)	0.13***	0.30(+)	0.08(0.12)
Food Environment(UHI11.1)	-0.13**	0.29(-)	-0.07(0.10)	0.04	0.15(+)	0.06(0.32)

Table 40: Estimators of BMI (adj.) and HR (adj.) employing GWPCA components and a spatial sampling lag of 200m. Estimators are showed for OLS regression (Estimator and respective p-value), for DNN regression (Interquartile range and the sign of Kendall rank correlation) and MGWR (mean of local estimators and standard error). The values in the OLS coefficient (Est.) indicates the average change in a health measure by modifying the respective BE attribute, while the p-value expresses the significance of the coefficient: * for 0.05, ** for 0.01 and *** for 0.001. Similarly, the mean of MGWR coefficients (Mean Est.) displays the mean change since each measure owns a local coefficient. The variability of local coefficients is expressed by the standard error (se). The Interquartile range (IQR) displays the variability of BE attributes' shap values so that larger IQR are interpreted as more relevant contributors. The direction of the shap values contribution is displayed by the sign on Kendall rank correlation between shap values and the respective BE attribute: positive signs imply that a BE attribute contributes to increasing the estimation value. In contrast, negative signs imply that a BE attribute contributes to a decrease in the estimation value.

5.2.2.4 Direct analysis of high-value contiguous clusters

The HH LISA cluster of adjusted BMI has been split into six areas (Figure 56), and the HH LISA cluster of adjusted heart rate (HR) has been split into five areas (Figure 57). About the BMI HH clusters, one of the areas of contiguous clusters is located in the east, and the other five are in the western periphery. The first area displays the greatest mean z-score (1.35), while the second area has the greater surface and number of participants belonging to the BMI HH cluster (Figure 56). Those areas do not show higher significative noise levels (from the rail and road estimates), air pollution estimates, or significative reduced accessibility to public transports (transport quality index and stops density) and sports facilities. The only shared significantly different HBE features between those clusters are related to the intrinsic location of those areas because they are located at the limit of the urban agglomeration, far from the lake shores, and far from the central train station whose are not reported in Table 41. The six contiguous clusters (Figure 56) present significant adverse HBE characteristics, displayed in Table 41. Cluster 1 is a residential area with low land use mix, lacking services such as food stores, physicians' cabinets and pharmacies, public spaces, commercial activities, pedestrian areas, and parks. The cluster 2 area is located proximal to the airport, and it also displays lower accessibility to healthcare services (hospitals, clinics, and ambulatories) and higher ambient temperatures. Cluster 3 is also located close to the airport and is characterised by higher ambient temperatures, and generally shows a lack of active mobility networks, food stores, healthcare services and physicians cabinets. The higher values of road hierarchy and length are related to the highway that crosses the area underground in the tunnel of Vernier. Cluster 4 lacks shared active mobility networks and multiple services, such as healthcare, physicians' cabinets, pharmacies, and food stores. Cluster 5 is only related to a higher road hierarchy. The HH6 is characterised by higher ambient temperatures and a higher density of road networks with h higher hierarchy due to its location on the motorway junction. It misses pedestrian and cycling networks, healthcare services and physicians' cabinets compared to the rest of the study area. In brief, in term of housing characteristics, the cluster 1 and 3 is a residential area with low population density and independent or attached housing, the cluster 2 and 5 is characterised by high-rise condominiums, cluster 4 and 6 have both low-rise independent housing and high-rise condominiums. Differences in housing characteristics (UHI Indoor environment) in those areas are reported in Appendix.

After, all the HR HH clusters are in the southwest area of the urban agglomeration. The regions 1–4 all have a z-score greater than 0.6, while clusters 4 and 2 are the areas with the most individuals belonging to the HH cluster (n=182) and the area with the most extensive surface (SUs=72), respectively (Figure 57). All areas do not show lower accessibility to services, such as community spaces, food places, urban green areas, public transports, and shared networks for active mobility. Some of the significantly different HBE features between those clusters are intrinsic to the location of those areas, which depict the remoteness to the lake, to the train station or rural areas. Indeed, all clusters display a significantly greater road network density, also displaying a higher road hierarchy (Table 42). Cluster 1 is positioned near principal road transport axes, resulting in increased noise levels and the absence of separate pedestrian and bicycle zones, as well as medical cabinets. Cluster 2 and 3 are the closest to the town centre, and they are characterised by a dense road network and consequently by noise and air pollution, and cluster 2 is also proximal to the rail network. Cluster 4 is characterised by higher ambient temperatures besides the road network density. Cluster 4 partially overlap with cluster 5 of BMI (Figure 56). In summary, clusters 1 and 4 are comprised chiefly of high-rise condominiums but also low-rise independent housing; clusters 2 and 3 are composed of medium rise attached condominiums with a high density, and cluster 5 is composed of dense low-rise housing. Further results about differences in housing characteristics (UHI Indoor environment) in those areas are reported in Appendix.

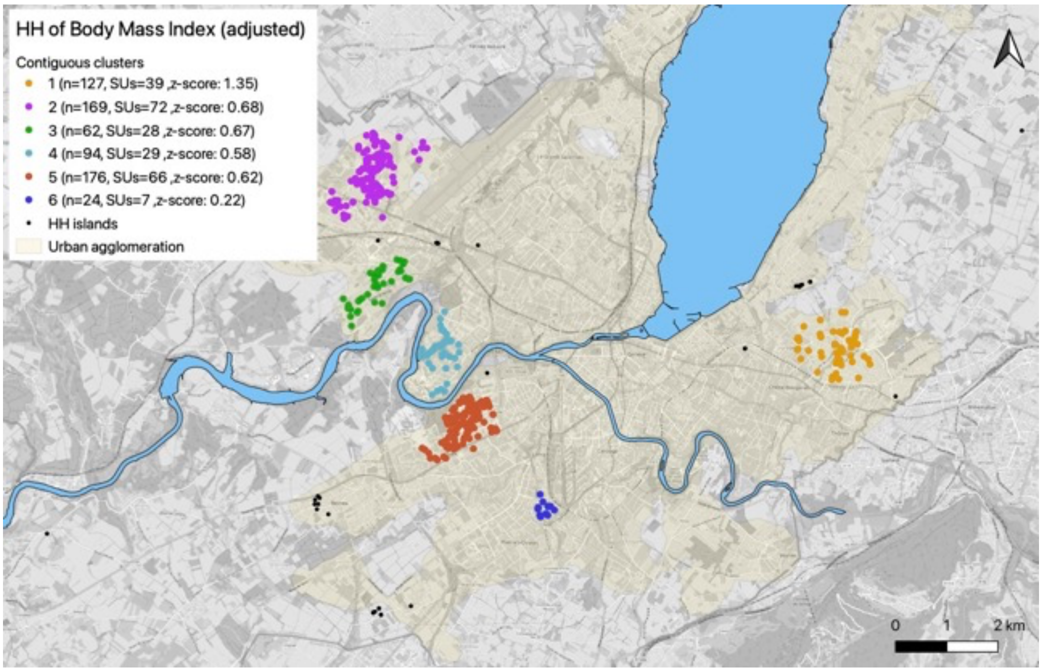

Figure 56: Contiguous HH LISA clusters of body mass index (BMI adjusted).

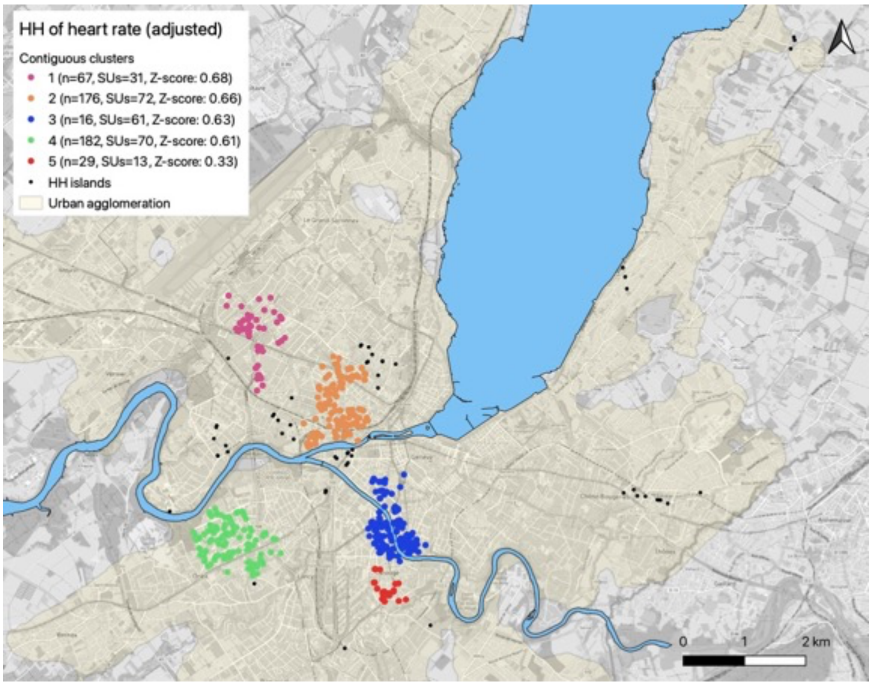

Figure 57: Contiguous HH LISA clusters of heart rate (HR adjusted).

Table 41: Characterisation of HBE features in contiguous HH clusters: T-test (Welch) and Kolmogorov-Smirnov test between contiguous HH clusters on the whole study area (in the following page). Multiple HBE features were not shown when they were not significantly different (p-value >0.05). Their contribution is likely to improve cardiovascular risk factors, i.e. higher values of public transport quality. Positive T values are related to high values of an HBE feature in the HH cluster compared to the study area, while negative values respectively indicate lower values. Bold font signifies that both p-values of the T-test and Kolmogorov-Smirnov test are below 0.05. Thus an HBE feature displays a significant difference in terms of mean and distribution.

AREA	HBE FEATURE	T	PV(T)	D	PV(D)
1	**Active mobility network (exclusive, nodes)**	**-4.4**	**<0.001**	**0.21**	**0.05**
	Community places	**-5.1**	**<0.001**	**0.27**	**0.006**
	Food environment	**-16.6**	**<0.001**	**0.32**	**<0.001**
	Urban green	**-6.0**	**<0.001**	**0.30**	**0.001**
	Pharmacies	-6.2	<0.001	0.17	0.186
	Physicians cabinets	**-15.4**	**<0.001**	**0.34**	**<0.001**
2	Airport	8.3	<0.001	0.07	0.845
	Healthcare services	-4.4	<0.001	0.09	0.542
	PET (temperature)	**5.9**	**<0.001**	**0.26**	**<0.001**
3	Airport	3.569	**<0.001**	0.03	0.698
	Active mobility network (exclusive, nodes)	**-15.5**	**<0.001**	**0.43**	**<0.001**
	Active mobility network (exclusive, lenght)	**-11.6**	**<0.001**	**0.44**	**<0.001**
	Active mobility network (shared, nodes)	-5	**<0.001**	0.23	0.094
	Active mobility network (shared, length)	-3.87	0.001	0.24	0.074
	Food environment	-3.91	**<0.001**	0.22	0.127
	Healthcare services	-22.6	**<0.001**	0.20	0.21
	PET (temperature)	**2.911**	**0.007**	**0.27**	**0.024**
	Physicians cabinets	**-23.3**	**<0.001**	**0.26**	**0.042**
	Road hierarchy	**10.38**	**<0.001**	**0.62**	**<0.001**
	Road (lenght)	**3.714**	**0.001**	**0.46**	**<0.001**
4	**Active mobility network (shared, nodes)**	**-2.15**	**0.039**	**0.292**	**0.011**
	Active mobility network (shared, length)	**-1.7**	**0.01**	**0.285**	**0.014**
	Food environment	**-8.01**	**<0.001**	**0.281**	**0.016**
	Healthcare services	-22.6	**<0.001**	0.195	0.195
	Pharmacies	**-40**	**<0.001**	**0.374**	**<0.001**
	Physicians cabinets	**-2.74**	**0.01**	**0.312**	**0.005**
5	**Road hierarchy**	**4.049**	**<0.001**	**0.275**	**<0.001**
6	**Active mobility network (exclusive, length)**	**-1.38**	**0.215**	**0.438**	**0.098**
	Healthcare services	-22.6	<0.001	0.195	0.91
	PET (temperature)	**5.022**	**0.002**	**0.559**	**0.014**
	Physicians cabinets	-7.98	<0.001	0.307	0.439
	Road (nodes)	**5.492**	**0.001**	**0.751**	**<0.001**
	Road hierarchy	**6.462**	**0.001**	**0.737**	**<0.001**
	Road (lenght)	**6.283**	**0.001**	**0.793**	**<0.001**

AREA	HBE FEATURE	T	PV (T)	D	PV (D)
1	Active mobility network (exclusive, nodes)	-4.4	<0.001	0.23	0.057
	Active mobility network (exclusive, lenght)	**-7.3**	**<0.001**	**0.37**	**<0.001**
	Noise level	**7.3**	**<0.001**	**0.47**	**<0.001**
	Physicians cabinets	**-3.9**	**<0.001**	**0.38**	**<0.001**
	Roads (nodes)	**5.3**	**<0.001**	**0.51**	**<0.001**
	Road (hierarchy)	**14.8**	**<0.001**	**0.73**	**<0.001**
	Roads (length)	**5.8**	**<0.001**	**0.50**	**<0.001**
2	NO2 (air pollution)	2.5	0.015	0.11	0.296
	Noise level	**8.9**	**<0.001**	**0.41**	**<0.001**
	Rails (counts)	**6.2**	**<0.001**	**0.64**	**<0.001**
	Rails (lenght)	**9.1**	**<0.001**	**0.65**	**<0.001**
	Roads (nodes)	**16.8**	**<0.001**	**0.74**	**<0.001**
	Road (hierarchy)	**11.1**	**<0.001**	**0.60**	**<0.001**
	Roads (length)	**17.1**	**<0.001**	**0.71**	**<0.001**
3	**NO2 (air pollution)**	**3.4**	**0.001**	**0.19**	**0.019**
	Noise level	**12.2**	**<0.001**	**0.53**	**<0.001**
	Roads (nodes)	**25.6**	**<0.001**	**0.88**	**<0.001**
	Road (hierarchy)	**47.1**	**<0.001**	**0.90**	**<0.001**
	Roads (length)	**33.8**	**<0.001**	**0.89**	**<0.001**
4	**PET (temperature)**	**3.1**	**0.003**	**0.23**	**0.001**
	Roads (nodes)	**3.6**	**0.001**	**0.35**	**<0.001**
	Road (hierarchy)	**6.2**	**<0.001**	**0.34**	**<0.001**
	Roads (lenght)	**3.5**	**0.001**	**0.30**	**<0.001**
	Healthcare services	-4.5	0.001	0.28	0.228
5	Noise level	4.0	0.002	0.41	0.019
	Roads (nodes)	**9.3**	**<0.001**	**0.83**	**<0.001**
	Road (hierarchy)	**19.7**	**<0.001**	**0.88**	**<0.001**
	Roads (length)	**11.0**	**<0.001**	**0.78**	**<0.001**

Table 42: Characterisation of HBE features in contiguous HH clusters (HR adjusted): T-test (Welch) and Kolmogorov-Smirnov test on the whole study area between contiguous HH clusters. Multiple HBE features were not shown when they were not significantly different (p-value >0.05) or when their contribution is likely to improve cardiovascular risk factors, i.e., higher values of public transport quality. Positive T values are related to higher values of an HBE feature in the HH cluster compared to the study area, while negative values respectively indicate lower values. Bold font signifies that both p-values of the T-test and Kolmogorov-Smirnov test are below 0.05. Thus, an HBE feature displays a significant difference in terms of mean and distribution.

5.2.2.5 Clustering reconstitution from regression estimates

The calculations of the LISA cluster of the estimates obtained with the aspatial approach, thus by DNN, display almost no spatial dependence, so that cluster sizes do not exceed 1%. The 99% (n=6763) of the estimate by PCA components can be considered randomly distributed, and the 98% (n=6690) of the estimate by GWPCA (Figure 58, first line of maps). The clusters that utilise GWPCA components are slightly larger than those obtained with PCA components (Figure 58, first line of maps and Table 44). The regression with the spatial-aware method generated estimates with high spatial dependence so that only the 33% (n=2218) of points is randomly distributes using PCA components and the 31% (n=2121) using GWPCA components (Figure 58). Also, the LISA cluster obtained by MGWR estimates is composed of LL clusters which size (35% for PCA components and 36% for GWPCA components) is greater than the HH clusters (20% for PCA components and 24% for GWPCA components). The clustering in the health measures initially classed 57% of individuals as non-significant, 9% as HH and 16% as LL. The LISA clusters generated by the MGWR estimates more than double the clusters obtained with the actual values of BMI (adjusted) (Figure 58 and Figure 59). The HH and LL clusters are displayed separately in Figure 60 to visualise the differences among LISA cluster locations of BMI and its estimates. The LISA clusters obtained by DNN estimates define different locations, which identify percentages below 9% of the BMI LISA clusters regardless of the independent variables set because of the minor spatial dependence and alco because different locations are identified (Figure 60 and Table 44). Instead, the MGWR estimates that employ PCA components generated LISA clusters which identify 91% of HH clusters and 94% of LL clusters. Likewise, the MGWR estimates that use GWPCA components generated LISA clusters that identify the 94% HH and the 95% of LL clusters (Table 44).

	Means		
LISA cluster	BMI (adj)	PCA estimate	GWPCA estimate
Non-significant (NS)	0.02	0.01	0.01
High-high cluster (HH)	1.01	0.22	0.31
Low-low cluster (LL)	-0.87	-0.15	-0.18
Low-high outlier (LH)	-0.76	-0.06	-0.11
High-low outlier (HL)	0.81	0.06	0.10

Table 43: Mean Z-score of BMI (adj.) values and estimates with MGWR employing PCA and GWPCA components.

		Surface [ha]	
Method	Feature	HH	LL
Health measure	BMI (adj.)	554.4	911.8
DNN	PCA	71.4 (0%)	89.1(8%)
	GWPCA	130.8 (4%)	26.1 (7%)
MGWR	PCA	1387.0 (91%)	1529.7 (94%)
	GWPCA	1086.5 (94%)	1554.5 (95%)

Table 44: Surfaces identified by LISA cluster locations for BMI (adjusted) and its estimates by DNN and MGWR. The surfaces represent the area in hectares defined by a circular buffer of 100m around each point. Percentage in brackets indicates the number of overlapping surface estimates concerning the clusters obtained by the health measure.

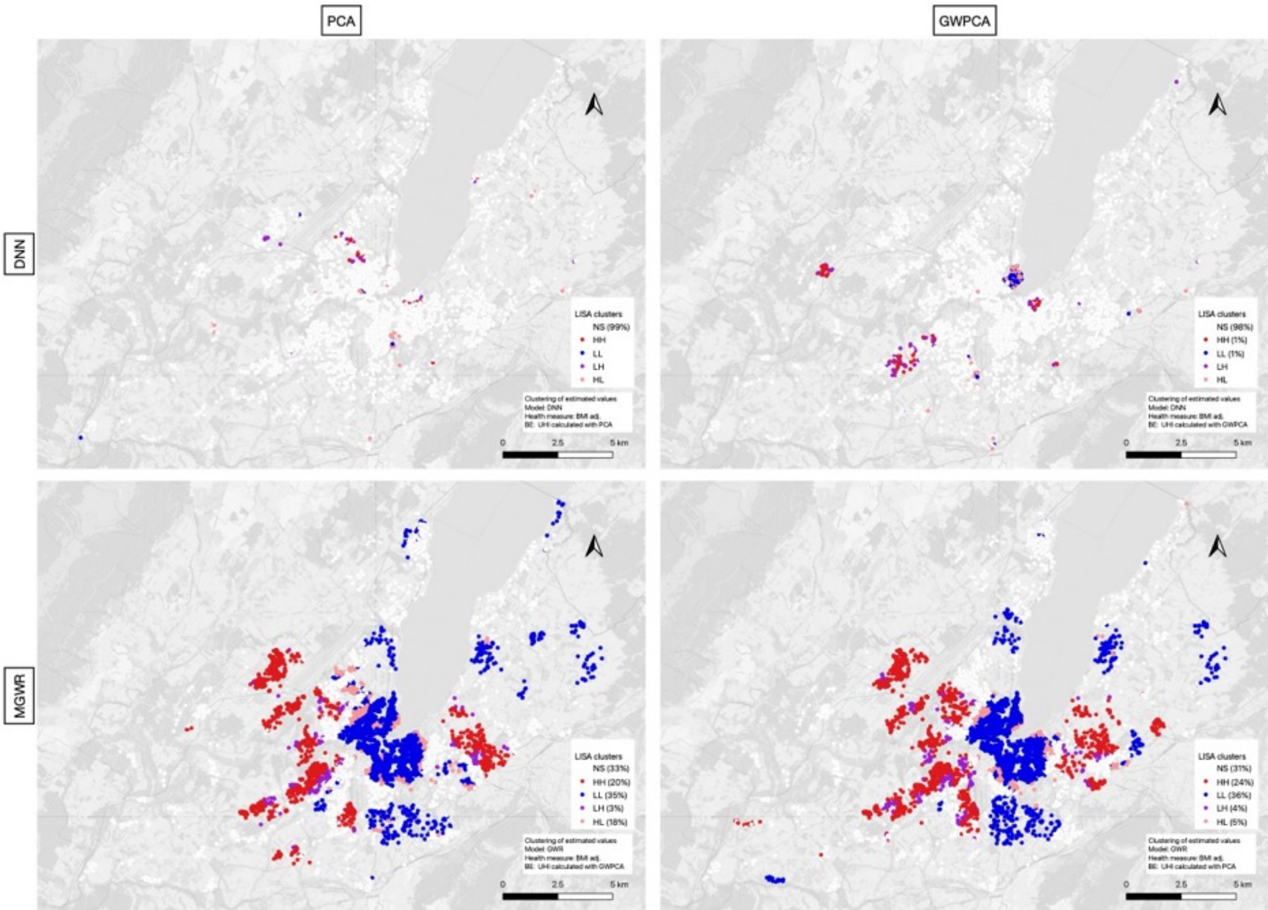

Figure 58: Map of LISA cluster of BMI (adjusted) estimates. The estimates were calculated using DDN (first line of maps) and MGWR (second). The regression used as independent variables is the PCA components (left column of maps) or GWPCA components (right column of maps). White dots represent estimates which do not exhibit a substantial spatial dependence on the standardised value of a particular health parameter. Red who(HH) show estimates which are characterised by significant high z-score in a neighbouring area of high z-scores. Blue dots (LL) show estimates characterised by y significant low z-score in a neighbouring area (spatial lag) of low z-scores. Purple (LH) and pink (HL) dots represent estimates that show a significant z-score discordant from the z-scores in the neighbouring area (spatial lag).

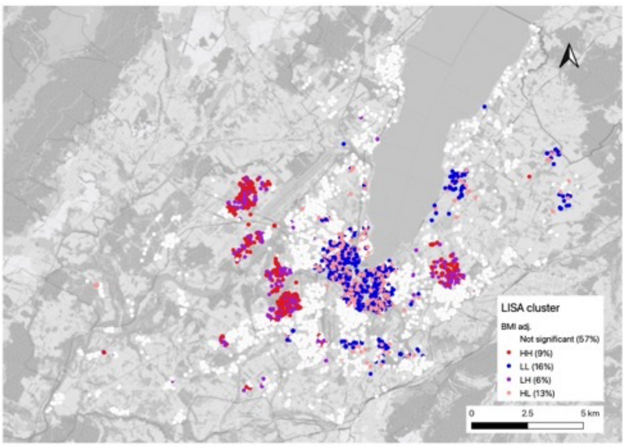

Figure 59: Map of LISA cluster of BMI (adjusted). White dots represent individuals who do not exhibit a substantial spatial dependence on the standardised value of a particular health parameter. Reho(HH) shows individuals characterised by significant high z-score in a neighbouring area of high z-scores. Blue dots (LL) show individuals characterised by significant low z-score in a neighbouring area (spatial lag) of low z-scores. Purple (LH) and pink (HL) dots represent individuals that show a significant z-score discordant from the z-scores in the neighbouring area (spatial lag).

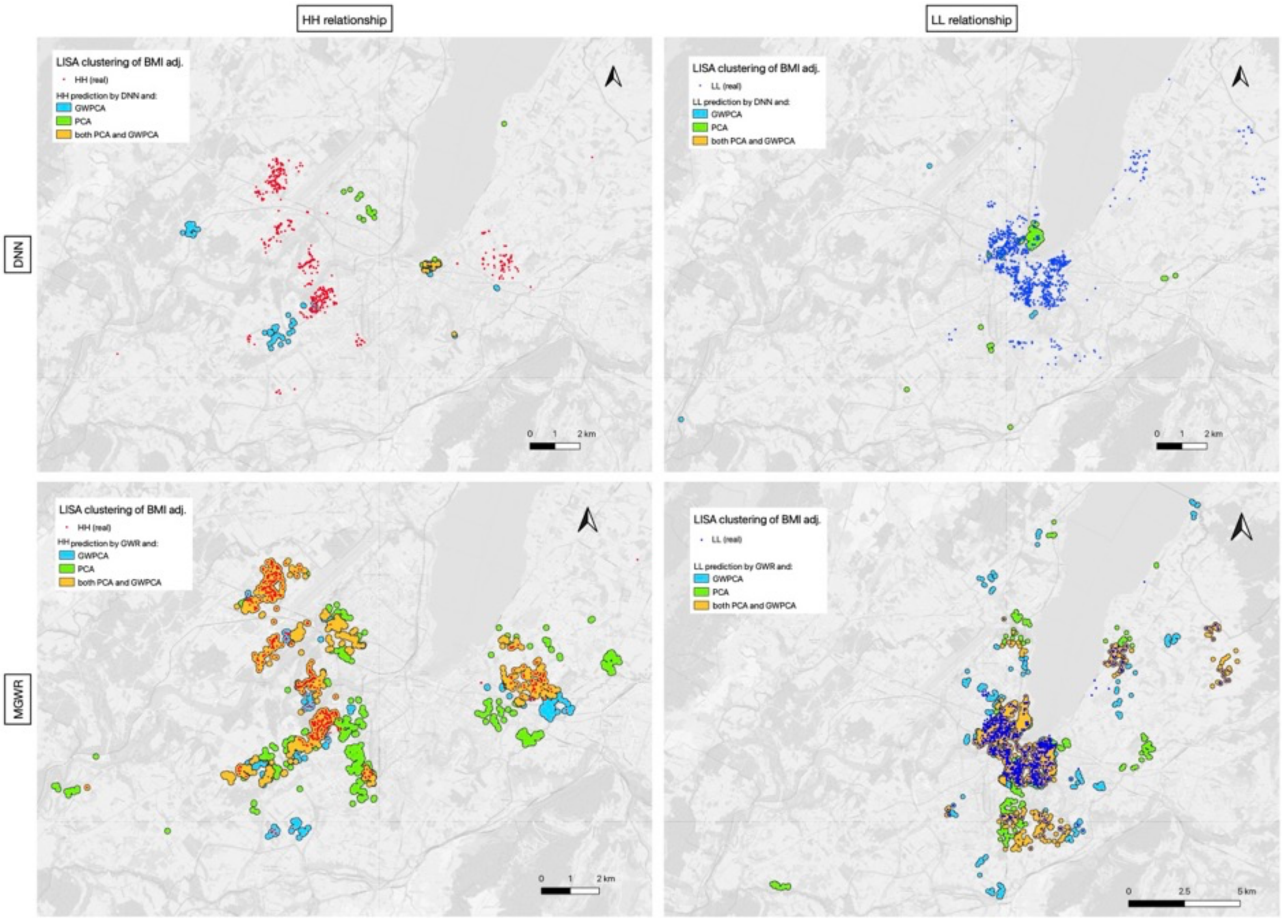

Figure 60: Locations of LISA clusters with positive spatial dependence for BMI (adjusted) and the estimates obtained with DNN and MWGR regressions. The maps column on the left shows HH clusters, and the left column the LL clusters. The clusters generated with the health measures clusters calculated from regressions' estimates are represented by a solid buffer of 100m around the points. The buffer colour indicates whether the estimate employed a different set of independent variables.

5.3 Discussion

5.3.1 Spatial anlysis of cardiovascular risk factors

Using participants' residential postal addresses, we calculated spatial clusters of six CVRFs measured during medical visits identifying the locations of low and high values. The high and low values clusters identify geographically proximal areas, showing a spatial gradient in small distances. We observed that spatial clusters of five CVRFs, BMI, WHR, MAP, BS, and LDL, display similar cluster's locations after adjusting for age, gender, and education. Instead, the HR clustering displays a different spatial pattern compared to the other CFRFs. The strong correlation, either positive or negative, among CVRSs allow the latter to be represented by a single indicator able to explain at least 86.2% of the total variability of all CVRFs.

Each CVRFs measures display a spatial dependence so that the percentage of participants belonging to a cluster range from 19.1% to 41.4% for unadjusted variables and from 28.5 to 43.3% for adjusted variables. The clusters do not display a cluster of specific health conditions defined by a threshold value used to classify illness from healthiness, such as the state of obesity deducible from the value of BMI. Instead, it shows where values are higher or lower in the study area and if they display spatial dependence, meaning that CVRFs are not homogenously distributed in space in the study area.

The adjustment for age, education level, and gender impact differently and significatively the CVRFs' measures, so that changes in clustering after the adjustment are observed in at least 30% of participants across all variables. Overall adjustment reduced differences between clusters of positive spatial dependence but impacted cluster sizes differently. In terms of location, all unadjusted CVRFs except for HR identified un-matching areas in the eastern suburbs. After the adjustment, those CVRFs identified similar areas in the east area of the urban agglomeration and a new cluster in the west area of the urban agglomeration, which was persistent only for MAP clusters. For the same five CVRFs, after the adjustment, all low values clusters were differently reshaped to identify the city's central area jointly. Stronger correlations also display the agreement between all CVRFs after the adjustment, which was negative in the case of heart rate (results are not shown). The adjustment affects HR differently so that the high-values cluster occupies the central-eastern part of the urban agglomeration and the low values the western area of the city and multiple spots in rural areas. The differences observed between HR and other CVRF can be explained by the fact that HR is the only health measure that is related to proximal determinants in terms of time; this is expected to be associated with exposure and behaviours closer in terms of time (Paül I Agustí et al., 2019), i.e. air pollution (Weichenthal et al., 2011), noise pollution or (Tzaneva et al., 2001), or greenness (Lanki et al., 2017). Instead, a measure such as BMI and MAP is generally related to life-course exposure and behaviours, thus mediating the long-term effects of nutrition and physical activity (Gamborg et al., 2009). In terms of cluster colocation, the adjustment increased the agreement among both high and low-value clusters. Therefore, the number of participants who belonged to two or more clusters of positive spatial dependence increased after the adjustment.

The synthetic indicator of CVRF allows summarising the adjusted CVRF, by using a global approach (PCA) for dimensionality reduction, by using a local approach (GWPCA). The latter outperform the first approach in part of the rural areas of the canton of Geneva, explaining CVRF variability up to 97%. The spatial variability of the synthetic indicator is mainly explained by MAP and BMI, which is expected since both showed greater spatial dependence and thus larger clusters. The clustering of the synthetic indicators regardless of the amalgamation method delivered a similar result to the LISA clusters of all CVRF except for heart rate.

These results for BMI clusters are partially coherent with the previous study of Guessous et al., which pointed out the same eastern area of the urban agglomeration, but not the smaller western cluster identified after the adjustment. This difference can be caused by two factors: the different datasets and the different spatial lag and. Firstly, the datasets overlap only partially since we used measured data from 2005 to 2014 instead of 2001 and 2010 (Guessous et al., 2014a). Therefore, the observed differences between our findings may display a temporal variation of BMI clustering in the study area, despite data were not longitudinal. Secondly, the study of Guessous et al. employed a spatial lag of 1800m not to exclude any participant a priori, those the most isolated point in the rural areas, and to obtain the same Moran's I in both geospatial datasets used. In general, when the spatial lag increases, the size of significant clusters increases and the size of small one's decreases (Aldstadt, 2010). Indeed, increasing the spatial lag, each participant "sees" more neighbours, so clusters observed in the denser areas propagate. In our study, the participants with the nearest neighbours "sees" less than 10% of all participants (n= 652), minimising the effect of locations with denser participants and minimising the exclusion of isolated participants. The choice of a spatial lag of 800m is coherent with consideration of the defined neighbour by walking accessibility (paragraph 3.3). In this way, two individuals at 800m share a geographic location at 400m which is considered an acceptable walking distance for activity space approximation (Yang and Diez-Roux, 2012). Moreover, we observed this effect of the propagation of major clusters by testing the robustness of clusters by increasing the spatial lag of clustering at 1000m, 1400m and 1800m which maps are reported in the Appendix.

Different approaches to tackling CVDs can be driven by spatial clustering of health metrics. However, while clustering identifies a spatial association with the geographic location, this does not clarify if clusters are explained by social selection or a systematic mechanism capable of inferring a health condition in determining locations (Eid et al., 2008; Glass et al., 2013; Rydin, Bleahu, Davies, Dávila, Friel, De Grandis, Groce, Hallal, Hamilton, Howden-Chapman, Lai, CJ Lim, et al., 2012). In both cases, the understanding of cluster location can drive intervention to optimise it by concentrating resources or efforts in specific locations. For example, in the social selection, short-term interventions such as campaigns can engage residents in boosting awareness of CVDs or stimulating healthier behaviours (Foster et al., 2005; SNYDER et al., 2004). Otherwise, in identifying systematic mechanisms linked to a specific location, spatial planning can intervene by shaping the BE that allow residents to ameliorate multiple CVRFs, i.e. improving active mobility and the food environment (Koohsari et al., 2020, 2021; Malambo et al., 2016).

Several limits limit the first part of this chapter. First, we calculated the spatial clusters of CVRF from the residential address, considering that the residence can be more or less relevant representative of individuals' health since the latter depends on the daily activity space, and thus on other unknown factors, i.e., workplace location. Investigating an individual's activity space in health research would necessitate a substantial increase in data collection. For example, Zenk et al. suggest to monitor as at least fourteen days of mobility per participant (Zenk et al., 2018). The study of activity space is crucial when the causal pathway to health conditions is investigated (Matthews and Yang, 2013; Zenk et al., 2018). Second, the spatial analysis is based on data from a cross-sectional study, which means that it was collected throughout multiple years on different participants. While studying the evolution of clusters over time is worthwhile, it would necessitate a substantially more significant number of observations. Also, clustering was not significantly different among sub-periods of the dataset. Thirdly, we used a fixed binary spatial lag, meaning that points are weighted equally whether their location is within or outside the fixed radius of the spatial lag.

Additionally, spatial lag can vary locally, allowing spatial lags to be stretched or compressed based on the spatial distribution of points. Recent implementations of the Geoda package and software allow for distance-based weighting utilising a kernel density technique, which in brief prioritises nearby locations over distant ones. However, this approach still requires the number of nearest neighbours, whose choice is still affected by a strong assumption.

Moreover, the CVRFs measures were not adjusted for nationality or income. However, the canton of Geneva displays a low segregation index depending on nationality and country of birth among swiss cities, which is the lowest among Swiss cities (OFS, 2018), which suggests that nationality is likely to not contribute to spatial dependence in CVRFs. Also, most studies on health, including CVDs, adjust health measures for economic factors such as income. While the link between income and health is well known, there is a lack of knowledge regarding their causative relationship: whether wealth results in improved health or vice versa, or whether there are hidden factors for income and health to covariate(Larrimore, 2011; Wilkinson, 1999). The correlation between economic factors can be strong enough to mask health variability in space. For example, the study of Huang et al. displayed how BMI clusters obtain with autocorrelation disappeared after adjusting for residential property value (Huang et al., 2015). The previous study employing the same geospatial health dataset reported that clusters of BMI were robust to income adjustments (Guessous et al., 2014a).

Also, the first part of this chapter is characterised by different strengths. Preliminary spatial analysis is performed continuously in space since data are not spatially aggregated. Participant location is characterised by the postal residence address rather than aggregated in spatial units, such as blocks or census units. The majority of current studies employing geospatial health records is based on aggregated spatial units to avoid issues related to confidentiality at the cost of increasing the modifiable areal unit problem (Ajayakumar et al., 2019; Andrew Swift et al., 2014). Then, the CVRSs were measured by trained personal rather than self-reported, reducing multiple errors, i.e. self-report bias or measurement error (Althubaiti, 2016). A sampling of participants is supposed to reduce the participation bias caused by measuring CVRF rather than using self-reported data, thanks to a mobile station visiting different urban agglomeration areas (Guessous et al., 2014a).

5.3.2 REGRESSION ANALYSIS OF CVRF

We explored the relationship between geospatial data of six CVRFs, and the contextual characteristics of the BE performing a total of 540 regression using the first as dependent variables and the second as independent variables. The relationship was tested across multiple dimensions: varying regression methods (a global and local approach), using different sets of BE variables (BE features or the derived indicators), varying the size of neighbour (spatial sampling lag), and testing different health measures (six CVRFS and spatial clusters of the latter). The regression analysis evaluated the model's performance depending on the configuration across the multiple dimensions and then summarised the regressions' interpretation. In addition, we tested how estimates of CVRF values formed clusters and preserved the information of the clustering of the CVRF measures.

REGRESSION ON THE WHOLE DATASET

The characteristics of the HBE in the study area were not able to estimate the CVRFs in the study area regardless of the method, the spatial sampling lag, the representation of the BE when the regression was performed on the whole dataset of health measures. In particular, the regression estimates cannot explain the variability in data and still deliver an acceptable error. The mean local R^2 scores were slightly better using the local approach than the global one, despite still being unsuccessful in estimating health measures. The inconsistency of the relationship between the CVRFs and the BE attributes was expected for two reasons. Firstly, the CVRFs values previously analysed displayed how most of the dataset is randomly distributed in space rather than display spatial dependency. The clustering allowed the identification of outliers, individuals whose CVRF values display a negative spatial dependence, thus are exposed, or experience the same BE of individuals belonging to high and low-values clusters. Therefore, mainly randomly distributed values are unlikely to match any environmental variable representing the respective geographic context. Indeed, when the impact of the BE is not extreme compared to other factors, and the aethiology is complex, such as in the case of NCDs (Blangiardo et al., 2020; Rydin, Bleahu, Davies, Dávila, Friel, De Grandis, Groce, Hallal, Hamilton, Howden-Chapman, Lai, CJ Lim, et al., 2012), we might expect that individuals differently respond to HBE, either resisting to BEs that slightly promote healthy behaviour, either remedying the effect of slightly unhealthy BEs (Mason et al., 2021). Secondly, previous literature reviews on the relationship between CVDs and BE report inconsistent and significant BE associations. For example, the systematic review of Durand et al. showed how changes in built environment factors were not significantly related to BMI in 174 in 204 cross-sectional studies analysed (Durand et al., 2011). The study of Sallis et al. across five continents described how seven different BE indexes objectively measured were not significantly related to BMI and how associations were weak between BMI self-reported BE variables (Sallis et al., 2020). Instead, the study of Chandrabose et al. reviewed only longitudinal studies on BE and three health outcomes, obesity, diabetes (type 2) and hypertension, and reported significant association with walkability measures for all health outcomes and with urban sprawl and recreational facilities for obesity (Chandrabose et al., 2019). The review of Diez Roux et al. on multiple CVRF showed how multiple studies in the US, both cross-sectional and longitudinal, report a negative association between diabetes, hypertension and BMI with BE that supported physical activity and a healthy diet (Diez Roux et al., 2016). Also, the review of Malambo et al. reported a significant association between walkable environment and food environments with blood pressure, BMI, diabetes and metabolic syndrome (Malambo et al., 2016).

Overall, the majority of studies on CVRFs deals with the weight status, firstly body mass index and the derived categorisation of obesity, and secondly studied diabetes and hypertension prevalence. Health measures which rely on invasive measurements, so that requires the involvement of trained personal and laboratory tests are scarce, or limited to people who access healthcare services. Also, the Waist-hips ratio (WHR) is scarcely studied due to the high measurement error despite being self-reported (McCormack et al., 2018). However, reviews of CVDs and factors and BE attributes explore the influence of statistical and spatial analysis methods or the scales of spatial aggregation approaches. Overall, disaggregated health data is limited in literature (Boulos et al., 2009; Yang et al., 2013a). In addition, among the many reviews on CVDs and CVRFs, except for one (Chandrabose et al., 2019), BE attributes were related to a behaviour or a change in behaviour in the expected direction, i.e. characteristics that promote walking were linked to walking habits (Diez Roux et al., 2016; Durand et al., 2011; Malambo et al., 2016; Sallis et al., 2020). This suggests a leakage between healthy behaviours and health conditions when both are studied in their geographic context. The difference in findings between behaviours and health conditions could be explained by exploring the temporal evolution of this relationships (Chandrabose et al., 2019). Longer is the temporal dimension of the aetiology of a health determinant; more complex is the pathway to illness in NCDs (Blangiardo et al., 2020)

REGRESSION ON THE SUB-SET OF CLUSTERS

Afterwards, we performed the regression analysis on the sub-set of health data belonging to health measures. Spatial clustering is widely used to identify hotspots of diseases and drive interventions, including interventions on the characteristic of clusters' location (Aldstadt, 2010; Jacquez, 2014). However, only a few studies explore the relationship between health and BE within clusters (Chen et al., 2014; Vallarta-Robledo et al., 2021; Valson et al., 2019). For example, used spatial scan statistics to identify spatial clusters of diabetes, reporting significant differences in BE attributes in the low-values clusters (Valson et al., 2019). Also, few studies demonstrated how heterogeneous is the relation of health with BE in CVDs (Adachi-Mejia et al., 2017; Chi et al., 2013), meaning that it is unlikely that a universal determinant can estimate health in the population (Mason et al., 2021). In particular geographic contexts, i.e., the US, multiple studies were able to identify universal CVD determinants in BE characteristics, such as sprawl, criminality, or walkability. Otherwise, different geographic contexts, such as Europe, showed less consistent findings (Mason et al., 2021). In addition to the clustering of health data, the interest in exploring the relationship in extreme values was suggested after observing an increase of stability in shap values contributions in extreme values (finding not shown). This change suggested that extreme values could have provided a stronger association of CVRFs with the BE. However, the totality CVRFs values, including extreme values, were mainly randomly distributed (Moran's I below 0.1), motivating the need to consider the spatial dependence of CVRFs.

The sub-sets of high and low values comported a significant reduction of the size of the cohort of participants, differently depending on the CVRFs values clustering shown in Paragraph 5.2.1. The regression analysis provided an estimate of clustered CVRFs to describe the variability in data and deliver more than acceptable errors. The regression on clusters of CVRFs outperformed the regression on the whole dataset in terms of error and describing the variability in CVRFs values. Regardless of the configuration of methods, regression clusters could estimate CVRFs so that EV was above 0.2 and R^2 was above 0.27 (Figure 52 and Figure 54). Similarly, in terms of errors, MAPE was below 5%. The errors (MAPE) were mainly stationary across spatial lags and sets of independent variables. Also, errors were minor in MAP compared to other health measures, and the errors were more significant in OLS than DNN and MGWR. In terms of R^2, we have different results. The estimate of CVRSs improved by increasing spatial lag for OLS. At the same time, it decreased for MGWR. It displayed more fluctuation and non-monotonic behaviour for DNN, but by averaging all parameters (R^2 and EV) it shows a better estimate by increasing the spatial lag. The considerable fluctuation in both R^2 and EV of DNN models are related to the stochastic processes integrated into the model. The improvement of the prediction by spatial lag is coherent with an increase in correlation caused by increasing the data aggregation, a misleading effect related to the modifiable areal unit problem (MAUP) (Fotheringham and Wong, 1991; Manley, 2019). This effect is not displayed in the local regression model, which restrains the regression to proximal areas. OLS and DNN provide a similar prediction among the global regression approaches, but the second report slightly smaller errors and explains data variability less consistently. The local regression method (MGWR) displays better performance parameters and results at smaller spatial lags.

The summary of the contribution of BE attributes displays that the most relevant estimators across the different regression contributions are related to transportation networks or one of its effects. The significant contributions were coherent in frequencies between different regression methods. Among HBE features, estimators were often the greatest in terms of absolute values in the pedestrian and cycling network shared with motorised vehicles, in road network characteristics (intersections and length) and secondly in environmental temperature estimate. Among PCA components, the first components were predominant and dealt mainly with air pollution, noise pollution and urban heath island. Instead, among GWPCA, significant contributions were more distributed among multiple components, such as air pollution and noise pollution, indoor environments, community places and food environments. The summary of significant contributions displayed how BE attributes displayed both positive and negative estimators across the regression's configurations. Three factors can explain this result. Firstly, there is a strong correlation between independent variables. The multicollinearity among independent variables can significantly affect the regressions coefficients (Daoud, 2017; Yoo et al., 2014). In this case, two correlated features may display non-null discordant coefficients so that their combined effect is not relevant. Secondly, the heterogeneity of spatial distributions of CVRFs could deliver contrasting coefficients. Indeed, studies that explored the spatial non-stationarity of CVD and CVRFs with the BE; reported that the latter was heterogeneous at multiple geographic scales (Adachi-Mejia et al., 2017; Chi et al., 2013; Mason et al., 2021). Thirdly, we previously showed how spatial clusters of HR did not overlap with the others CVRFs clusters, which potentially led to discording findings with the BE attributes. HR can be linked with shorter chronic exposure to BE (Paül i Agustí et al., 2019; Weichenthal et al., 2011) than to metabolic disorders such as obesity and diabetes (Gluckman and Hanson, 2004).

This third factor was confirmed by observing the partial discordant contribution of HBE between HR and BMI, which were chosen to provide a representative example of the regression analysis by choosing a spatial sampling lag of 200m. In particular, the complete analysis of estimators of the regression methods displayed how most estimators were significant. The local regression method displayed a high variability, thus highlighting the heterogeneity of the relationship between CVRFs and BE. Across the sets of BE independent variables, the PCA components display the greatest values in estimators and the smallest proportion of significant estimators (Table 39). On the contrary, GWPCA components have the smallest estimator values and the greatest proportion of significant estimators (Table 40). Overall, the study of the estimates highlighted the importance of road networks and active mobility networks for HR and BMI spatial clusters. BE attributes related to noise, and public transportation had an unexpected relationship with the CVRSs so that individuals with exposure to higher noise levels showed higher BMI and HR. Individuals with higher accessibility to public transportation showed higher BMI.

Afterwards, the separation of clusters in contiguous areas allowed the exploration of how directly HBE features were different within the cluster of high values for BMI and HR. The clustering of CVRFs identified groups of points belonging to different geographic areas, defined as contiguous clusters, and we excluded the most isolated participants. Firstly, the contiguous clusters display different values in BMI and HR, have different sizes in terms of participants and terms surface. Concerning the contiguous clusters of BMI, there were no standard HBE features that suggest an adverse impact across all areas compared to the whole study area. About the contiguous clusters of HR, road characteristics (hierarchy, length, and nodes) had significantly higher values across all contiguous clusters compared to the whole study area. In general, contiguous clusters displayed a variable number of significantly different HBE features. The differences among contiguous clusters indicate the relationship between CVRFs and BE in the high-value clusters. In the end, the contiguous clusters were composed of different housing characteristics, such as high or low-rise housing, residential density, and built surface. Only the cluster of high values of BMI was predominantly composed of detached housing composed of both condominiums and independent housing. The analysis of the HBE within the cluster location may be incomplete if relevant factors characterise those areas from outside. In the case of BMI, clusters identify areas surrounded by physical constrains, differently permeable to mobility. Eastern areas (contiguous cluster 2,3,4,5 and 6) are partially enclosed by the airport, the border with France, the highway and other primary road networks and the river. Despite the high coverage of public transportation, those areas may be disconnected or segregated compared to other areas. In this case, the use of small-scale spatial units could hinder to capture external determinants, which potentially influence population health depending on the side on which are placed. Segregation is mainly studied in relation to racial segregation, which in turn is considered the lowest in Switzerland (OFS, 2021). Principarly in US geographic cotexts, segregation is associated wih higher prevalence of cardiovascular illness depending on the ethnicity (Corral et al., 2015; Kershaw and Pender, 2016). Instead, architectural segregation (SCHINDLER, 2015), or transportation inequities (D'Agostino et al., 2021) could be investigated in future research on CVRFs, and explore external and border factors that characterise differen districs of urban areas.

CLUSTER RECONSTITUTION

For this case study, geospatial health measures were fundamental in understanding the relation between CVRFs and HBE because of spatial clustering. Despite the ineffective regression on the whole dataset of CVRSs, we explored whether the regression methods could preserve the cluster locations by studying the spatial dependence of estimates for BMI. The estimates of the local model (MGWR) do not treat CVRFs values as independent and take into account the spatial autocorrelation between data (A. Stewart Fotheringham et al., 2002; Düzgün and Kemeç, 2008). The MGWR estimates can identify approximately the totality of the clusters generated with the CVRFs measures (> 90%) despite the low performances of the regression previously calculated. Overall, the clusters obtained with the MGWR estimates overestimate the size of the cluster, extending clusters location in neighbouring areas. Contrarily, the aspatial regression method does not generate similar clusters and does not preserve spatial data dependence. Clusters were similarly reconstructed by using estimates also for the other CVRFs. The reconstruction of the clusters was also effective by using the composite indicators of the HBE, confirming their capability of describing HBE features.

The overestimation of the clusters can be related to three factors. Firstly, the estimates were characterised by a non-null error so that the latter consequently influenced clustering. Secondly, spatial clustering by LISA identifies the core points of the clusters so that participants with high or low values of the frontier of the cluster are excluded from it. The regression at the local level should deliver a smoothed estimate of CVRFs values, thus reducing extreme values (A. Stewart Fotheringham et al., 2002), also observed in Table* (z-scores). Thus, a secondary effect of the regression can lead to the inclusion of the border points and extend the clusters. Thirdly, the areas identified by the estimate's clusters but not from the CVRFs clusters can be characterised by the same combination of multiple BE attributes in proximal geographic areas. The last factor is a hypothesis that could drive interventions to be extended to those areas, rather than only on the cluster location of health measures.

5.3.3 Limitations and strenghts

Multiple limitations and strengths characterise the second part of this chapter. The regression analysis relies on the findings of the Paragraph 5.2.1 and the representation of the HBE in Chapter 3. Therefore, it encompasses the respective limitations and strengths.

Primarily in this chapter test the application of a DNN model to estimate multiple CVRFs from characteristics of the HBE. To avoid an incorrect conceptualisation and use of the DNN model, we successfully tested it on two cases of dependent features and compared it with the OLS regression. Despite the lack of overfitting observed by the DNN model, performance parameters were observed across all dimensions of the regression analysis. By averaging the performance parameters, findings were more stable. This issue might be related to the stochastic processes implemented by the model, which could be tackled by employing a probabilistic model, such as Bayesian Neural Networks (Kononenko, 1989), that was recently implemented for Python environments (Salama, 2021). The geographically weighted approach, such as MGWR, allowed to consider CVRFs in the local spatial context but rely on local linear models. For example, models such as Convolutional Neural Networks can consider the spatial context while performing non-linear regression or classification (Kamel Boulos et al., 2019). Then, we employed a novel method to interpret DNN estimates, which, as other machine learning approaches are frequently depicted as "black-box" thus unable to interpret (Papernot et al., 2017). Also, the contribution of estimators by the regression model is based on a different concept compared to the interpretation of OLS and MGWR models (Chen et al., 2020; Parsa et al., 2020; Shapley, 1953; Wang et al., 2021), which did not allow a direct comparison of estimators between models.

The choice of multiple dimensions to explore regression performances allowed a more profound insight across all dimensions and avoided excessive use of arbitrary assumptions, thus testing the robustness of the regression by using different methods, different sets of independent variables and dependent variables, and different spatial sampling areas. However, the large number of regressions (n=540) did not allow a direct interpretation approach but relied on the analysis of frequencies of the most important contributors. A complete analysis of contributions was limited to two health measures by using single spatial sampling. The analysis of the complete set of contributions could have led to further insight into the relationship between BE and CVRFs. Still, the authors intended to understand above all the magnitude and the limitations of this relationship for this case study. Also, we limited the test of contiguous clusters to high values and the cluster reconstitution to a representative example to sharpen the understanding of the information we need for planning healthier cities.

This chapter does not rely on guideline thresholds to classify what is healthy or not and who is healthy and ill, but it deals with a continuous representation of health and the HBE. The findings contribute to understanding the crucial role of geospatial health data and the study of the spatial context in the case of CVRSs. Two factors were essential in describing the relationship between health and BE: the study of spatial dependence in health data and the heterogeneity of the relationship in the geographic space. The findings, which are coherent with the recent findings in detangling this complex relationship (Adachi-Mejia et al., 2017; Mason et al., 2021; Valson et al., 2019), sharpen the necessity of employing local approaches capable of extrapolating where relationships are significant in a precise geographic context. Planning for health should be based on data from the multi-attribute representation of BE and multiple health sources, i.e. measures, perception and behaviour, geographically disaggregated to optimise interventions and programs (Hills et al., 2019; Mason et al., 2021). Avoiding the assumption that health, HBE and their relationship are stationary in space and across the population can facilitate understanding the relevant contemporary challenge of NCDs, and it's not excluded that it can contribute to other applications, such as infectious diseases injuries, mental health, and wellbeing. The precise output of this explorative spatial analysis can drive interventions where and on what is needed, bypassing unnecessary interventions, or tackling inequities hidden inadequate approaches.

Overall, the spatial analysis is based on a geric assumption, the first law of geography, so that what is close is more relevant that what is further. Therefore, studying the local HBE may miss to capture border or external condition. For example, external factors can be reconducted to physical constrains which can resume to segregation issues at different geographic scales and for different economic classes Part of high-values clusters identified in this chapter were not only located in the sub-urban areas, but also cropped by mayor road axes, rivers or the airport.

5.4 Conclusion

The relationship between CVRFs and the BE is complex and should not be studied without its spatial context.

Firstly, the study displayed how a significative spatial dependence characterises geospatial data of six measured CVRSs among adults in the canton of Geneva. The spatial cluster of CVRFs can guide intervention to tackle the burden of CVDs, by improving the HBE through spatial planning. However, by performing a regression between CVRFs and the HBE, the latter cannot provide a reliable estimate of the totality of CVRFs at individual level, whose values are partially randomly distributed. Still, the geographically weighted approach allows the estimates to identify spatial clusters of CVRFs previously calculated completely. Preferably HBE can successfully estimate the subset of spatial clusters of CVRFs. Among the significant estimators, road network characteristics and active mobility network attributes are the most frequent. However, the local variability of estimators upholds the non-stationarity of the relationship between CVRFs and BE in space. In fact, by splitting spatial clusters by geographic locations, HBE displays different associations and broad significative contributions. The findings underline the need to measure a broad range of BE attributes, account for spatial dependence in geospatial health data of CVRFs and understand the local variation of their relationship. The health of individuals in the case of Non-Communicable Diseases, such as in CVDs, results from a unique complex process, which should not be considered uniform in its relationship with the BE, but rather necessitates comprehension of the geographic context.

Future research could extend this approach by integrating the temporal dimension to the spatial dimension (Daiber et al., 2019; Şener and Türk, 2021). A longitudinal approach could detangle the complex relationship between CVDs and places (Chandrabose et al., 2019) by reconstructing a lifetime that explores residential and medical history (Ben-Shlomo and Kuh, 2002) or by comprehending the activity space of individuals (Chaix et al., 2009; Matthews and Yang, 2013). Research should also explore how self-selection is related to CVDs rather than the association with the BE only (Eid et al., 2008). In addition, the social mechanisms at the interface between health and BE should not be assumed to be uniform within the population or across different cultures (Schulz et al., 2005). However, while phenomena that shape our health can be more or less related with a direct impact of the BE (Barton and Grant, 2006), the latter should not constrain individuals from recovering from adverse conditions or aggravate existing conditions, but instead, promote healthier behaviours and prevents illness for all, in particular for the most vulnerable population.

5.5 References

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Chapter 6 Conclusion

6.1 Main findings

CHAPTER 2: Addressing a broad range of disciplines: a framework of Urban Health Issues

The broad range of disciplines under the umbrella of urban health has been summarised and structured into a conceptual framework of urban health issues (UHIs). The study takes a semi-systematic approach, developing a framework for data analysis on the healthy built environment (HBE) and supporting spatial planning. The conceptual framework is intended to be used for a generic case study to address the most significant topics that spatial planning must confront to develop healthier cities. The proposed framework collects fourteen UHIs: air pollution, noise pollution, hydrogeologic risk, extreme ambient temperatures, contaminated sites, road injuries, healthcare (geographic) accessibility, indoor thermo-hygrometric comfort, safe water and sanitation, housing safe design and accessibility, household air pollution, active mobility, community places and food environment. The framework is the conceptual structure used across the thesis to categorise the multiple urban health challenges, particularly to frame the characteristics of the BE into composite indicators.

CHAPTER 3: Spatial analysis of the Healthy Built Environment in the canton of Geneva

Using the objectively measured geospatial data of the HBE, we performed a spatial analysis of the canton of Geneva. We collected geospatial disaggregated opensource data extracting 61 HBE features. The study employed small geographic scales of aggregation and spatial interpolation to improve the spatial resolution of analysis and consider accessibility, respectively. The representation of the HBE consequently employed global and local methods to reduce the dimensionality of the dataset and thus summarise the information of the HBE features. The principal components allow summarising HBE grouped according to the adapted framework proposed in the second chapter. Each UHIs is represented by a small number of variables (mean of 2.8 components) able to describe at least 70% of the variability in HBE features. The use of a global and local approach delivers complementary information to understand the spatial distribution of the HBE. The global approach allows to compare all areas between them and combine indicators to understand how multiple issues are stratified in the different geographic contexts. The UHIs of flooding, contaminated sites and indoor environment are contextual to specific areas, public spaces and services concentrate their beneficial impacts increasingly by approaching the town centre and also secondly across multiple hotspots, while environmental exposures and road injuries display a general decrease by moving away from the city centre, except for contextual geographic specificities, i.e., the airport. The comparison of values per each UHIs allows us to understand how inequities deal with (in decreasing order of disparities): road injuries, urban heath island, noise and air pollution. Then, the UHIs indicators are synthesised into domains that briefly address exposures and injuries, housing and services. The domains and the respective UHIs display an association with median income. Wealthy neighbours are principally characterised by a lower density of services and public spaces, and low-income neighbours are characterised by unhealthier HBE in pollution and injuries. Afterwards, the HBE index condenses the information of the domains of UHIs equally, showing a spatial pattern capable of capturing the potential impact of HBE by delivering advantages related to public places and services; or penalties related to hazardous environments. The HBE index shows a convex curvilinear increase in values, therefore an unhealthier HBE, increasing residential density. Rather than that, the index exhibits a (maximum) peak at 1800m from the town centre and a concave curvilinear decline as the distance from the town centre increases. The local approach can better represent the variability of the HBE features (up to 95%) using the same number of components compared to the global approach. The latter make use only of neighbouring areas to synthesise the HBE features. The contribution is considerable for more than half of the HBE characteristics, implying that single attribute indicators should not describe complex urban health challenges. Mainly the local approach allows understanding the non-stationarity of the variation of HBE in the geographic space, thus underlining the spatial heterogeneity of the HBE in the canton of Geneva. In the end, extreme spatial gradients are observed in HBE across the UHIs, particularly for active mobility, urban heat Island and road Injuries. Overall, this chapter provides a detailed representation of the spatial distribution of the HBE for a broad range of UHIs at local and global levels.

CHAPTER 4: Viewpoints on urban health issues, and healthy planning integration

Stakeholders' viewpoints belonging to three groups, international experts on urban health, local experts in urban planning (in the French-speaking region of Switzerland), residents of the canton of Geneva, were collected during a structured survey.

Explore participants' perspectives in directly rating the importance of health and wellbeing among planning objectives, the general importance of BE in shaping our health, and the relative importance of UHIs (from the framework generated in chapter 1). The responses among stakeholders displayed more significant different responses than agreements. International experts reported the most independent responses, while the local citizens averaged the responses between the other two groups. Stakeholders uniformly identified green areas, public transportation, active mobility, and sustainability as the most relevant planning objectives. Local urban planners also favoured aesthetics and culture compared to international urban health experts who preferred mainly utilitarian objectives. About UHIs, stakeholders rated as most crucial air pollution and differently rated as relevant issues, such as active mobility, community places, food environment, safe water and sanitation, and household air pollution. Inconsistently from the relevancy of sustainability among planning objectives, effects of climate change were less relevant among UHIs. Overall, health and wellbeing and its related determinants were perceived as relevant, particularly among international experts of urban health. After weighting, UHI indicators defined in the third chapter using survey ratings didn't significantly differ due to limited variability in values and methodological constraints. In the end, citizen responses displayed different geographic patterns in planning objectives and UHIs related to the actual BE in the canton of Geneva. The participants in the northern areas on each lakeshore prioritised public services and housing quality, while urban and suburban areas rated as the most important objectives related to employment, economy, and equity. Then, citizens mainly identified air pollution as the most important UHIs, which few exceptions related to the geographic context, i.e. noise pollution and the airport's air-traffic axe. This study helps us grasp the importance of health in planning for stakeholders from diverse groups with varying decision-making powers, professional profiles, and responsibilities in the planning process. The findings shed light on the potential relevance of that approach in urban planning by integrating community and public health stakeholder perspectives.

CHAPTER 5: Spatial clustering of geospatial health data and spatial association with the Healthy Built Environment: the case study of Cardiovascular risk factors in the canton of Geneva

Firstly, the Bus Santé cross-sectional study cohort was used to study the spatial variation of six cardiovascular risk factors (CVRFs) in the canton of Geneva. Secondly we studied the link between georeferenced health data and the geographic context using the characteristics of the HBE analysed in the third chapter. The study uses a continuous representation of health and HBE rather than employing thresholds and guidelines to binary classify them. Also the study uses CVRFs measures georeferenced by the postal address of residents of participants. The calculation of the spatial autocorrelation allowed the identification of spatial clusters and the outliers. A significant proportion of participants (ranging between 28.5% and 43.3%, n=6835) was spatially dependent, therefore forming spatial clusters. The significant proportion of participants belonging to a spatial clusters suggests that the characteristics place of residence may be associated with health outcomes. The adjustment by age, gender and education had a minor impact on body mass index (BMI) and arterial pressure (MAP). The adjusted CVRFs displayed two spatial patterns. All CVRFs, except for heart rate (HR), identified high-values clusters in multiple peripheral areas in the east and one in the west area of the canton of Geneva. The clusters of high values of HR are in the east area of the urban agglomeration. In addition, the covariation among CVRFs allows describing the 86.2% of data variability by using a single composite indicator like the indicators of HBE created in the third chapter. After that, we performed a regression analysis to understand if the HBE can predict CVRFs values. In the regression analysis, we performed 540 regressions, exploring the performance parameters and the estimators across multiple dimensions: across aspatial and geographic weighted regression methods, across different sets of HBE variables, across multiple spatial sampling lag to define neighbourhood area, across CVRFs and by using the sub-set of spatial clusters of CVRFs. The regression that employed the whole dataset of participants could not explain the variability of CVRFs values, consequently the partially random distribution values. However, using the geographic-weighted method, thus the local approach, estimates could reconstruct the previously identified spatial clusters overestimating the cluster size. The regressions on the sub-set of spatial clusters of CVRFs allowed an excellent estimate of data variability (mean R^2= 0.56, SD= 0.21) with a relatively small error (mean MAPE= 3.01, SD= 0.27) regardless of the other dimensions of the regression analysis. The regression provided a better estimate at small spatial sampling lag using the local approach contrarily to the global approach. The machine learning regression displayed more inconsistent results across all dimensions of the regression compared to the other methods. By studying the frequency of significant contributors, the most relevant estimators dealt with road network characteristics and the active mobility network attributes. However, by studying the contributions of estimators for a representative case, for both BMI and HR, large proportions of contributions are significant, and the latter are highly variables. This outcome assumes that the relationship between CVRFs and the HBE is not stationary in space, so that the characteristics of the BE potentially shape the health of residents in some areas, while they don't in other areas. Subsequently, we subdivided high-value clusters depending on the location, directly measuring the HBE within those areas in the case of BMI and HR. The different locations of high-value clusters were associated with multiple significative different HBE features, varying depending on the location. The high-value clusters of HR commonly identified a higher density of road network and higher road hierarchy than the whole study area. In brief, this chapter highlight how crucial is spatial dependence and spatial heterogeneity in studying the association between CVRFs and the HBE. The study provides a precise spatial analysis of six CVRFs and their relationship with multiple characteristics of the BE in the canton of Geneva.

6.2 Implications of significant results

The diagnosis of the HBE in the canton of Geneva presented in Chapter 3 presents a set of indicators to represent eleven UHIs that synthesise the spatial variation of multiple features at a precise geographic scale using existing geospatial data. The availability of disaggregated spatial data in the study area allows multiple thematic maps that can drive spatial planning interventions acting where is more needed to deliver a healthier BE equally. The complexity of HBE geographic variability across various UHIs suggests using multi-attribute composite indicators to identify priorities since they allow for BE synthesis while retaining a substantial amount of the original data. The synthetic information provided by the indicators is prone to guide planning at a strategic level, and it can be interpreted or implemented with additional data at the operational level. The HBE potentially exacerbates disparities in Geneva's canton through undesirable consequences like traffic injuries, urban health island, air pollution, and noise pollution, rather than through public service. The spatial analysis displays how low-income areas are characterised by those issues that outline the health penalties of urbanisation, thus by exposure to pollution, extreme environmental conditions and road injuries (Choi et al., 2015).

Road injures and urban heath islands are considered less relevant than other UHIs, contrarily to air pollution and noise pollution, by both local planners and residents in the canton of Geneva, as shown in the findings of chapter 4. Also, air pollution and urban heat island pressure are expected to increase shortly in Switzerland (NCCS, 2017). The distinction between measures and perspectives of view should be investigated further to ensure that these difficulties are not and will not be neglected.

In aggregate, services associated with private activities, guided by economic market processes, saturate the town centre, notwithstanding a rise in land use mix outside it. The development of the inner urban agglomeration is a frequent topic of dispute in the canton of Geneva's spatial planning,. This issue is solved only in part by an excellent system of public transportation. Indeed planning strategies call for decongestion across transportation, housing, workplaces, and gentrification mitigation (Canton de Genève, 2021; Ville de Genève, 2009). About this topic is also important to further develop the research by including the neighbouring urban agglomeration in the French territory.

The spatial heterogeneity of the HBE is observed across multiple UHIs, underlining the necessity of studying how locally BE attributes are distributed. Also, at the local level, road injuries and urban heath islands develop the highest variation related to negative BE attributes. The local availability of HBE is essential for the low-income population, which have fewer resources to mitigate the adverse impact on the health of the BE. Compared to the high-income population, they are more likely to display a smaller activity space in terms of the number of destinations (Lu et al., 2021).

The findings of chapter 4 set the stage for the contribution that the local community and the experts in urban heath would deliver, integrating their perspectives compared to local planning practitioners. The perspectives of urban health would introduce the significant change in the direction of improved health integration and towards the preference of functionality in spatial planning. Priorities among UHIs are similar between stakeholders, which agree in prioritising air pollution and services related to active mobility, food environment, and community places.

The study of geospatial data of CVRFs in chapter 5 makes evident the necessity of employing them to support healthy urban planning (HUP). Despite a low prevalence of cardiovascular issues, participants in cross-sectional research in the canton of Geneva exhibit considerable spatial dependency, which means that the values of six CVRFs for a large proportion of participants are not randomly distributed. The areas characterised by high values clusters of CVRFs are mainly located in the western areas of the urban agglomeration. The geographical heterogeneity of the link between the HBE and CVRFs values precludes discovering a silver bullet for spatial planning intervention. Still, it points out different characteristics of the HBE that can contribute to worsen or preserve adverse health conditions. The HBE in clusters of high and low values of CVRFs are different, and the characteristics of active mobility network and road network explain the most the variation in CVRFs. Mitigating the road network's impact could improve the HBE in all clusters of high heart rate variability. At the same time, it is unlikely that further development of public transportation would benefit clusters of high values of CVRFs. Differently across locations, mitigation of noise pollution, air pollution, urban heath island should be addressed to reduce the spatial inequalities in CVRFs.

6.3 Future Research

6.3.1 Spatio-temporal contextualization of individuals and health

Overall, studying impacts on health involves both exposures and experiences to both HBE disadvanges and benefits, which have multiple spatial and temporal outreach. Firstly, time has not been widely accounted for in the relationship between the built environment and population health (Brook et al., 2018; Saarloos et al., 2009; Spring et al., 2012). To draw causal inferences with built environment characteristics, prospective studies are needed. Only a small proportion of studies were prospective or focused on follow-up data in the fields of urban health (Brook et al., 2018; Northridge et al., 2003; Schulz et al., 2018; Verma et al., 2017; Yen and Syme, 1999). A large body of urban health research is based on cross-sectional studies, while longitudinal studies are still rare (Elsey et al., 2016; Petteway et al., 2019). Population health inquiry could be based on the concept of the exposome to study the complexity of urban health. Wild (Wild, 2005) defines exposome as the measure of the totality of exposures in a lifetime span. The study on total exposome to the built environment could be based on a contextual collection of exposures and experiences across time and space (Matthews and Yang, 2013; Vrijheid, 2014). Following an approach based on exposome's concept also means dealing with multiple sectors simultaneously, i.e. adopting a comprehensive approach (Vrijheid, 2014).

Nevertheless, to demonstrate that health is a product of multiple exposures, multiple measures that did not exist or were not collected in the past would be needed. Instead, ongoing exposome studies can gather multiple measures during the expected time lag between the beginning of exposure and the illness diagnosis (Louis and Sundaram, 2012; Vineis, 2019). Furthermore, research cannot efficiently address exposome because the time lag between intervention and health outcomes can be more significant than the changes in the built environment, such as the city plan itself (Grant, 2015). In contrast with different time lags separate intervention and health outcomes, cities applying HUP intervention report a systematic change in terms of human response, such as the involvement of key stakeholders and a better understanding of the social environment (Grant, 2015). The contextualisation of the health of individuals in space and time is then affected by two factors at different temporal scales: the study of individual residential history and the activity space to consider daily exposure to and daily experience of the BE. The first factor is limited to studying health conditions related to chronic health conditions, such as NCDs.

Assuming that health is a product of the built environment where people live, the analysis should include the amount of time spent in each place. This consideration is valid when the assessment encompasses non-communicable diseases, which may occur many years after the exposure or result from exposure over a long time. Relation introduces a significant variation in terms of lifespan time and spatial dimension (Lawson et al., 2016). Spatial epidemiological studies on non-communicable diseases commonly filter participants choosing individuals with fixed residence for several years. Altogether studying chronic diseases and exposome demands longitudinal approaches. Accordingly, places of exposure (or experience) are multiple depending on the residence history (Ben-Shlomo and Kuh, 2002; Matthews and Yang, 2013). Therefore, individual health could be a stratification related to different places. Relocation has been only recently considered as a change of approach for health spatial contextualisation (e.g. to study active mobility and health determinants after relocation) (Beenackers et al., 2012; Braun et al., 2016; Foster et al., 2015; Giles-Corti et al., 2013; Hirsch et al., 2014). The study of Wu et al. on blood pressure and air pollution compared built environments after and before relocation, using both movers and permanent individuals (the latter as control population) (Wu et al., 2013). Generally, relocation habits have been studied jointly with health such as stressors (e.g. during childhood (Jelleyman and Spencer, 2008), in aged adults (Sara Sanders et al., 2004)) or as positive indicators of self-reported health in adult movers (Lin et al., 2012). To assess the healthiness of the built environment, a residence history study could allow the comprehension of the stratification of exposure and experience of different settings. However, the study of urban health that integrates residential history would require the collection of a large set of BE datasets made even more complicated by making BE data comparable and by the availability of historic BE geospatial data. The study of relocation may help detangle the causal pathway between illness and urban forms or self-selection of unhealthy environments. For example, after investigating the relationship between sprawl and obesity, Eid et al. concluded that individuals who are more likely to be obese select residences in a sprawling neighbourhood showing some influence by the urban environment (Eid et al., 2008).

Then, the relevant areas of exposure and experience of urban features depend on the activity space. Thus the geographic location of residence and frequent primary destination, such as workplace and schools (Chaix et al., 2009; Kramer and Raskind, 2017; Smith et al., 2019). The neighbourhood of individuals can be "fluid", varying with time, space and other driving factors (Giles-Corti et al., 2013), including individual determinants, such as age, proximity, utility, and density of destinations. To put people into place" (Entwisle, 2007), and therefore to relate built environment and population health, the spatial extent of exposures and experiences within cities has to be investigated. The complexity of addressing this goal is encompassed by the Uncertain Geographic Context Problem (UGCoP) of Kwak al. (Kwan, 2012). Initially applied in social sciences, the concept has been used in urban health about its Spatio-temporal contextualisation of individual health measures and urban environmental characterisation (Lu and Delmelle, 2019). Indeed, research in HUP needs to "address the individual space-time behaviour that underlies the interaction between the built environment and health", addressing the question of "where does the built environment impact health of one individual?" (Saarloos et al., 2009). Therefore, geospatial information about the built environment and individuals would be needed at more minor geographic and temporal scales. The definition of the activity space can rely on assumptions that approximate it using pre-determined spatial units (territorial units or neighbourhoods) or individual-based units (ego-centred neighbourhoods) (Chaix et al., 2009; Gomez et al., 2015). Studies on place and health are widely based for convenience on aggregated data on geopolitical units, such as administrative boundaries, postal codes or census districts (Elsey et al., 2016; Gomez et al., 2015; Kanaroglou and Delmelle, 2016; Rothenberg et al., 2015; Schulz et al., 2018; Yang et al., 2013). Indeed, neighbourhoods have been used as the activity space and spatial unit, despite the inconsistency in the perception of its spatial extension (Chaix et al., 2009; Matthews and Yang, 2013; Saarloos et al., 2009). Meanwhile, we know that "neighbourhoods do not exist in isolation" (Martin and Michael, 2004). Describing urban environments does not shift immediately and discreetly but displays different gradients of variation between neighbourhoods (Chaix et al., 2009). Otherwise, the spatial unit is defined by the perceived neighbourhood by residents (Coulton et al., 2013; Diez Roux, 2007) rather than the objectively experienced neighbourhood (Chaix et al., 2009).

Furthermore, the geographic location of residence or other frequent destinations may assess the built environment using multiple distance buffers to multi-modal transport buffers. Attributes of urban environments may show different spatial extensions and vary within a given population (Bhat and Guo, 2007; Schulz et al., 2018). For example, public green areas may affect potential physical activity when accessible, therefore in a buffer around its location following a decay proportional to travel time (Brownson et al., 2009; Zhang et al., 2011). Instead, night-time noise pollution can be modelled by expected sources and built environment design within a buffer around the residence (Khan et al., 2018). On the contrary, indoor characteristics have no spatial extension from the residence location (Badland et al., 2017). Accordingly, the spatial extension in shape and size depends on the element of interest, and it cannot be easily approximated (Kramer and Raskind, 2017). The concept of "spatial polygamy" encloses this variability in individual mobility and the spatial extension of urban features that influence health differently. Matthews and Yang defined spatial polygamy as "the simultaneous belonging or exposure to multiple nested and non-nested, social and geographic, real, virtual and fictional, and past and present contexts" (Matthews and Yang, 2013). Knowledge of individual space-time behaviour is fundamental in studying the inference between experience/exposure to BE and health outcomes (Entwisle, 2007), which could be studied directly using location-aware technologies (Matthews and Yang, 2013; Miller and Tolle, 2016), such as geo-trackers, smartphone application or activity diaries (Oh et al., 2018; Roswall et al., 2017; Saarloos et al., 2009; Zhang et al., 2018); or indirectly by models like activity-based modelling (Saarloos et al., 2009; Wang et al., 2018). The use of wearables also allow the collection of health data, and thus real-time responses (Bayoumy et al., 2021).

In brief, the study of the complex relationship between health conditions and BE could be untangled by integrating a precise spatio-temporal contextualisation able to reconstruct impacts in short and long terms on the health of individuals. The quality and quantity of data collected are crucial barriers to addressing this issue in urban health research. For example, this purpose could be attained by monitoring the healthiness of the BE and then integrating this information with the medical record at the level of healthcare services, or in the form of opensource tools, i.e., web platforms or smartphone applications, for both planners and individuals. The joint collection of multiple attributes from the HBE and health data encompass the concept of precision medicine, which at the current time mainly addresses individual specificities rather than environmental factors (Kamel Boulos et al., 2019; Kamel Boulos and Le Blond, 2016).

6.3.2 The data issue

Data availability and quality are fundamental in understanding urban health and guide spatial planning (Elsey et al., 2016; Friel et al., 2011). Data issues are related to missing data or missing characteristics in data and concern both BE data and health data. Data issues identified in this study can be generic or case-specific, thus about CVDs or the canton of Geneva. As discussed in the previous paragraph, urban health research should be improved by integrating a temporal characterisation in data, either for BE or geospatial health data. By including time into health and place research, we can better understand the time lag between changes in HBE and health outcomes and address inference in urban health studies in part.

The study of BE data is mainly related to the study of density or the characteristics of the HBE. The BE can also be characterised by morphological characteristics, which are mainly investigated in physical phenomena, such as urban heat islands or air pollution (Yang et al., 2020; Zhou et al., 2017). For example, a recent study by Martino et al. Jointly integrated morphological characteristics of the BE in studying the liveability in Vancouver (Canada) (Martino et al., 2021). Also, the study of the BE could collect more qualitative data on the BE and study its relationship with individual data that mediate health outcomes, such as behaviour and perception. Qualitative data of the HBE can play an essential role in shaping health outcomes, particularly in describing the capacity of services to deliver a health benefit (Centre for functional design (NYC), 2010). The study of the qualitative characteristics of the built environment is instead performed at more minor spatial scales, i.e., within buildings and blocks (Centre for functional design (NYC), 2010; Healthy urban design, 2019; Rice and Drane, 2020), rather than a neighbour or city level (Giles-Corti et al., 2013) and regardless its spatial distribution. Improving the efficacy of structures in providing a healthier BE is mainly driven by individual or isolated effort rather than a systematic approach through spatial planning and policies (Carmichael et al., 2020). Addressing this requires intervention at both macro and micro dimensions, and research on both is still limited.

The data collection for this study was based on open-source geospatial data. The search for BE data related to a broad range of topics allowed multiple missing geospatial data identification in the third chapter. Firstly we lacked data about private properties as a direct consequence of privacy (Bloustein, 2017). Spatial planning has a regulatory function concerning private property, such as standards and policies, rather than direct control through spatial planning (Webster, 2007). However, in studying health and places, the place of residence matters. The residence is the place where we spend the majority of our time: countries the such UK, Germany, the USA, and Canada are characterised by percentages above 63% of daily time spent at home (Brasche and Bischof, 2005; Farrow et al., 1997; Leech et al., 2002). In 2015, more than 1.6 billion people did not live in adequate housing worldwide, according to Habitat for Humanity (Habitat for Humanity, 2019). The health impacts of housing are multiple and complex (*WHO*, 2018) and should be better explored in the context of Switzerland (Kahlmeier et al., 2001; Pagani et al., 2021). Data on housing exist but are instead owned by private institutions, such as real estate or external governance partners, and are partially available for consultation only (Swiss Confederation, 2020).

About the study area, geospatial data about air traffic noise pollution were not found. According to the cantonal reports, noise pollution is the most relevant stressor (Canton de Genève, 2019, 2020). However, data were found for rail and road traffic (FOEN, 2018), while air traffic noise levels are only available by real-time punctual measures (Genève Aéroport, 2019). Also, air pollution geospatial data were characterised by a rough estimate of a single pollutant (SITG, 2021). The canton of Geneva put in place more than one decade ago a project to monitor air pollution in the metropolitan area of the canton of Geneva and neighbouring France, namely Grand Genève (BRULFERT et al., 2016). However, results are published in qualitative data, and quantitively geospatial data are not available. Also, data are modelled from measurements station predominantly at the border with France rather than within the urban agglomeration within the canton of Geneva. Recently, air pollution data can be consulted in real-time from the application Air2G^2 (Air2G^2, 2021).Spatial planning is moving toward the public responsibility of reporting about the HBE. In the Swiss context, data availability and quality have a great potential that is only partially employed. While data are widely available, their access is limited, i.e., for consultation only, due to geospatial data ownership. Boost the collaboration among multiple institutions and data owners is expected to contribute to transparent reporting about the HBE.

Afterwards, individuals' data can be improved by including time performing a longitudinal study or by studying the activity space in the short term or the residential history in the long term, as discussed in the previous paragraph. In general, the study of the BE could be implemented by integrating a qualitative characterisation of the HBE. For example, in the previous studies on CVDs, objectively measured characteristics of the BE is frequently studied in relation to healthier behaviour (Charreire et al., 2012; Frank et al., 2019; Malambo et al., 2016) (Chandrabose et al., 2019; Leal and Chaix, 2011). However, spatial studies principally measured behaviours rather than including perceptions and motivations of behaviours, mainly explored independently from the geographic context in social sciences (Martin et al., 2014; Meyer et al., 2019). Beyond the study of CVDs, urban health research lacks a complete picture of the effect of BE on mental health (Buse et al., 2019; Maas et al., 2019); and the joint study of social environment and health in the geographic context.

6.3.3 Planning documents in the canton of Geneva

The study of urban health generally relies on measured characteristics of the HBE, on health data, or participation, but lacks insight on planning documents (Bird et al., 2018; Grant, 2015; Sallis et al., 2016). Analyses of the content of planning papers and reports may shed light on the integration of health into planning, spawning the idea of HUP. Additionally, the collaborative study on planning documents and geographical analysis of the HBE may argue for health measures directly. In the context of the canton of Geneva, the cantonal master plan (Canton de Genève, 2021) as well the conjoint spatial planning of the Grand Genève agglomeration (Grand Genève, 2019), primarily address the lack of housing, and secondly the transportation planning able to ease the congestion caused by the necessity of commuting related to the lack of housing and the economic advantage of cross-border employment. Since today, the canton of Geneva over preserved its natural and agricultural land, building the second densest large city of Switzerland, employing infilling growth rather than sprawling urbanization. The major project within the canton area directly addresses the need for housing along the existing transportation axes and hubs and by considering the creation of public spaces and services and the creation of workplaces. The strategic principle of the planning documents (Canton de Genève, 2021; Grand Genève, 2019 ; Ville de Genève and PDCOM, 2009) more or less encompasses planning for population health but do not explicitly link the HBE with human health except the interface of healthcare services. Even when dealing with air pollution reduction, the latter is reported to contribute to climate, avoiding any mention of the possible impact on health, both positive and negative.

Similarly, health is not explicit in addressing active mobility, water quality, flooding risk, water quality, green areas. There is no mention of issues related to urban heath island, road injuries and housing quality, despite housing being a primary driver of planning projects in the canton of Geneva. This quick overview of the planning documents for the study area indicates a lack of integration of health into planning across several disciplines, even though a portion of its strategies currently incorporate HUP. Also, the analysis of planning practice could investigate the subdivision of strategic and operational planning responsibilities that affect the integration of health in spatial planning within the canton of Geneva.

Additionally, the canton of Geneva is a unique case due to its geographic location. In fact, despite the border with the canton Vaud, the canton of Geneva could be considered an enclave in the territory of France. The canton of Geneva's cross-border link with neighbouring France provided an opportunity to disperse demographic pressure outside the canton's limits, preserve its territory, and reduce land consumption. In addition to the border, Geneva is also shaped by the water bodies, which split the territory into three parts. The combination of the financial attractivity and the border proximity of the canton of Geneva may have caused general gentrification of the whole area about the territories beyond the border (Rérat et al., 2008). This effect is particularly marked in the municipality of Geneva, whose planning strategies aim to bring back the population an urban environment for the local community (Ville de Genève and PDCOM, 2009). The canton of Geneva's other particularity is that it has the largest concentration of international organizations in the world, which helps create an international melting pot and attracts a sizable proportion of semi-permanent inhabitants that may be less likely to build a stronger community.

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Chapter 7 Appendix

Conceptual framework of urban health issues description

The following appendix describes the urban health issues (UHIs) and domains developed in the Chapter 2. The framework is composed of three domains which groups fourteen UHI grouped in three domains.

Outdoor Environment

The domain of Outdoor Environment gathers characteristics of the built environment that impact health passively an individual depending on his geographic location of characteristic in the outdoor environments. This group mainly gather issues that can be defined by exposures and in part by accidental injuries.

The most important human-made stressor is air-pollution (WHO, 2016a). Worldwide, air pollution is a public health emergency: 91% or the global population is exposed to air pollution over the WHO guidelines limits, and every year 4.2 millions deaths are attributed to outdoor pollution (WHO, 2019). Indicators of air pollution for health protection, are particular matter, ozone, aromatic compounds, sulfur dioxide and nitrogen oxides among the many. Air pollution increase mortality through multiple diseases; among the others the principal are acute lower respiratory disease, chronic obstructive pulmonary disease, stroke, ischemic heart disease and lung cancer (WHO, 2016a)(Brunekreef and Holgate, 2002). The primary sources of human-made air pollution are caused by fuels burning (for energy production, transport and households), industry and agriculture (WHO, 2016a). Transportation contributes to a large part of air pollution (IPCC, 2014), where road transport is the principal component (Chapman, 2007). Household and transportation pollution have an important impact on health also due to their proximity to receptors. Road commuters, those within vehicles or outside, are overexposed to air pollution (Xu et al., 2018)(Barnes et al., 2018). Land use strategies and policies can turn away sources given by energy production, industry and agriculture or reduce their impact (Hankey and Marshall, 2017). Air pollution from households and transports can be targeted directly with emission reduction strategies or indirectly, managing the urban form; for example increasing the compactness and density to reduce the impact of transports (Hankey and Marshall, 2017). Nevertheless, increase of pollutants concentration can be experienced inadequately densifying urban environments. Geometry design may create urban canyons where pollutants concentrate (Baik and Kim, 2002; Taseiko et al., 2009). Separation of sources of pollutants and receptors can attenuate exposure to pollutants, for example setting pedestrian areas and roadside vegetation (Abhijith et al., 2017). Heat island effect can reduce energy spending in heating but increase spending for climatization as well as boosting photo-smog (Fallmann et al., 2016). Despite efforts in planning, other factors beyond urban planning, as seasonal weather, may be preponderant (Liu et al., 2018).

The second human-made stressor is noise pollution, a factor of raising concern for health protection (WHO, 2011). In Europe, sources of noise are mainly given by transports (in order, road, rail and airports) and industrial sites (WHO, 2011). Only in Europe, it is calculated that 1.5 millions DALYs (disability-adjusted life years) are lost due to noise pollution (WHO, 2011). Exposure to high noise levels is primarily associated with cardiovascular diseases, cognitive impairments, sleep disturbance, tinnitus and annoyance. Health effects of long term exposure to noise pollution , and noise-related mental health are not frequently studied (Muzet, 2007; Okokon et al., 2018; Stansfeld and Clark, 2011). Noise pollution is considered differently when exposure takes place at nigh-time or day-time (Luz, 2019). Noise exposure differs within the city, strictly depending on the transport network and commuting behaviour as well as quality of pavements and building noise insulation. Reducing noise level mainly means reducing road vehicles transportation (Brown, 2015) (WHO,), which has additional advantages as active mobility and air pollution reduction. Noise barriers or trees canopies can additionally reduce noise level(CDC, 2018).

Hydrogeological risk is included despite its occasional occurrence since its effects can be mitigated by the urban planning. Flooding and wet mass movement caused respectively more than 272000 deaths and 38000 deaths between 1970 and 2012 (World Meteorological Organization, 2014). Phenomena such flooding and landslides, depend on the topography within the city, affect a large number of settlements and occur frequently within decades compared to other catastrophic events (European Environment Agency,) (Links - Flood risk management - Environment - European Commission,). Furthermore hydrogeologic risk depends on human activities, at regional scale, such deforestation, and at large scale through climate change (Links - Flood risk management - Environment - European Commission,)(Cool Earth, 2018). The impact of hydrogeologic events can be reduced, providing hydraulic construction, managing water paths, adapting building standards (e.g. limiting underground living spaces), and increasing the permeability and the retention of the urban environments with green surfaces.

Environmental thermal stress in urban environment is a product of the Urban Heath-Island (UHI) effect. The over-heating of built areas compared to natural environments, affect health directly through exposure to higher temperatures, causing among the others heat stroke, exhaustion syncope and cramps (Kovats and Hajat, 2008); or indirectly exacerbating health impacts, as by air pollution(Heaviside et al., 2017). Further evidence about thermic stress is listed in the following paragraph of Indoor Environments. UHI may also have a positive effect mitigating extreme cold temperature, which is negligible in case of suitable shelter. Besides the mitigation and the control of urbanization and human activities at city scale, provision of blue and green spaces, green or cool roofing mitigates the impact on health (US EPA, 2014) and improve air quality too (Akbari et al., 2001).

Contaminated lands, or brownfields are frequently a heritage of a dismissed industrial activity, waste disposal or release of pollutants following accidents. Exposure pathways are multiple and mainly given by groundwater infiltration, soil ingestion (including soil-borne dust), vegetable consumption and vapor or particles inhalation (Swartjes, 2015). The effect on health are multiples and depends on the contaminant substance, ranging from nausea to cancer, due to hazardous exposures of few hours to years (Swartjes, 2015). Impact on health of soil pollution has a lower profile, since outcomes can take place years after the contamination, and because effects can hardly be isolated from other risk factors (Swartjes, 2015).

Road traffic crashes are responsible of approximately 1.35 million deaths each year, of which 93% happen in low- and middle-income countries (Road traffic injuries,). In more than 50% of cases, injuries involve vulnerable commuters, pedestrians and cyclists (Road traffic injuries,). Road injuries are products of human errors that depends on inadequate infrastructures (Road traffic injuries,)(WHO,). Cities lacking in safe transportation infrastructure, can show permanent spatial cluster of road injuries (Prasannakumar et al., 2011). Roads become safer adopting infrastructure intervention, such safe passageways for pedestrians, bicycle and motorcycle lanes, speed calmers, crash barriers and forgiving road side features, safer intersections, separate access from through-roads, vehicle-free zones, traffic and speed restriction in vulnerable zones (as schools, residential) (WHO,). Furthermore, road injuries can be reduced reducing road transportation itself, investing on public transport and active mobility. Road public transport has similar but smaller impact on health compared to cars. For example, a study on the city of Montreal shows 3.7 rate of injuries of car occupants on bus occupants, as well as lower rates of injuries on pedestrians and cyclist of busses compared to cars (Morency et al., 2018).

Healthcare services are composed by hospitals, specialized clinics, surgeries, diagnostic services, pharmacies, among the many. Travel distance to care is fundamental for emergencies, and it is an indirect cost that impact the access to care. (Graves, 2008). Geographic accessibility of healthcare services is an important factor for cardiovascular diseases, the most common cause of death worldwide (WHO, 2018b) (WHO,). Geographic location and resources of healthcare can be optimized to answer to the care inflow, balanced on needy populations, as elderly or socio-economic deprived population. Kelly et al. reviewed 108 studies in high-income countries, on differences in travel distance to healthcare services and patients outcomes, finding out that 77% of studies reported poorer health with increased distances (Kelly et al., 2016a). Also Japan, which is characterized by excellent healthcare and the highest life expectancy in the world, experiences unbalanced healthcare geographic distribution, which result in a reduced accessibility to healthcare (Shinjo and Aramaki, 2012). Geographic accessibility to healthcare can be improved densifying a city, improving transport network and creating new healthcare facilities where geographic accessibility is inadequate is another intervention to be adopted. Knowledge of whether healthcare is accessible, or even oversized to the demand, would allow a better allocation of resources in the healthcare system (Shinjo and Aramaki, 2012).

Indoor Environment

This domain gathers health issues related with living indoor environment. Other indoor environment such as workplaces, are differently regulated depending on the activity and are not considered in this research. Residence is the place where we pass the majority of our time: countries such UK, Germany, USA, and Canada are characterized by percentages above 63% of daily time spent at home (Brasche and Bischof, 2005; Farrow et al., 1997; Leech et al., 2002). While developed countries shows percentages above 70% of time spent home (al,), percentages get higher with higher rates of unemployment and work-at-home jobs (World Employment and Social Outlook: Trends 2016, 2016). In 2015, more than 1.6 billion people did not live in adequate housing according to Habitat for Humanity (Habitat for Humanity,). First of all, it should be known weather housing is present or not: more than 1 billion people lives in slums and about 2% of the world population is homeless (YaleGlobal). Living indoor environment has different impact on health grouped hereunder: thermos-hygrometric comfort (dump habitats and extreme indoor temperatures), safe design and accessibility, sanitation and household air pollution.

Thermo-hygrometric comfort does not deal with wellbeing alone: extreme condition of temperature and dampness impact health outcomes as well. Each housing unit contribute passively with its composing materials and actively with its systems, to the regulation of the indoor environment to target an optimal temperature and humidity for its inhabitants. Inadequate thermo-hygrometric regulation may lead to persistent dampness, allowing the development of mould and exposing tenants to complex microbial indoor pollutants (WHO Europe, 2009). Exposure to microbial pollutants is linked with developments and exacerbation of respiratory symptoms, allergies, asthma and immunologic reactions (Mendell Mark J. et al., 2011; WHO Europe, 2009). In USA, indoor dampness is associated with 8 to 20% of cases of respiratory infection and 30 to 50% cases of asthma (Mendell Mark J. et al., 2011) . In Europe, USA and Canada, building showing signs of dampness are estimated to be 20%, while worldwide estimates range between 10% and 50% (WHO Europe, 2009). Thermic stress, as anticipated, can be experienced outdoor and indoor. Hot temperatures are able to exacerbate health conditions generally besides discomfort, operating mainly by cardiac failure, heatstroke, hyperthermia and dehydration (WHO,). Cold temperatures may increase risk of respiratory condition (such asthma and chronic obstructive pulmonary disease); induce stress of circulatory system worsening and triggering cardiovascular diseases conditions; and it associated with poor mental health (WHO,). Between 1970 and 2012, deaths cause by extremes temperature were more than 175000 (World Meteorological Organization, 2014). During the heatwave of 2003, 45000 excess deaths have been estimated in Europe (WHO). Instead between 2004 and 2008, United Kingdom 130000 people elderly people died due to cold-related illnesses (WHO). Furthermore, climate change challenges the thermo-hygrometric regulation for health protection from excessive temperatures and dampness (Cool Earth, 2018; Wierzbicka et al., 2018). Despite climate favourable climate conditions, countries with milder climate show higher mortality due to cold temperature than cold countries, due to structural deficiencies (WHO,). Thermo-hygrometric wellbeing improves adopting better insulation from excessive temperatures and sources of dampness, with ventilation, using thermos-hygrometric systems and controlling crowding. Provision of adequate isolation and system prevents reduce outdoor air and noise pollution input and also prevent concentration of hazardous chemicals (Wierzbicka et al., 2018).

The indoor built environment can be characterized by design capable to cause domestic accidents and impede the access (Keall et al., 2008) (WHO, 2018a). Unsafe designs can be responsible of domestic injuries such falls and falling objects, poisoning, electrocution, fire, or explosions (Safety at Home,)(Bhanderi and Choudhary, 2008)(WHO, 2018a). Among the others, falls are one the most frequent accidents at home (Runyan et al., 2005): in USA, between 1996 and 2012 more than 24 million people reported a stair-fall to healthcare services (Blazewick et al., 2018). Presence of hazards at home is associated with higher incidence of domestic injuries (Keall et al., 2008) (Leclerc et al., 2009)(Pearce et al., 2012). Moreover, accessibility needs to be perfectioned since approximately 15% of world population is affected by a form of disability (WHO World Report on Disabilities, 2010). Dwellings that are not accessible and designed for universal needs, show mainly higher rates of injuries for disable people, and secondarily worse quality of life, mental health and other social aspects (WHO, 2018a). Domestic injury's prevention and accessibility depends on the quality of housing that includes multiple aspect of the design of housing units and its systems, such as smoke detectors, safe guards, safe stairs and surfaces (WHO, 2018a). Another aspect linked with the design but also the use of indoor environment is crowding. Crowding boosts transmission of infectious diseases (Wynne, 1925) and increases stress and sleep disturbance out of other social aspects (WHO, 2018a). Hazardous crowding is mainly associated with tuberculosis and other respiratory diseases, diarrhea, gastroenteritis and other infectious diseases (WHO, 2018a). Overcrowding boost the speed of diffusion and the magnitude of epidemics, allowing the spread of infectious diseases with high mortality rates as Ebola virus (WHO,). Measuring crowding itself is ambiguous, and depends on the target of the inquiry (Ramalhete et al., 2018). United Nation (UN) between many urban indicators, defines overcrowded a housing unit when there are more than 2 people per room (UN-HABITAT, 2006) or when the floor area per person is inferior to 20 m2(United Nations Population Division | Department of Economic and Social Affairs,). The 89% of housing units in developing countries is under the limit of 20 m2 per person, and 42% in developed countries respectively (United Nations Population Division | Department of Economic and Social Affairs,). WHO formulated less flexible classes of crowding to tackle epidemics, depending on the number of people per bedroom area (WHO, 2018a). European commission defines more strict categories of maximum crowding per bedroom depending on age, marital status and gender, thus taking care of socially constructed aspects (Eurostat, 2018). Overcrowding is mainly studied in developing countries studies due to higher occurrence of epidemics with higher prevalence of overcrowding itself.

Access to "sufficient, continuous, safe, acceptable, physically accessible, affordable water" has been recognized by UN as a fundamental right (UN, 2010). Access to clean water is also the goal n°6 for the SDG 2030 Agenda (Sustainable Development Goals .:. Sustainable Development Knowledge Platform,). In 2015, 79% of the world population used a safely managed drinking water service, while 89% had at least a basic service (Drinking-water,). The population of low- and medium-income countries has minor access to clean water (Drinking water | JMP,). Clean water is necessary for drinking but also domestic use and food production. Unsafe water is responsible every year of 0.5 million deaths worldwide for diarrhea only. Unsafe water is also related to cholera, typhoid, polio, hepatitis A, shistosomiasis among the many others (Drinking-water,) (WHO, 2018a). Water may be contaminated by pathogens as Escherichia coli and Legionella spp., or chemicals as antimony, benzo(a)pyrene, copper, lead, nickel, vinyl chloride, arsenic, fluoride or nitrate (WHO, 2018a). Systems extracting, carrying, and storing water should avoid contamination from wastewaters or other pollutants, stagnation, heavy metals plumbing or inappropriate materials prone to bacteria proliferation (WHO, 2018a). When the water supply location does not coincide with residence, contamination should be avoided during the transport. Displacement for water supply mean also unbearable physical efforts: 1km distance is considered as a maximum distance by WHO (WHO, 2018a). Access to safe water is related to collection of wastewaters of sanitary systems: estimates show that in 2015, 2 billion people were drinking waters contaminated by feces. Sanitation is a key feature for communicable diseases prevention in urban health. Sanitation is the provision of "toilet or improved latrine, not shared with other households, with a system in place to ensure that excreta are treated or disposed of safely"(Sanitation,). Only 39% of the world population have access to adequate sanitation, while 2.3 billion people do not have access to toilets or improved latrines at all (Sanitation,). Without adequate sanitation, pathogens are able to contaminate drinking water and food: it is estimated that at least 10% of the word population eat food irrigated with wastewaters (Sanitation,). Wastewater pathogens cause diseases such cholera, diarrhea, dysentery, hepatitis A, typhoid and polio, intestinal worms, schistosomiasis, and trachoma (Sanitation,). Deaths caused by diarrhea given only by poor sanitation are approximately 0.3 million (Sanitation,). An adequate sanitation system is able to provide discharge of excreta, containment, treatment, collection, processing, disposal and safe reuse.

The indoor air pollution is caused by inefficient fuel combustion, radon infiltrations, chemical building products, cleaning products, and outdoor air pollution too (WHO,). The most important factor is inappropriate fuel combustion due to rudimental cooking equipment and fuels such biomass or coal. It is estimated that 3.8 million premature deaths every year are caused by inappropriate cooking (Household air pollution and health,). Approximately 3 billion people use inefficient practices using polluting stoves paired with solid fuels and kerosene, and thus resulting in higher risk of pneumonia stroke, ischemic heart disease, chronic obstructive pulmonary disease and lung cancer among the many (Household air pollution and health,). Furthermore, fuel collection (e.g., biomass) may constitute an unbearable physical effort able to generate orthopaedic disorders. This health burden impacts the poorer fraction of the world population essentially in low- and medium-income countries. Access to electricity, adequate equipment, and safe fuels, are the main driver of better indoor air-quality. High-income countries experience mainly indoor pollution from unsafe heating or from other sources, such asbestos, radon and toxic mould, each of which requires appropriate measures. The most important chemicals traced indoor are benzene, carbon monoxide, formaldehyde, naphthalene, nitrogen dioxide, polycyclic aromatic hydrocarbons, radon, trichloroethylene and tetrachloroethylene (WHO, 2018a).

Healthy lifestyle

Health is widely recognized as a product of individual behaviour among multiple leading factors. Social behaviour related to health can be shared by homogenous groups (Stutzer and Frey, 2008), and follow epidemic characteristics of diffusion (Rhodes, 1997;

WHO,). Instead, whether behaviour can be influenced and shaped by the built environment is still an ambit of heated debate in many fields. The amenities and services listed hereunder can be health promoter depending not only on their availability and accessibility moreover their quality. This group collect three fundamental aspects of living in urban environments related to health and wellbeing: the way people provide to food supply, and the way people move within the city and do physical activity, and the way people gather and use public space.

Active travel consists in performing physical activity to commute within the city, as cycling and walking instead of using motorized vehicle. Physical activity, when performed regularly, reduces risk of hypertension, coronary heart disease, stroke, diabetes, breast and colon cancer, depression and the risk of falls, Improves bone and functional health, and is key factor for weight control (WHO,). Physical inactivity is a risk factor considered to be responsible of 6% of global deaths (WHO,). Instead commuting by car is considered as a sedentary, and among the main effects it is related with weight gain and its relative risks (Sugiyama et al., 2013). Car commuters may report higher stress levels compared to public transport or active mobility (Gottholmseder et al., 2009; Stutzer and Frey, 2008) or subjective health (Künn-Nelen, 2016). On the other hand, commuting in cities is not feasible due to travel distances and requires faster transportation such as public transports. Public transportation operates indirectly reducing the car use and boosting the active travel. Busses improves the efficiency of road transport (Titos et al., 2015) (Woodcock et al., 2009). Other public transports as metros, trams and cable-cars uses do not contribute fuel consumption within the cities and consequently air pollution. Furthermore, public transports either do not contribute to road traffic or their contribution is lower compared to private transports. As for health, public transport is associated with lower stress compared to cars (Gottholmseder et al., 2009). Public transport impacts health differently and has multiple health benefits (Woodcock et al., 2009). Public transport is coupled with active travel (specially walking) (Woodcock et al., 2009), allowing people to commute medium and large cities. Nevertheless walkers as cyclists are vulnerable to road injuries (Road traffic injuries,) and easily exposed to noise and air pollution. Despite the increased risk intake by exposure to air pollution, health benefits of physical overtake it (Tainio et al., 2016). The attractiveness of active travel depends on multiple characteristics of the built environment related with his availability, accessibility, and quality. In fact, active travel promotion is possible whether destinations are available in a reasonable distance depending on the transportation. Urban settings with higher land-use mix allow a more homogenous distribution of destination with multiple implication on urban health (Frank et al., 2006). A denser network of commercial activities, services, as well as place of employment, can lead to active travel rather than car commuting (Christian et al., 2011). Interventions to ameliorate transportation, land-use mix and public open spaces for active travel has synergic impacts on the following UHI, the food environment and the social environment.

Diet is able to prevent multiple diseases when healthy, diversified and balanced; while it increase health risk when it is not (WHO,). Healthy nutrition is not merely product of individual behaviour, but it is possible when healthy food environments are geographically available (Story et al., 2008). The food environment is composed of food retail stores, markets, restaurants and all the physical place where to consume or buy food. Research on eating environments arises many complexities. The review of Caspi et al. on local food environments reports how availability of healthy food environment is associated with healthy diet; while travel distance from residence shows inconsistency with healthy diet (Caspi et al., 2012). Similarly to the review of Bivoltsis et al. on dietary intake and food environments reports inconsistencies in accessibility but a significative association between availability (Bivoltsis et al., 2018). Nevertheless the association of food environment accessibility with healthy diet is still an open debate (Bivoltsis et al., 2018; Sadler et al., 2013; Shannon, 2014; Story et al., 2008), inquiry on food environment is limited in other health impacts beside obesity and cardiovascular diseases despite the recognised effects on health (WHO,). Besides the impacts listed above, the practice of urban agriculture allow local food production and serve as place for local community or phical activity (Audate et al., 2018).

Public open spaces such as squares, blue and green spaces, and the street network; are places where social environment can be built (Sallis et al., 2006; Thompson, 2002). The social environment has been widely studied for its relation with health following the common agreement that social capital can contribute to better health in all-cause mortality and wellbeing though social cohesion , equity, support, diversity, inclusion among its many component (Chuang et al., 2013; Kawachi et al., 2008). While Individual perception of social cohesion is positively associated with better health, the relation between objective structural social cohesion remains unclear (Inoue et al., 2013; Poortinga, 2006). Furthermore, perception of public open space and the related social environment play an important role for the activities related with use of the public open space, such as leisure, transport, physical activity and good provision as discussed in the previous sections (*WHO*,). Management and design of pubic open space has been widely used in urban planning has a tool to ameliorate the social environment and its included in protocols of health promotions (LHUDU, 2017), and assessment (Cole and Fielding, 2007). The public open space and its related social environment can have negative impacts on health for example through overcrowding (McClelland and Auslander, 1978) and social disorganization and contagion (Cantillon et al., 2003; Galea and Vlahov, 2005). For example, crime cases presents an heterogeneous spatial distribution (Dutt and Venugopal, 1983) (Liu et al., 2016) (NIJ U.S. Department of Justice, 2005). Violence deaths may show spatial clustering associated with socio economic status (Minamisava et al., 2009) or generally urban violence may be associated with neighbourhood characteristics (Morenoff et al., 2001). Out of its direct effects on physical and mental health, higher crime rates cause a perception public space ass less safe, resulting in fear to walk, to use public space, and do recreational activities, e.g. outdoor physical activity and its previously anticipated benefits, among the many health-enabling resources (Tung et al., 2018). Among the multiple factors associated with crime, rapid urbanization as poor urban planning, design and management are listed (UN-HABITAT,): for example, street lights, visual barriers, or cleanness permit the stigmatization of urban area increasing the attractiveness for crime, which feeds back the stigmatization loop. Beside these intervention, public open spaces can benefit many interventions able to ameliorate its availability, accessibility, and quality. Out of the anticipated effects of active travel, the use of public space boost the social cohesion within community (Dannenberg et al., 2003) (Sampson and Raudenbush, 1999), and improving the social control and conduits (Corcoran et al., 2018). Also, walkable neighbourhoods show greater sense of community and stronger social networks (Rogers et al., 2011)(French et al., 2014).

Joint-count statistics of self reported cardiovascular issues

Joint-count calculates the degree of clustering or dispersion among a group of spatial units characterised by binary data type. The approach compares similar or distinct features in surrounding locations.

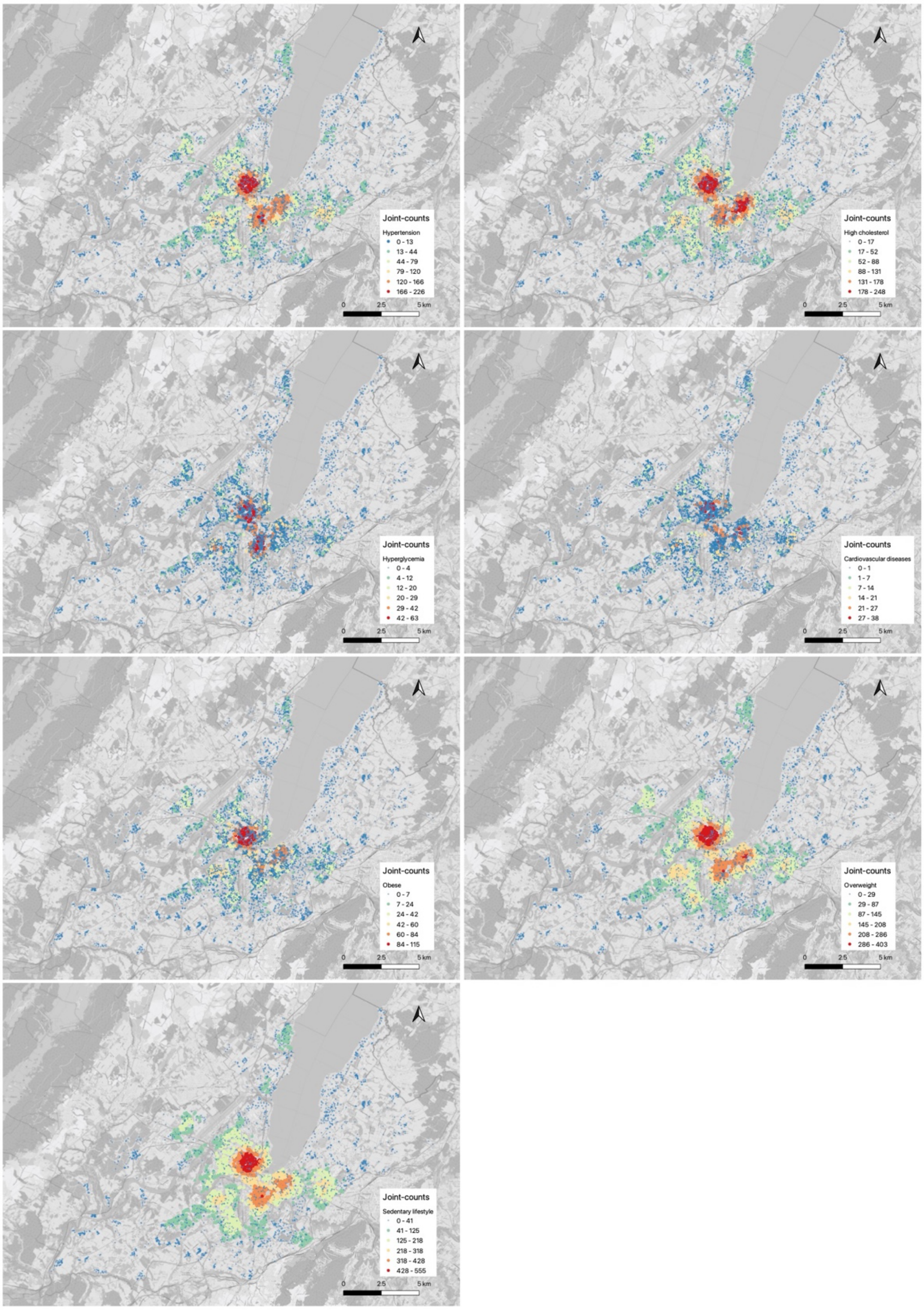

Figure 61: Joint-counts of reported CVRFs (n =9443).

Alternative spatial lags in LISA clustering

The choice of the spatial lag in the calculation of LISA clusters has been explored by testing multiple spatial lag. Larger spatial lags (than 400m) allow the propagation of clusters in its surroundings. Instead smaller spatial lags arbitrarly exclude the most isolated points (islands).

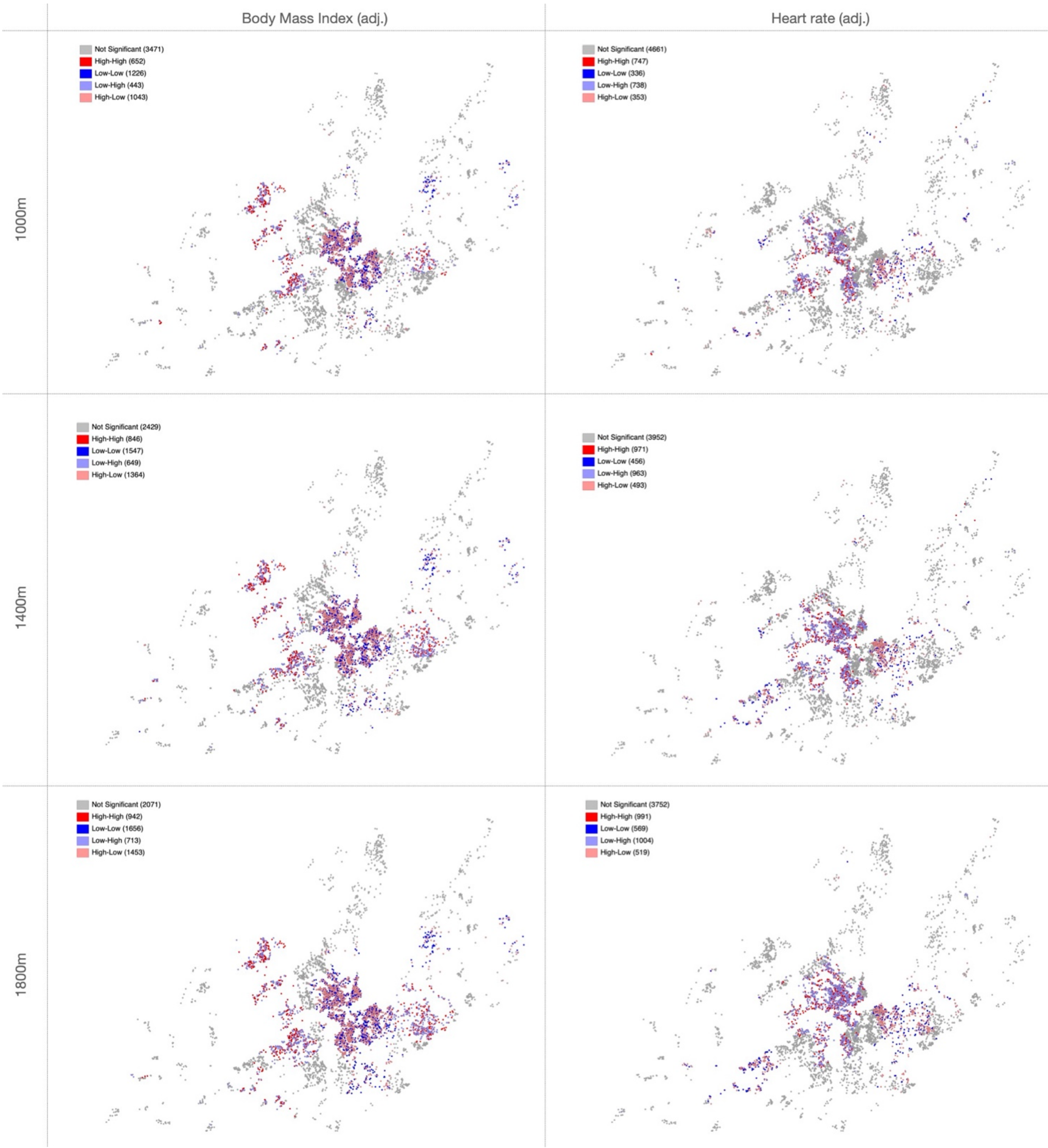

Figure 62: Spatial lag alternatives of LISA clusters for BMI and HR.

Colocation of sptial clusters of high-values (HH) and lo-values (LL) before and after the adjustment

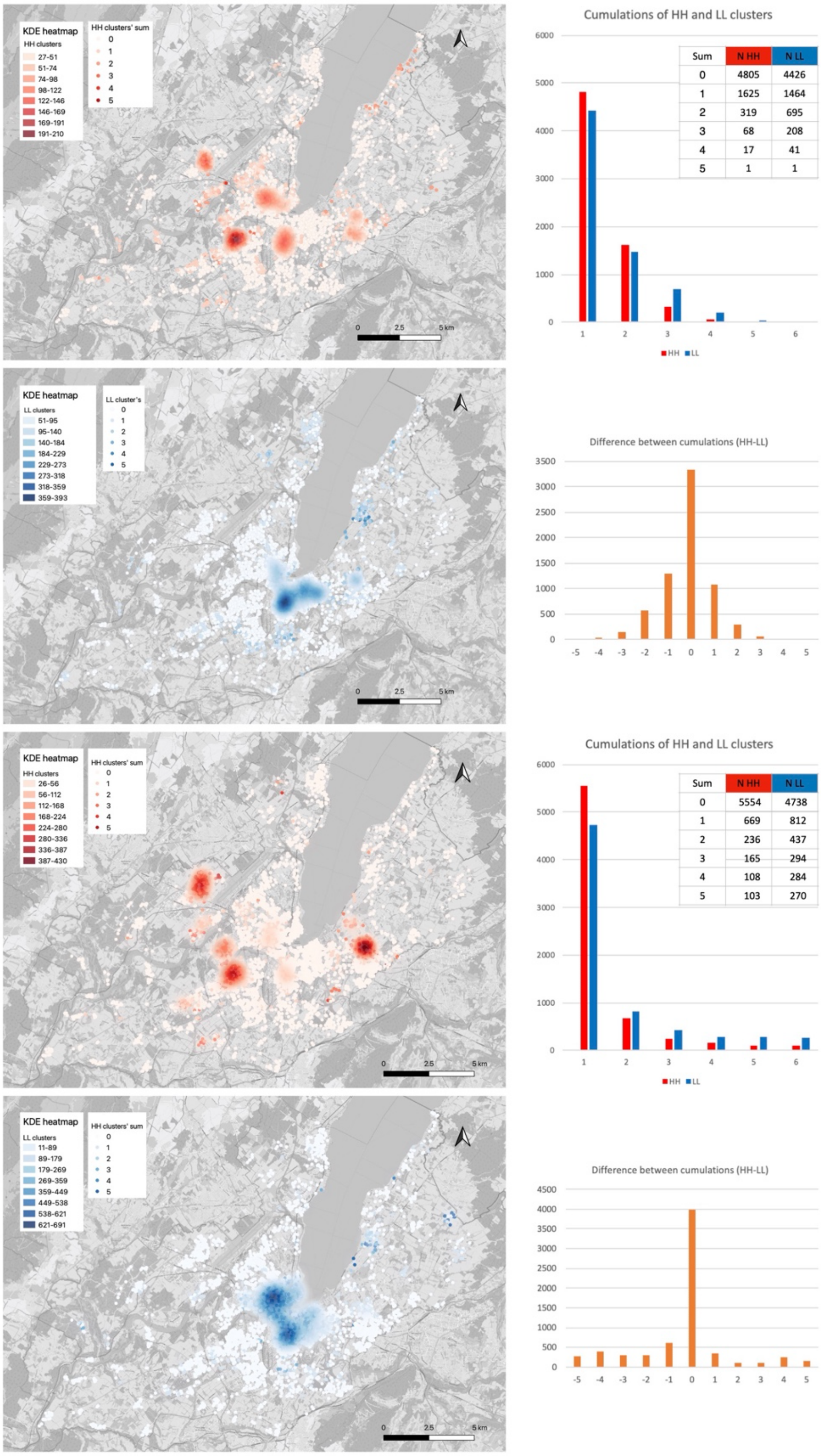

Figure 63: Colocation of spatial cluster for unadjusted and adjusted values for the six CVRFs. The density of colocations before and after the adjustement is displayed by a kernel density heatmap on the left. The histograms on the right display the counts of participants belonging to a HH or LL cluster for all CVRS before and after the adjustment.

Housing characteristics withing contiguous clusters of high-values of BMI and HR:

AREA	HBE FEATURE	T	PV(T)	D	PV(D)
1	Building number	4.4	<0.001	0.40	<0.001
2	**Building age**	**2.5**	**0.013**	**0.28**	**<0.001**
	Building hight	**8.3**	<0.001	**0.55**	<0.001
	Energy consumption index	**11.1**	<0.001	**0.63**	<0.001
	Mean pop. per building	**9.4**	<0.001	**0.60**	<0.001
	Population density	**9.0**	<0.001	**0.60**	<0.001
3	**Building number**	**3.012**	**0.006**	**0.31**	**0.008**
	Mean pop. per building	1.277	0.212	0.22	0.122
	Population density	**2.056**	**0.05**	**0.42**	**<0.001**
4	**Building age**	**2.724**	**0.011**	**0.251**	**0.043**
	Building height	**3.011**	**0.005**	**0.374**	**<0.001**
	Building number	**2.973**	**0.006**	**0.361**	**0.001**
	Mean pop. per building	**3.548**	**0.001**	**0.404**	**<0.001**
	Population density	**3.489**	**0.002**	**0.417**	**<0.001**
5	**Building age**	**12.41**	**<0.001**	**0.26**	**<0.006**
	Building hight	**9.522**	**<0.001**	**0.584**	**<0.001**
	Building surface	**3.361**	**0.001**	**0.35**	**<0.004**
	Energy consumption index	**18.18**	**<0.001**	**0.696**	**<0.002**
	Mean pop. per building	**7.972**	**<0.001**	**0.646**	**<0.003**
	Population density	**11.6**	**<0.001**	**0.697**	**<0.005**
6	Building age	27.14	**<0.001**	0.431	0.107
	Building height	**4.142**	**0.006**	**0.732**	**<0.001**
	Energy consumption index	**9.247**	**<0.001**	**0.819**	**<0.001**
	Mean pop. per building	**7.737**	**<0.001**	**0.951**	**<0.001**
	Population density	**2.966**	**0.025**	**0.806**	**<0.001**

Table 45: Characterization of Indoor environment features in contiguous HH clusters (BMI adjusted): T-test (Welch) and Kolmogorov-Smirnov test between contiguous HH clusters on the whole study area. Multiple HBE features were not shown when they were not significantly different (p-value >0.05). Positive T values are related to higher values of an HBE feature in the HH cluster compared to the study area, while negative values respectively indicate lower values. Bold font signifies that both p-values of the T-test and Kolmogorov-Smirnov test are below 0.05. Thus an HBE feature displays a significant difference in terms of mean and distribution.

AREA	FEATURE	T	PV (T)	D	PV (D)
1	Building age	10.2	<0.001	0.24	0.046
	Building hight	**4.9**	**<0.001**	**0.46**	**<0.001**
	Energy consumption index	**4.6**	**<0.001**	**0.57**	**<0.001**
	Mean pop. per building	**5.3**	**<0.001**	**0.53**	**<0.001**
	Building number	**3.2**	**0.003**	**0.34**	**0.001**
	Building surface	**3.3**	**0.002**	**0.41**	**<0.001**
	Population density	**5.8**	**<0.001**	**0.56**	**<0.001**
2	**Building age**	**2.9**	**0.005**	**0.34**	**<0.001**
	Building hight	**15.7**	**<0.001**	**0.75**	**<0.001**
	Energy consumption index	**26.3**	**<0.001**	**0.84**	**<0.001**
	Mean pop. per building	**12.1**	**<0.001**	**0.81**	**<0.001**
	Building number	**6.8**	**<0.001**	**0.38**	**<0.001**
	Building surface	**11.9**	**<0.001**	**0.65**	**<0.001**
	Population density	**17.7**	**<0.001**	**0.79**	**<0.001**
3	**Building height**	**18.1**	**<0.001**	**0.74**	**<0.001**
	Energy consumption index	**27.6**	**<0.001**	**0.90**	**<0.001**
	Mean pop. per building	**13.7**	**<0.001**	**0.73**	**<0.001**
	Building number	**6.1**	**<0.001**	**0.34**	**<0.001**
	Building surface	**9.6**	**<0.001**	**0.60**	**<0.001**
	Population density	**12.2**	**<0.001**	**0.76**	**<0.001**
4	**Building age**	**7.9**	**<0.001**	**0.27**	**<0.001**
	Building hight	**8.9**	**<0.001**	**0.55**	**<0.001**
	Energy consumption index	**12.6**	**<0.001**	**0.65**	**<0.001**
	Mean pop. per building	**7.6**	**<0.001**	**0.65**	**<0.001**
	Building surface	**3.5**	**0.001**	**0.33**	**<0.001**
	Population density	**11.5**	**<0.001**	**0.68**	**<0.001**
5	**Building height**	**2.3**	**0.037**	**0.52**	**0.001**
	Energy consumption index	**9.9**	**<0.001**	**0.86**	**<0.001**
	Building surface	**3.8**	**0.002**	**0.51**	**0.001**
	Population density	**3.6**	**0.004**	**0.71**	**<0.001**

Table 46: Characterization of Indoor environment features in contiguous HH clusters (HR adjusted): T-test (Welch) and Kolmogorov-Smirnov test between contiguous HH clusters on the whole study area. Multiple HBE features were not shown when they were not significantly different (p-value >0.05). Positive T values are related to higher values of an HBE feature in the HH cluster compared to the study area, while negative values respectively indicate lower values. Bold font signifies that both p-values of the T-test and Kolmogorov-Smirnov test are below 0.05, and thus an HBE feature displays a significant difference in terms of mean and distribution.

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Curriculum Vitae

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Education

January 2017 – November 2021 / Ecole Polytechnique Fédérale de Lausanne, Switzerland : PhD candidate ; « Spatial analysis of the healthy built environment: an application on cardiovascular risk factors in the canton of Geneva ».

2012-2015 / Università di Modena e Reggio Emilia: MSc Engineering for Environmental Sustainability (grade 109/110) comprehensive of the qualification for energetic certifier (DPR 75/2013); project on geochemical characterization of organic matter for unconventional sources of hydrocarbons (partnership with EPFL).

2009-2012 / Università di Modena e Reggio Emilia: BSc Environmental Engineering (grade 97/110), project on risk for environmental soil remediation, an implementation of Risknet software.

Employment history

January 2017 – November 2021 / PhD candidate – Urban and regional planning community, EPFL, Switzerland.

- Teaching assistant Planification dans le Sud (PENS-307)

September 2016-January 2017 / Research and Development consulent - Warrant Hub, Italy.

January 2016- June 2016 / Scientific Assistant in geomechanic, geochemistry – Laboratory of Soil Mechanic, EPFL, Switzerland.

- Experimental test and research: gas-breakthrough test, direct shear test on bentonite and interface shear test, total suction, and retention behaviour (for nuclear waste disposal HLW).

May 2015-September 2015 / Intern in oil&gas organic geochemistry – Laboratory of Soil Mechanic, EPFL, Switzerland.

- Experimental test and research: petrological characterisation of organic matter (XRPD, FTIR, TGA, DMA, TOC, BIB-SEM, Rock Eval, EDX, MIP) for unconventional sources of hydrocarbons (partnership with Chevron corporation).

June 2015 - September 2015 / Intern in renewables energies - Amplio group, Italy.

- Research on energy storage technologies, focussing on Methanation process applied to renewables energies.

Submitted manuscripts

Salmi, A., Jaligot, R., Chenal, J. (2021). How do we appraise the healthiness of the built environment? Challenges and paradigms for urban health assessment, Cities & Health.

Salmi, A., Kemajou A., Chenal, J. (2022). Beyond slums classification: a housing survey for health impacts in Lome (Togo), African Cities Journal.

Salmi, A., Jaligot, R., Chenal, J. (2022). Spatial clusters of cardiovascular risk factors and non-stationary spatial association with the built environment in Geneva (Switzerland), Health and Place.

Salmi, A., Jaligot, R., Chenal, J. (2022). Framework of urban health issues: a narrative review, Journal of Urban Health (Springer).

Salmi, A., Jaligot, R., Chenal, J. (2022). Spatial mapping of the healthy built environment in Geneva (Switzerland), International Journal of Environmental Research and Public Health.

Conferences

Salmi, A., Chenal, J. (2021). Spatial analysis of the built environment and estimation of spatial health data with DNN: the case study of Cardiovascular Risk Factors in Geneva, Switzerland. In 2021 International Conference of Urban Health.

Salmi, A., Chenal J. (2019). Expert's perspectives on Healthy Urban Planning. In 2019 International Conference of Urban Health.

Salmi, A., Chenal, J, Guessous, I., Joost S., (2018). Learning to plan healthier cities with precise data. In 2018 International Conference of Urban Health.

Salmi, A., Chenal, J, Guessous, I., Joost S., (2018). Body Mass Index, and Insomnia association with exposure to nighttime noise in the state of Geneva. In 2018 International Conference of Urban Health.

Salmi, A., Joost S., Chenal, J. Healthy urban planning: Spatial dependence of body mass index and exposure to night-time noise. In 2017, International Conference on Sustainable Development and Green Technology.

Salmi, A., Chenal, J, Guessous, I., Joost S., Healthy Urban Planning: Body Mass Index association with exposure to night-time noise in the canton of Geneva. In 2017 GEOMED.

Lenguages: Italian (mothertongue), English and French (full professional proficiency, C1).

Oganizational skills: Participation to Screening planning of PSC 2013 (Piano Strutturale Comunale), Modena (Italy); Student Coordinator 2009-2012 UNIMORE.

Informatic skills: Python, QGIS, R, Pack Office.

Professional qualifications: QSHE Lead Auditor (ISO 9001, ISO 45001, OHSAS 18001), qualification for energetic certifier (DPR 75/2013)

Interests: sports (swimming, trekking and bike touring), photography, painting, cooking, travelling.