Reversing Urban Food Deserts

Data-driven adaptive food networks for urban resilience

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Dense urbanization highlights the need to explore metabolic processes and mechanisms for developing resilient and adaptive solutions to ecological challenges. The recent pandemic intensified the pressure to re-evaluate the existing urban foodscapes by revealing disparities in food accessibility. Studies indicate that food deserts are present even in the centre of metropoles, bringing forth the question of the relation between food, segregation and urban morphology. This research introduces a Machine Learning-assisted computational tool that evaluates food networks and identifies optimal new spatial configurations based on curated data analytics, unsupervised machine learning models and space syntax. Its primary focus is the creation of a unified model connecting urban morphology, socioeconomic and temporal data. The output provides the planners and local authorities with a set of possible intervention patterns for food-related functions aiming to assist decision-making processes.

Keywords: *Computational Design, Machine Learning, Urban Analytics, Food Accessibility, Design Tool.*

INTRODUCTION

Dense urbanisation leads to the transformation of urban environments as the main human habitat (Boeri, 2022), highlighting their expansion as moderators for the growth of their complexity (Hanna, 2022). The new urban fluidity, perceived as "hyperreality" (Picon, 2003) where physical and digital boundaries are blurred, accepts that dynamic information flows consist of an additional layer in spatial perception (Manovich, 2005).

This research presents a computational design tool, in the form of a novel ensemble of conventional and machine learning (ML) techniques. More precisely, said tool is based on data analytics, unsupervised machine learning methods and space syntax. It aims to identify optimal intervention strategies and generate new spatial configurations by evaluating the existing food and spatial networks through the exploitation of these additional data layers.

The recent pandemic exposed the fragility of the urban food system and the need for adaptable approaches, equivalent to a resilient urban ontology. A plethora of researchers (Specht et al, 2014; Krupitzer et al, 2022; Su et al, 2017; Janatabadi et al, 2024) have developed prototypes accommodating urban agriculture, or focused on analysing food accessibility and food systems. However few methods address the topic on the urban scale taking into consideration the existing morphology and combining spatial analytics methods such as space syntax (Hillier, 2006) with unsupervised machine learning models.

The developed methodology operates in three distinct stages, defined by variation of input data, urban scale and algorithmic approach. The workflow is based on the quadrilateral decomposition of the urban space where the main parameters of each stage are projected. During the first stage, datasets related to food accessibility are projected as a value on the aforementioned grid while dimensionality reduction methods such as K-means and Principal Component Analysis assist in the identification of correlation patterns on a large scale.

Subsequently, the depicted clusters are further analysed during the second stage where high granularity datasets along with spatial analytic values deriving from space syntax methodologies function as input to the proposed algorithm resulting in an "activation" pattern of grid cells. The algorithm is divided into two parallel functions, a stochastic and a deterministic method that develop variations in the outcome. During the final step of the algorithm, the depicted "activated" cells are identified as potential food-related functions through an evaluation process of balanced distribution of the existing food system.

Developing such a tool allows the possibility of adaptability and evaluation during the first stages of design practice and policy development for planners and local authorities. On one hand, it can be included as an indicator in the decision-making processes, and on the other it can be incorporated as a virtual reality application, receiving feedback and encouraging collective participation. Overall, this work intends to bridge the gap between data, spatial analytics, machine learning and foodscapes in a virtual environment equal to the hybrid identity of its urban context.

DECONSTRUCTING URBAN FOOD RELATIONS

The hybrid urban space is characterized by the abundance of information flows and the connectivity between scales. Kluitenberg (2006) emphasizes that the urban environment cannot be perceived as solely local, due to its interference with the global scale through wireless networks. This overlay of information, knowledge and innovation permits function optimisation for the new urban entity (Komninos et al, 2020), navigating through complex data structures. Under that notion, urban food systems should be included in the optimisation process, aiming for the transformation towards equal neighbourhoods.

"We may no longer live in walled citadels, but we rely just as much on those who feed us as any ancient city-dweller did" (Steel, 2008). Food flows remain invisible in the urban context but they affect the urban morphology since the formation of the first settlements. In recent years, the distribution system of alimentation has changed from a fine-grained network of local shops to larger supermarket chains without an equal transformation of its urban context (Steel, 2008). That transition affected food accessibility indiscriminately even in large metropoles creating the phenomenon of "food deserts".

Food deserts are defined as areas with low accessibility to fresh food and can function as an indicator of spatialised food injustice. Studies conducted with focus on association of food deserts and deprivation-related data present mixed results (Janatabadi et al, 2024). Some findings indicate that demographic inequalities affect the food accessibility while others argue that UK presents reasonable food accessibility in its population centres (Lake et al, 2010). In addition, given that social segregation, equally related to deprivation, is a complex spatial phenomenon with morphological characteristics (Vaughan et al 2006, Vaughan and Arbaci, 2011), it can be assumed that food desert indexes might spatially co-exist with high deprivation and segregation values.

Expanding on the phenomenon, the e-food desert index on the LSOA level for the UK (Newing and Videira, 2020) includes the proximity and density of retail facilities, the transportation system, the local socioeconomic and demographic characteristics as well as the e–commerce availability. The inclusion of the latter in the framework created a wider "score" distribution between urban and rural areas (Newing and Videira, 2020). During the recent pandemic, the e-food desert score was essential for better understanding the emerging patterns, even though, it can be argued that additional actors, such as allotments, farms and small retailers should be included.

Recent studies have focused on the exploration of new types of urban agriculture as a future morphology for resilient cities. Investigations of the possibilities of zero-acreage farming (Zfarming) where cultivation is combined with the available building envelope, building integrated agriculture (BIA) which includes building transformation processes, as well as vertical farming consist some of these types (Specht et al, 2014). On an urban scale, Krupitzer et al (2022) developed a digital twin model that tracks the current production and traces the food flows throughout the supply chain. This type of "biophysical" model allows a real-time connection and assists with predictions and adaptation strategies.

In general, food stores are not equally distributed across the urban space and their geographical location can be associated with health issues such as obesity (Su et al, 2017). Su et al (2017) explored the healthy food accessibility in Shenzhen by calculating various transportation methods for food access and concluded on the necessity for expansion of the definition of "food retailer" in existing indexes. Understanding further the inequalities in the urban context and predicting the possible outcomes of design choices in the health of the inhabitants can be investigated in-depth with the use of Machine Learning methods in urban studies (Newton, 2022).

ML-assisted methodologies are increasing in popularity, providing the possibility for in-depth analysis and correlations of data and urban morphology. Methodologies such as the calculation of ideal urban green space using ML (Zertuche and Neira, 2022) support the argument that artificial intelligence can be the key to understand the algorithms of space (Tsigkari et al, 2021). Combining ML methods with conventional spatial analytics can reveal human interactions with their spatial context, transforming such methodologies into powerful tools for the design process.

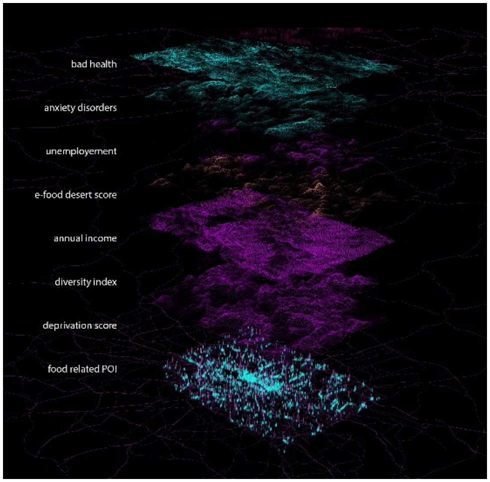

Figure 1
Graph comparing all datasets, highlighting the complexity of the input data

CONFIGURATIONS OF ADAPTIVE FOODSCAPES

This research investigates a methodological framework for the evaluation, interpretation and prediction of food networks aimed towards sustainable and equal neighbourhood development. The methodology consists of a three stage process, created in a virtual environment which allows the tool's integration in simulations. The output presents locations of interest for new food-related activities taking into consideration the urban morphology, socio-economic data and advanced spatial analytics (see figure 1). Currently, the proposed tool has been tested in the city centre of London, but it is built in such a way that allows easy integration and adaptation in other locations or smart city models.

The "Growth Network Framework", as an ensemble of methodologies combined in one design tool, functions on three distinct processes, namely identification, evaluation and proposal. They operate in two different scales and include a different subset of parameters related to the metho-

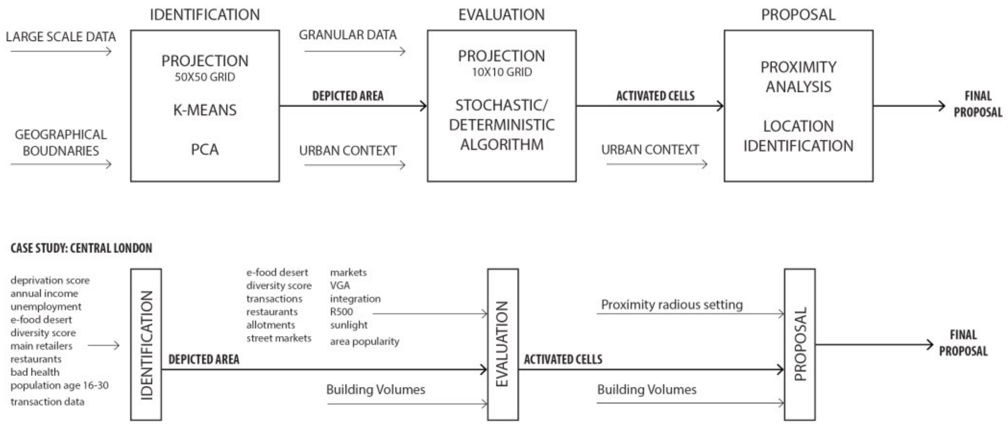

Figure 2
Generalised diagram of the Growth Network Framework (top) and its adaptation to the case study (bottom)

dological stage and scale (see figure 2). The workflow acts on the structured, quadrilateral decomposition of the surrounding urban space and the projection of the main parameters of each stage. More precisely, and without loss of generality, in the following case study, a grid of square cells of size 50×50m is introduced (quadrilaterals of aspect ratio 1) that covers the whole area of the site to be analysed (see figure 3). The cell size is selected based on the granularity of the data and the compatibility with current limitations of computational resources. A set of weights is prepared for each cell based on the geographical zones of study (LSOA/ Borough/Ward). Assuming a cell is fully encompassed in a zone the weight corresponds to the ratio of the cell surface area over the full zone surface area. If a cell crosses more than one zone, a similar weight for each zone is stored. This grid consists the base of analysis and it will be used as a location indicator.

During the first stage of the aforementioned study in London, the datasets included in the identification process are related to consumption and socio-economic status, such as deprivation score, annual income, unemployment percentage, e-food desert score, diversity score, supermarket transactions, health data, demographics as well as location of main retailers. Based on the contradictory results of the aforementioned literature (Janatabadi et al, 2024), along with observations of the geographical projection of the data, this study proposes to include socio-economic data. The input variables consist of open source data available from the Office for National Statistics Census for the UK (2011), Geolytix and Google Maps, and correspond to LSOA geographical level of analysis or Points of Interest (POI). The selection of data was based on the criteria of availability, logical relation to the food topic according to the literature (Newing and Videira, 2020; Janatabadi et al, 2024), as well as a trial and error process testing the correlation between datasets.

Having chosen the data layers, their values are projected onto each of the grid cells multiplied by the corresponding weights. It should be noted that cells that correspond to multiple geographical divisions receive a value equal to the sum. In the case of POI data, a buffer zone is implemented around each location. The buffer zone is defined based on the function assigned to the POI, e.g. food supply corresponds to a diameter of 250m and 100m for restaurants. POI values describe the existence of a food-related object. As such, they are binary, meaning that if a zone is projected to the grid, the cells within the radius gain the value 1. Otherwise they get 0 (similarly, if one cell collides with two buffer zones, gets the value 2). All data are projected with the use of geospatial analysis software (QGIS) to the corresponding cells. This step allows for higher accuracy at the local level and comparability between datasets.

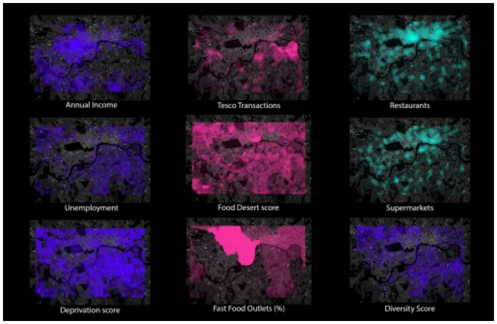

Figure 3
Visualisation of some of the datasets projected on the 50x50 cell grid. Higher values are indicated with brighter colors. Colors are defined by data category.

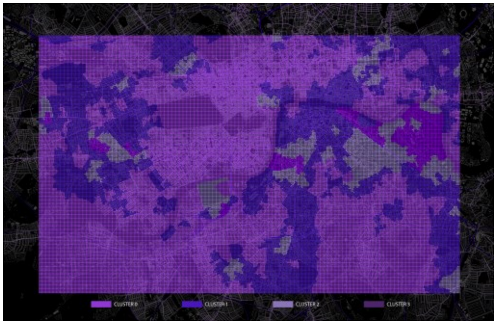

Figure 4
K-means clusters visualized on top of the map. For this study we consider k=4.

The projected data are visualised on top of their urban context for deeper understanding of their spatial distribution and the characteristics of the analysed area. However, the cost of using conventional analytics methods for the interpretation of the results, as per the so-called "curse of dimensionality", increases quadratically based on the size of the study area and linearly, at best, exponentially, at worst, based on the amount of the parallelly-examined datasets and parameters. This issue is addressed with unsupervised machine learning algorithms that manipulate the data and transform them into a more manageable form. Two different techniques were implemented: K-means clustering and the Principal Component Analysis (PCA).

Machine Learning algorithms are susceptible to the range and distribution of the input values. Since the nature and subsequently the values of the datasets may vary significantly, the selected data are cleaned and normalized (either by the L^2 norm, or the absolute maximum value) to ensure higher accuracy and avoid skewed or biased results. The K-means method aims to identify similarities between grid cells and by extension urban areas. It achieves this by finding the centroids and partitioning the data in subsets such that it minimizes the variance within each subset (cluster). The K-means algorithm results in clusters of unequal sizes and densities, a fact that is not necessarily considered an issue, due to inequalities in size and significance between different urban neighbourhoods. Through the elbow method, the number of clusters, k, is defined as four (see figure 4).

Additionally, the Principal Component Analysis (PCA) aims to aid, visually at first, the in-depth understanding of the qualitative characteristics of the datasets and reduce their complexity. Starting from the data ensemble, the PCA method calculates the optimal coordinate system, i.e. the basis that minimizes the square of the error between the data and their projection on any other possible orthonormal mapping. The new coordinate system represents dominant patterns, which in this case, can be combined linearly to re-express the data. In extension these patterns highlight spaces with unique characteristics. The combination of the described methodologies and the identification of highly correlated datasets, such that clustering can be applied on a reduced, or more readily available dataset helps identify the grid cells presenting specific correlations. Locales highlighted by the clustering result, especially ones that form an area of multiple clusters can be classified as areas with potentially fragmented and uneven food networks in need of further analysis.

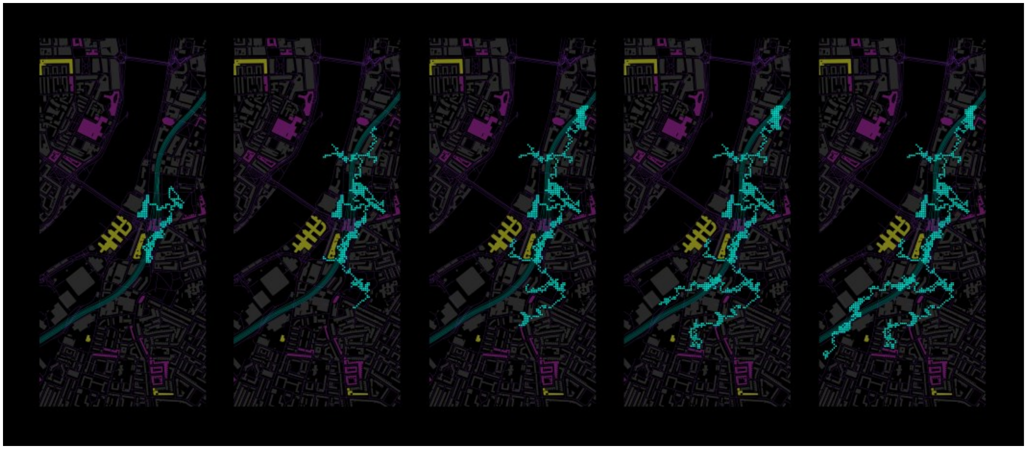

Figure 5
Example output of the Growth Network Framework, activation of target cells

The depicted grid cells consisting of the outcome of the first process (identification) are further evaluated as the input area for the next, high-fidelity, stage. The analysis at this stage focuses on a smaller scale with the refined grid cells adapting to 10×10m size. Therefore, the datasets from the previous stage are considered inadequate due to their granularity level. Instead during this step's evaluation process, the input data are categorized into four groups: census data with a high granularity from the National Statistics Census for the UK (2011) such as e-food desert score and diversity score, detailed geo-location of food-related facilities, purchase habits data per area (Tesco dataset), spatial analytics simulation results using graph-based space syntax methodologies (integration and visibility scores) and real-time input collected through simulations (sunlight analysis) and online platforms (area popularity).

During this stage, all partial predicates mentioned above are calculated concurrently and independently and projected (numerical integration) on the same quadrilateral cell grid according to the process described above. Spatial patterns, perceived as configuration, have a numerical representation that allows them equal status in a dataset (Vaughan, 2007) and thus are included as parameters. Space syntax integration is calculated as angular segment analysis defined by Turner (2007) and visual integration through the visibility graph analysis algorithm (VGA), also defined by Turner (2001). The road and building data used were downloaded from Open Street Map (OSM) and simplified with the use of the Space Syntax Toolkit (Gil et al, 2012). DepthmapX (Varoudis, 2015) was implemented for the calculations. The Normalised Angular Integration (NAIN) is given as $NAIN = \log(Integration(r) + 2)$ where Integration(r) is the Space Syntax integration for the radius r (Van Nes and Yamu, 2021). The Visual Integration [HH] values derive directly from depthmapX software and are calculated as $VisualIntegration[HH] = 1/RRAD$ where RRAD is Real Relative Asymmetry (Koutsolampros et al, 2019).

Sunlight values are calculated from solar analysis simulations applied on the same grid projected in a Rhinoceros3D environment with the use of Ladybug Tools. The area popularity score, is defined as a combination of geolocated Twitter data and GPS data entries in a given day. It is aspired that as a next step of the study, this metric could include additional user data that will assist in the accuracy of the prediction. Currently, the additional data inputs are updated on a discrete period basis.

GROWTH NETWORK ALGORITHM

Following the analytical processes above, the developed outcome functions as input to an algorithm adapted to include the existing built infrastructure in its workflow (evaluation phase). This step is developed in Unity and C#, aiming to provide increased comprehensibility. The operation of the developed design tool in a virtual environment allows for direct interaction with the `data and educates on how the input will affect the end result by experiencing the "hyperreality".

The algorithm will decide which cells should be "activated" for food-related activities. Starting from an initial cell, or point-of-interest, the method can employ two different solvers for the identification of neighbouring cells, optimal for the construction of a food-network. The initial cell can be either preselected or manually appointed through the virtual space. The solvers include a deterministic and a stochastic method.

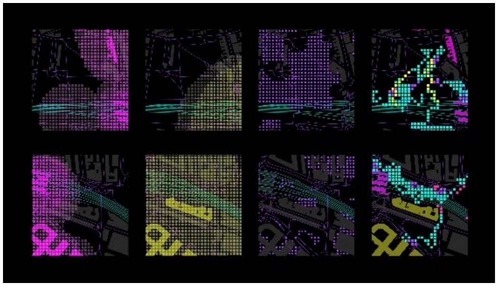

Figure 6
Diagram visualising the spatial configurations and distribution of food-related functions

The deterministic algorithm calculates the total weight of each neighbour and "activates" the one with the highest value (Type A). The weight of each grid cell is calculated as the sum of the normalized values of the input data, each multiplied by a corresponding coefficient factor, based on their perceived significance. These coefficients range from -10 to 10, and while they are unchanging for census data, they can present seasonal variations for data related to climate or user habits. Area popularity as well as cultivation-related points of interest present higher values during the spring and summer months, acting as poles of attraction. Since the value of these coefficients coincides with the perceived importance of each variable for the study area, local experts can assist with the precise definition to better represent the local context.

The progress of the "activated" cells evolves by approximately one step per week, while an additional "growth" function applies for the summer period, based on the assumption of increased demand for urban agriculture spaces. This function considers a stochastic method, in the form of an evolutionary algorithm (EA) where a set of possible network activations is chosen randomly and evaluated based on their total weight values. The best one is selected as a base and a new set is created from permutations of the base or untested cells and the process repeats. This iterative method continues until a prescribed set of steps is completed (see figure 5).

The stochastic method produces a new cell typology (Type B) that expands at a higher rate but is removed when the function has run its full cycle (when the summer period is through). This expansion operates based on weight values associated only with real-time data, such as sunlight and footfall while the cells' geo-location is confined in existing open areas due to their ephemeral nature. In general, the deterministic method will always choose the best neighbour, but tends to expand towards locally optimal areas and stop there, while the stochastic method works better when considering faster expansions, since given a wide enough search range can avoid stagnation at local optima.

The outcome of this stage consists of a network of "activated" grid cells evaluated as optimal locations for future food-related activities. As the last stage of the methodological approach (proposal), the developed network is included in a more accurate definition of locations for each of the defined potential functions: cultivation, retail, consumption and social. The location evaluation is performed via a function that has been implemented in the developed algorithm and aims to distribute functions equally in an area by minimising the average distance of any point from any given function type.

This process operates on the assumption that each resident should have access to food within a maximum of 250m radius and a restaurant within 100m (see figure 6). In order to avoid clustering of similar facilities in close proximity, a 50m radius buffer zone is added in between each considered location. The additional element of “social” is included, expressing the sociability of food, based on the correlations between deprivation, diversity and social segregation observed in the first stage of the analysis. More specifically, the algorithm iterates through the activated cell list while controlling the proximity of functions in space, concluding to a proposal that applies to the aforementioned principles.

The final outcome from the developed methodological approach consists of a series of iterations that depict optimal locations and potential functions to construct a new food network distribution. The hierarchical structure of multiple stages and scales involved in the process provides a better understanding of the outcome of each stage and higher accuracy. As an early-stage design tool, the “Growth Network Framework” was developed in a virtual reality environment (Unity) which facilitates its use further than solely a visualisation tool, by including it in simulations and evaluation of the consequences of the interventions.

The virtual environment is actively involved in the process by allowing the designer/user to interfere with the network expansion in 3D space, experiencing the temporal data update that contributes to the re-evaluation of the process, every time the iterative method starts over. By doing so, the tool maintains an active relation to its physical counterpart and contributes to a continuous information flow (see figure 7). This attribute facilitates the potential of integration in a digital twin (DT) model that can further monitor performance, evaluate different scenarios and predict possible issues. Subsequently, the functionality of such type of dynamically-updated virtual environment can be extended to that of an evaluation tool for the suggested output, or a virtual metric for success.

DISCUSSION

The proposed design tool consists of a prototype for optimising the placement of food-related functions in the urban fabric and it is developed with the combination of data analytics, graph-based space syntax and unsupervised machine learning methodologies. Its purpose is to assist planners and local authorities in early-stage decision-making processes while simplifying the communication between stakeholders and visualising hidden spatial patterns.

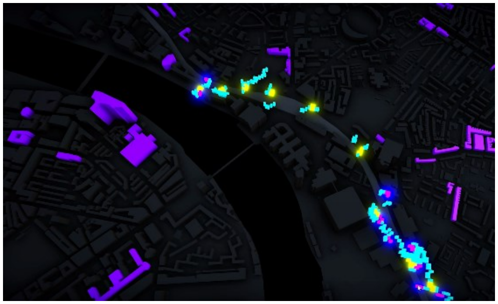

Figure 7
Snapshot from the VR environment, showcasing function distribution related to context as demonstrated live to academics and practitioners in London

Currently, a variety of 3D modelling and visualisation tools are available to designers for simulations, design exploration and construction management. Though, there is an evident lack of advanced computational tools that could assist designers and planners in the early design stages of large-scale development projects. Such tools can explore space-specific results and support with high accuracy decision, strategy and policy development. Specifically, in existing urban areas, it can provide a better understanding of the current situation to strengthen equal food accessibility, while for new development areas, it can further assist in evaluating the food networks' location with mobility and place-making.

Nevertheless, the described methodology presents limitations that lie in the necessity of properly sourced datasets. It might be the case, that extensive work is required to prepare the datasets. That includes, but is not limited to changes in format, low granularity, or more decidedly lack of useful data altogether. Moreover, one must consider the possibility of skewed census data for reasons unrelated to the study at hand and allow flexibility in the method to adapt based on a feedback loop. It is however axiomatic that lower accuracy inputs lead to higher errors in the predictions.

This research can be perceived as a starting point for further investigation on the integration of advanced computational methods in the early design and decision-making stages. By adding more relevant datasets, it can also be augmented to address other issues, such an example being social segregation. It can also be expanded as a participative design tool where the popularity input is collected from the users of the area. It is only through interdisciplinary workflows that we can aim to create better public spaces and the further we optimise the processes and integrate new methodologies in the field of urban design, the closer it brings us to the realisation of such goal.

While the complexity of urban environments increases, it is essential to develop such tools that will investigate further than the conventional methods and will allow the designers to include the digital notion of "hyperreality" along with the physical in the decision-making processes. A deeper understanding of the complex urban ontology will contribute to more sustainable and resilient cities focusing on residents' well-being.

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