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Urbanometrics: The art of modelling pluriform livable urban spaces

Abstract: Starting from the notion of cities as complex multiscalar organisms, this paper develops an urbanometric-configurational approach to modelling pluriform livable urban spaces. It uses micro-scenarios, shaped by human-based preference mappings of neighbourhood livability, as analytical cornerstones for quantitative urban planning. The place-based wellbeing of residents is measured through an urban happiness ('Smiley') indicator (also coined 'city love' or 'neighbourhood love'), which is a representation of the spatial appreciation of urban areas by residents. Next, the paper designs neighbourhood micro-scenarios as reference images for expressing space-specific preferences. The quantitative analysis is next tested for the case of Rotterdam, the Netherlands. The paper introduces an *urban happiness cube* using three perception-based micro-scenarios: Community Oasis, Vibrant Hub, and Eco-Urban Haven. These axes are used to classify Rotterdam neighbourhoods into *cubic livability regimes*. The neighbourhood Smiley Index then serves as an external validation measure. The quantitative results show that Rotterdam's neighbourhoods are not arranged along a single livability gradient. Instead, they form distinct configurations. Community-led regimes show the highest average Smiley Index, while vibrancy-led regimes show the lowest. Spatial maps and transition matrices further indicate that these regimes are geographically differentiated and temporally dynamic. The paper contributes to urbanometrics by shifting attention from conventional explanatory models to spatially dependent configurational pathways of livable urban places.

Keywords: urban livability, micro-scenarios, urbanometrics, decomposition, cubic livability regime

Introduction

Cities are dynamic entities shaped by a multitude of time-varying factors, including socio-economic dynamics, demographic shifts, technological advancements,

and various forms of disruptions (Kourtit, Nijkamp 2016, Nijkamp et al. 2022). Contrary to the notion of a uniform and static urban landscape, cities exhibit unique characteristics and spatial patterns influenced by diverse factors such as size, population, political history, and cultural heritage. While conventional urban studies often prioritize nomothetic or uniform principles, this paper endeavours to explore the heterogeneity of urban economic landscapes through a multidimensional perspective, uncovering the hidden 'X-factors' that drive complex spatial systems of human settlements. The present study is inspired by the idea that cities are not passive material objects, but comprise active people who shape their own life and urban future.

This publication has a distinct feature compared to the great many past publications on urban development issues. A look at the thousands of studies on urban affairs tells us that by far the great majority of urban studies has been produced as standard empirical case studies, stylized modeling studies, or comparative planning studies (Alonso 1964, Anas et al. 1998, Batty 2005, Burgess 2008). Notwithstanding the fact that these contributions often have high scientific quality, it is noteworthy that nomothetic or uniformity principles on the city tend to prevail – such as rectilinear or idealized spatial structures in urban economics, rational choice paradigms in urban planning, or stylized gravity-based models of spatial interaction in urban mobility and demography (Zipf 1946, Wilson 1970, Batty 2013). It may be an interesting question whether a different research methodology, theoretical framing, or policy perspective would have emerged if the field of urban studies had been governed more strongly by a different, people-oriented and place-based angle, as emphasized in critical urban theory and planning critiques (Jacobs 1961, Lefebvre 1991, Flyvbjerg 1998, Scott 1999).

Cities are man-made settlement constructs that have evolved in the course of centuries into complex and dynamic organisms. They are always 'work in progress' due to socio-economic dynamics, demographic developments, technological breakthroughs and unforeseen disasters of various kind. The urban fabric is by no means uniform; cities are distinct species with own indigenous features and spatial rhythms (Lefebvre 1991). In a strict sense, 'the city' does not exist: there is a multiplicity of cities with own characteristics that can be distinguished according to scale, population, density, connectivity, proximity, architecture, economic base, development, infrastructure, culture and many more features. Cities are shaped by people (the *microcosmic* perspective), by global forces (the *macrocosmic* perspective), and by governance and institutional mechanisms (the *mesocosmic* perspective). These interconnected triple perspectives shape the economy, morphology, social profile and future of the city. The present study seeks to develop and validate a human-based planning perspective on the geographic composition and evolution of cities as interconnected multiscale phenomena, with particular emphasis on areal heterogeneity of subsystems (e.g., districts) within the overall complex urban system.

The evolution of modern cities reflects a constant flux of various demographic and economic changes. This mainly *microcosmic* perspective views cities as complex interactive ecosystems where individuals, households, communities, and

governing bodies interact to shape urban life. By examining urban wellbeing and social interaction capital from a multidisciplinary viewpoint, the present paper aims to provide a nuanced understanding of the complex dynamics within urban environments, shedding light on the often overlooked 'X-factors' that influence human experiences and interactions in spatial urban systems.

In the modern globalized world, cities emerge as important nodes within interconnected networks, competing for economic, cultural, and political significance. The *macrocosmic* perspective on urban systems acknowledges the role of cities as dynamic entities influenced by global forces, while also highlighting their unique characteristics and competitive advantages in the global arena. The focus in this paper will be on the foundational 'X-factors' that shape urban landscapes, offering fresh planning perspectives on the interplay between local dynamics and macro trends.

The basic proposition in this study is that urban development is not a top-down process but rather a result of complex interactions among various stakeholders, including residents, policymakers, and civic organizations. This *mesocosmic* perspective recognizes the diverse governance structures and decision-making processes shaping urban social and economic landscapes. Through insights drawn from citizen science and participatory planning, this paper aims to shed light on innovative approaches to urban governance and policy-making, uncovering and decomposing the 'X-factors' that influence governance dynamics and shape urban futures. The analytical tool to explore place-based and people-centered urban developments is formed by *micro-scenarios*, which may be seen as possible spatial socio-economic mappings of urban areas (e.g., districts or neighbourhoods), which may be used as building blocks for citizen-based urban planning.

This paper contributes to the urbanometrics literature in three ways. First, it translates the conceptual idea of pluriform urban livability into an operational cubic framework, in which neighbourhoods, micro-scenarios, and happiness jointly define a three-dimensional analytical space. Second, rather than estimating another spatial regression model of neighbourhood happiness, it introduces a configurational decomposition of urban livability through cubic regimes. These regimes identify whether neighbourhood-year observations are community-led, vibrancy-led, eco-led, integrated, or weak/transitional in their micro-scenario structure. Third, the paper validates these regimes by comparing their Smiley Index values, spatial distributions, and temporal transitions in the city of Rotterdam. In this way, the paper shifts the focus from explaining happiness through marginal effects to identifying distinct pathways through which livable urban places are formed.

The present study on modeling people-oriented urban developments is organized as follows. After the present introductory section, Section 2 will outline in more detail the three above-mentioned urban scale perspectives (microcosmic, macrocosmic, and mesocosmic). The methodological framing of urban development is next sketched out in Section 3, in which urban-econometric principles in the form of the new paradigm of 'urbanometrics' are outlined. Section 4 lays the foundation for a multiscale actor perspective on the city and its districts or

neighbourhoods, while Section 5 provides a new angle based on spatial decomposition based on a cubic constellation. The next section (Section 6) offers an empirical illustration on the city of Rotterdam, the Netherlands, while Section 7 offers conclusions.

The City: a Complex Urban Galaxy

Prologue

It has become fashionable in recent studies to seek for the ‘X-factor’ of cities that is responsible for a disproportionally high performance. It should be noted however, that an X-factor is normally not a uni-dimensional achievement index, but comprises usually two or more driving forces that in synergy create a high achievement level.

The development of urban agglomerations is not shaped by anonymous or invisible forces, but by deliberate decisions and actions of a multiplicity of actors. But how can we determine the critical success factors (influencing key performance indicators – KPIs) that are responsible for an extraordinary performance in terms of socio-economic, technological, environmental or wellbeing results? How can we trace urban and regional growth champions, and which are their drivers? The growth potential of cities and regions depends in general on a positive and dynamic synergy between basic place-specific critical success factors or KPIs.

Cities are clearly evolutionary organisms which despite different morphological and functional appearances do exist due to a multiplicity of agglomeration advantages. Such advantages are usually interpreted as centripetal geographical forces, but in reality, there are also centrifugal forces which transmit urban advantages and disadvantages to the outer world thus reinforcing the position of cities in a spatial complex network. In other words, the through-flow of people, goods and ideas is essential for the ‘raison d’être’ of urban agglomerations. Emission and immission of flows of people and goods – material and immaterial – make up for the power of the urban force field or arena, and shape a complex but spatially converging urban agglomeration. This is called here the principle of *confluence*. Confluence is a generic structural determinant of the genesis and growth of cities as spatially interlinked human settlements. The confluence principle is a dynamic structuring principle, which has both strong internal and external connectivity linkages. Thus, it is a major challenge to identify the X-factor of the dynamics of complex urban systems.

The design and study of the city of confluence can be summarized as follows in the form of five *confluence anchor points*:

- Conceptualization: what is the city?
- Architecture + design: what is a good city?
- Statistical mapping: how to quantify a city?
- Urban modeling: mathematical and econometric images on how to model a city

- Digital visualization: geodesign, digital twins, and imagineering and metaverses on: how to imagine the city.

As mentioned above, a city is a human-made settlement system. And therefore, citizen science and participatory governance may be seen as critical constituents of urban science. An urban system in itself may be regarded as a complex galaxy which superficially and seemingly does not have a clear structure. But close scientific inspection uncovers clear multiscalar structures (Batty 2013, Bettencourt 2013). This also holds for the city. Therefore, the three above mentioned architectural and planning principles (microcosmic, macrocosmic and mesocosmic) of cities will be discussed and described in greater detail.

Cities from a Microcosmic Human Perspective

Modern cities are in constant flux, with ups and downs in demography and economy. They may be explored from the perspective as the home of people, in various strata of a 'microcosmic' systemic constellation: *individual*, *oikos*, *agora* and *polis*. Furthermore, they seek to manage to the utmost extent to achieve the highest quality of human life through a multi-attractiveness of places ('microcosmic' territories), as a result of their socio-economic and cultural-ecological functions. And consequently, they are able to gain a high appreciation and satisfaction by their multi-stakeholders and key-agents for their spatial-social constellation and design morphology – ranging from street level to public urban space (see Nijkamp 2008). Thus, capturing the complex and heterogeneous ramifications of a city in all its dimensions, functions and dynamics requires a broad multidisciplinary and multi-level spatial view on exploring urban wellbeing capital and social interaction capital in human settlements, with a sound mix of theory, practice and planning. The '*microcosmic city*' is a concept based on a functional and social decomposition of the urban territory in terms of detailed and individualized data on urban quality of life. From a research perspective, it also needs the mobilisation, operation and analytics of a multiplicity of up-to-date multi-data and information systems, in which realism may be achieved by an alteration from 1D to 3D statistical mapping and visualisation (adapting a deconstruction-reconstruction approach) (see also Kourtit 2021). This may become an important methodological step forward in understanding wellbeing of citizens from a microcosmic perspective on the city.

Cities from a Macrocosmic Global Perspective

Cities – and urban agglomerations such as metropolitan areas – are a *sui generis*, in which agglomeration advantages determine their relative economic and political strength. They compete for the favours of residents, visitors and business people. Cities rise and decline, depending – next to their external force field and networks – on foot-voting mechanisms of people (Tiebout 1956). Their relative power is dependent on competitive global systems of cities (e.g., accessibility, creativeness, cultural power, educational amenities, etc.), while they are also

hubs of economic power ('control and command systems'; Sassen 2001) in the global economy. The '*New Urban World*' (Kourtit 2019) is a globally networked settlement system, with cities as centripetal and centrifugal geographical entities. The ups and downs of urban areas – certainly in the context of networked spatial interactions – are one of the distinct features of the 'new urban world'.

Cities from a Mesocosmic Governance Perspective

Modern cities are shaped by people and decision makers. In a democratic society, urban systems are not top-down steered, but the result of complex interactive forces of inhabitants, institutions and networked stakeholders. There is not a central control mechanism for most cities, nor is there a grass-root bottom-up policy structure for cities. The development of cities is the result of complex interactive multi-level forces in which individuals and groups (including policy agencies, institutions and NGOs) play an ever changing role. There is not an unambiguous rational planning system, and consequently, cities are extremely diverse in nature. The development pace of cities in a complex network configuration of settlements reflects the vanity in government mechanism, in addition to external forces and internal choice processes. In this context, new management concepts emerging from 'citizen science' are noteworthy (see e.g., Bettencourt et al. 2007, Bonney et al. 2009, Wiggins, Crowston 2011, Batty 2013, Haklay 2013, Hecker et al. 2018).

Urban Modeling and Urbanometrics

Cities have been the subject of research for many decades, e.g., from a data-driven statistical angle (see e.g., Weber A.F. 1899), an institutional angle (see e.g., Weber M. 1958) and an economic angle (see e.g., Weber A. 1929). In recent times, the discipline of urban science (or urban studies; see e.g., Glaeser et al. 2001, Batty 2013, Bettencourt 2013) has gained much popularity as an analytical toolbox for mapping out, investigating, understanding, explaining and projecting the multidimensional complexity of cities or urban systems, seen from the perspective of their inhabitants, their functioning, their stakeholders, their proximity features, their appearance and physical attributes, their culture and history, their evolutionary development, and their institutional governance configurations. It goes without saying that the study of urban evolution needs a multidisciplinary approach: urban economics, urban geography, public administration, social psychology, urban sociology, environmental science, transportation science, and so forth.

Urban science has gradually moved from a reflective and qualitative methodological approach to a more quantitative-analytical study of cities and urban systems (see e.g., Isard 1956, Berry 1964, Haggett 1977, Nijkamp 1980). This '*quantitative revolution*' in geography was stimulated by the systematic availability of and access to empirical spatial and urban data. This has also led to the rise of

urban simulation studies and urban scenario models (see e.g., Forrester 1969). The rise of digital technology and new advances in statistical modeling techniques led to computer-aided urban models, also including multivariate statistical approaches and the first generation of urban econometric modeling.

In recent years, the rise of big data, the IoT (internet of things), social network analysis, geographic information systems, open street map data, and urban digital twins have really meant a radical breakthrough in urban analytics, in particular *urbanometrics* – a quantitative spatial-econometric approach in the new urban science – supported inter alia by AI. Urban complexity theory (Batty 2005), spatial syntax (Hillier 1998, Turner 2001), urban morphometrics (see e.g., Muratori 1959, Porta et al. 2006, Venerandi et al. 2018, Fleischmann et al. 2021) and fractal evolution (see e.g., Batty, Longley 1994, Frankhauser 1994, Banaszak et al. 2023) are contemporaneous examples of promising modern research developments in urban science. Such novel developments have also induced various actionable urban policy studies, for instance, on data-driven comparisons of urban systems, multi-attribute analytics of urban form, preference elicitation methods originating from social media information, etc. In the history of quantitative geographical research, a wide range of analytical techniques has been developed over the past decades. It would take too much space to review these or even to summarize these publications. For an overall and comprehensive overview of suitable, statistical and spatial-econometric techniques we refer to the Handbook of Regional Science (vol. 3), edited by Fischer and Nijkamp (2021), which contains more than 500 pages on quantitative techniques.

We emphasize once more that cities are living organisms, with many appearances and functions, like dense areas, slums, green neighbourhoods, sub-urbanization or residential sprawl, high-tech clusters, knowledge districts (universities, e.g.), industrial estates, and so on. Clearly, cities are no uniform spatial entities, so that their quantitative analysis has to take into account spatial heterogeneity (e.g., districts, neighbourhoods, streets, blocks, buildings, environmental areas, etc.). And consequently, quantitative urban planning and design are fraught with many difficulties of a statistical, econometric, and data-analytic nature. The emphasis on human-made city forms, functions and complex dynamics calls for advanced statistical, spatial-econometric and urbanometric approaches (see also Panagoulia 2019, Gras, Burke 2023). In this context, the rise of *urbanometrics* is noteworthy.

Urbanometrics is a recently developed sub-discipline within the broader area of spatial econometrics (see e.g., Kourtit et al. 2022a, b). It addresses the quantitative profiles and inter-linkages between socio-economic attributes of cities, seen from the perspective of spatial dependencies between heterogeneous urban actors, areas and policies. As mentioned above, the abundance of data in the modern digital age – in combination with survey data and official statistics – has stimulated the rise of urbanometrics. Clearly, urbanometrics may zoom in on a large variety of urban phenomena, such as land use, urban functions, behaviour of citizens, health and livability conditions, creative classes or urban social capital. From this perspective, urbanometrics may be a useful tool for smart or

intelligent urban planning and policy. The citizen perspective on planning means that citizens may also be regarded as data producers and data consumers (in other words, as ‘prosumers’; see e.g., Toffler, 1980). Against the data-driven perspective on urban life and policy for people, an urbanometric approach may shed new light and provide new analytical insights on: (i) the micro foundations of city life and urban space allocation; (ii) spatial choices of urban actors and relevant stakeholders involved; (iii) the dynamics in city formation, morphology and urban land use; (iv) the supply of and access to amenities and services in urban agglomerations; (v) the architecture planning and governance challenges of modern intelligent cities; (vi) and the new data metrics (including advanced geo-science and data mining research tools and methods) in contemporaneous urban sciences (‘the city as a data engine’; Batty 2018). It is noteworthy that urbanometrics has shown a rapid evolution over the past years.

A Multiscalar Actor Perspective

As mentioned, cities are adaptive and resilient organisms, which form a complex evolutionary system, with many actors and diverse multi-level network connections. The focus of this paper will be on the functioning and governance of multiscalar interactive urban systems in the form of neighbourhood micro-scenarios characterized by multiple layers of rich architectural design and historical heritage, a multidimensional pattern of many individual and collective interests and behaviours, a dynamic interaction between economic, technological, knowledge and business stakeholders, and a great variety of internal and external network linkage patterns. The present study departs from a systemic decomposition paradigm, starting from a micro-based analytical perspective on urban space use towards a macro-oriented integrative view on the essence of the city and its (public and private) space. This approach, which may be coined a *triple-cosmic* perspective on the city, serves to get a better understanding of the genesis, evolution, functioning, organization, governance, and resilience capacity of cities in the ‘*New Urban World*’ (Kourtit 2019). This novel methodological approach ties in with recent behavioural and experimental approaches in cognitive urban sciences, mirrored inter alia in micro-economics (wellbeing research), attitudinal psychology (happiness research) or behavioural sociology (quality-of-life research). The city becomes nowadays increasingly the platform for new theory development and advanced (‘big’) data application in the modern social sciences. The research architecture adopted in the present study is presented in Fig. 1.

Figure 1 shows the methodological analytical backbone of the present paper on urban evolution in different countries. The structural rise in urbanization all over the world and the continuing increase of city size in almost all countries suggests a homogeneous development pattern of cities. However, there is no city which shows an evolution that is similar to another city. There are marked differences in size, population composition, socio-economic functionalities, urban morphology, history, culture, political orientation, environmental quality, livability, or

educational facilities (see e.g., Stuhlmacher et al. 2022). Although cities exhibit some common scaling regularities, their social, economic, and morphological configurations remain highly heterogeneous (Bettencourt, West 2010, West 2017). This heterogeneity does not only relate to people in the city, but also to economic functions and urban form (Fleischmann et al. 2021).

The intra-city heterogeneity is often surprisingly high, as a result of historical development, socio-cultural evolution, and socio-economic stratification in the city. As a consequence, urban districts, neighbourhoods, or even streets or blocks show an amazing variety of performance, livability, safety or wealth. The city appears to comprise of many diversified subsystems which altogether shape a heterogeneous map of human activity (McPhearson et al. 2016). Thus, the city is a multidimensional and multiscalar organism, which shows a formidable complexity. However, in contrast to natural organisms, cities are governed by ‘thinking human beings’ who try to control their urban way of life and future in one way or another.

The heterogeneity of cities is most pronouncedly expressed in the varied composition of people and the pluriform nature of geographical areas within a city (boroughs, districts, neighbourhoods, etc.). Clearly, the socio-economic and geographical diversity in cities are not entirely independent. We may thus create a typology of both people and areas in a given urban agglomeration. This may be represented in a socio-economic geographical location matrix, in which the entries describe the relative presence (frequencies) of distinct citizens’ groups in various urban areas (see Figure 2). Both the human and the areal clusters can be further (dis)aggregated, so that this matrix represents essentially the foundation of a complex multiscalar urban system, while also a time dimension – as a third axis – can be added. Figure 2 represents essentially a decomposition perspective on the city (see Kourtit 2021). The present study uses the neighbourhood structure and databases employed in a previous study by Kourtit et al. (2024).



Fig. 1. Planning of heterogeneous urban neighbourhoods by means of micro-scenarios

Source: Author's own work.

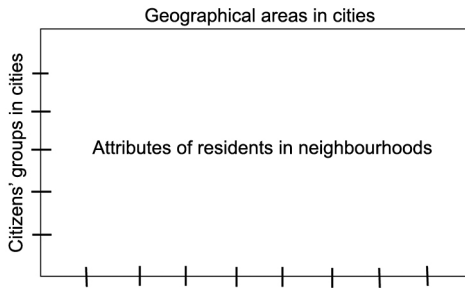


Fig. 2. Socio-economic geographical-location matrix

Source: Author's own work.

The economic choice or policy problem underlying the above matrix is essentially a *multi-attribute utility theory* problem (see also John et al. 2026). There are actors (or decision-makers), who have a preference pattern for the quality of their living environment. This living environment has a geographic locational component (an urban area, e.g.), whose attractiveness is determined by the locational features of the urban area concerned, such as accessi-

bility, environmental quality, safety, presence of amenities, or social cohesion. In the spirit of multi-attribute utility theory, we assume that the locational satisfaction of residents in a given area is co-determined by areal attributes. If we confront residents with distinct packaged attributes, they may be able to select one specific package – or rank the successive packages – according to their preference ladder. Such areal packages of residents' goods will be termed here residential *micro-scenarios*. They form the analytical backbone of the present study and will be presented now in greater detail.

Conceptualization of Actionable Micro-Scenarios: A Cubic Decomposition

The exploration of urban futures needs place-based neighbourhood images – coined here *spatial neighbourhood scenarios* – as tools for strategic and operational communication and interaction with residents. Such scenarios are not predictions, but possible images from a livability perspective. They represent how current residents' evaluations can guide planning for alternative neighbourhood improvements rather than predict actual futures.

To construct sustainable, citizen-oriented wellbeing scenarios (or decentralized images), this study draws inspiration from basic principles for scenario design, ensuring that our approach adheres to strict methodological rules and produces robust, comprehensive outcomes. The essence of our framework lies in weaving together several crucial components of social and sustainable wellbeing, including economic welfare, inclusiveness, environmental quality, health, and distributional justice (Jansen et al. 2024). This paper seeks to design alternative neighbourhood images (*micro-scenarios*) that go beyond mere resilience and instead proactively nurture the wellbeing of urban communities and the environment they inhabit (Folke 2006). Through innovative micro-scenario design, we aim to transcend traditional macro-level analyses and explore the microcosm of neighbourhoods – the building blocks of urban life (Batty 2008).

In modern spatial policy analysis under conditions of uncertainty and resilience, the use of scenario experiments has become widespread. A review of scenario analysis – and its foundations and application potentials – can be found in van der Heijden (2005) and Nijkamp et al. (1998). Most scenario studies take for granted a global or macro playing ground (e.g., conflicts among major key actors). Thus far, urban-scale scenario experiments have not gained significant momentum (though a few emerging studies demonstrate promising potential). However, at the intra-urban scale (e.g., district level), scenario studies remain rare, even though today's cities are characterized by significant socio-economic disparities and cultural heterogeneity. This empirical gap underscores the need for perception-based micro-scenario analysis that connects the macro-urban framework to residents' lived experience. Although neighbourhood scenarios are inspired by future-oriented thinking, they are empirically grounded in present-day perceptions and place-specific indicators.

As mentioned, a city is a complex agglomeration, comprising of people (population groups), areal locations, and space-time-social connectivity patterns. Its dynamic is – next to external forces – co-determined by people's preferences and choices. Clearly, whether agglomeration advantages actually lead to net socio-economic benefits for citizens is contingent on responsible residents' behaviour, environmentally-benign business practices, and adaptive and responsive policy actions. If an area meets people's preferences, we may expect a high level of citizens' satisfaction (*urban happiness* or *city love*). There is an abundance of recent literature on the geography of happiness of wellbeing (see e.g., Vaz 2023). Factors that determine city love are not only shopping and cultural amenities, but also negative factors such as crime, poverty, and limited accessibility. The findings highlight the need for integrated, neighbourhood-oriented strategies that combine objective statistical data with subjective perceptions of local livability. The main idea is to trace and explain the drivers of residents' wellbeing against the background of their geographical residential context. Such a multi-faceted and complex force field needs a methodological streamlining which maps out the various constituents from a systematic and conceptually-driven perspective based on *decomposition* principles (see Simon 1962). A contemporary exposition on decomposition theory and its implications for urban economic research can be found in Kourtit (2021).

The realization of the choice spectrum of urban residents is of course determined by their preference profile which expresses the relative priorities for items of their spatial living environment, such as community sense, safety, access to shops, distance to medical facilities, access to schools, air quality, quiet vicinity of green areas, etc. (see also Hårsman Wahlström et al. 2020, Kourtit et al. 2024). Thus, a *happiness index* (which may also be termed 'smiley index' or 'city love index') is a function of a broad portfolio of neighbourhood characteristics. This index is based on place-based survey data among citizens in Rotterdam, and comprises several indicators which reflect place attachment and neighbourhood satisfaction of inhabitants. Since the neighbourhood characteristics are site-specific and thus vary per neighbourhood, the smiley index – or neighbourhood love

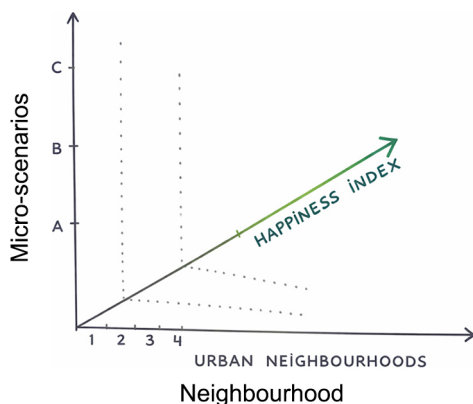


Fig. 3. The urban happiness cubic

Source: Author's own work.

index – varies for each population group in each urban neighbourhood or district (see Figure 3). The analytical challenge is now to model the happiness index of a given population sub-group as a function of the attributes of a given urban area.

The set of attractiveness indicators in each urban area is showing much variation across urban districts. In addition, the level of neighbourhood satisfaction of a certain population sub-group is also dependent on their perception of the availability of neighbourhood amenities. This raises the question of the human satisfac-

tion potential of neighbourhood goods and services (both public and private). To cope with this question, the above mentioned concept of *micro-scenarios* is introduced in this study. As mentioned, a micro-scenario is a spatially differentiated image (not necessarily a real-world or observed image) of a possible composition of residents' expectations or desires regarding access to a broad portfolio of amenities, goods and services. Neighbourhood planning then implies the search for a satisfying level and composition of available amenities, goods or services that lead to a high level of neighbourhood happiness or neighbourhood love (Kourtit et al. 2022 a,b).

The above preference elicitation problem can be mapped out in a three-dimensional cubic, in which the values on one axis (happiness index) are determined by the specific choice for a given micro-scenario expressed by a specific population group in a given urban neighbourhood or district.

The main analytical challenge is now to test the model implied by Figure 3 without reducing it to a single causal regression of happiness on neighbourhood attributes. In the present paper, the urban happiness cubic is treated as a configurational space. The three micro-scenarios define the main axes of neighbourhood livability, while the Happiness or Smiley Index is used as an external validation measure. The empirical task is therefore to identify distinct cubic regimes of neighbourhood livability and to examine whether these regimes differ in happiness, spatial distribution, and temporal transition patterns. This will be further tested in the present study by means of an application to the city of Rotterdam.

Rotterdam hosts one of the biggest ports in the world and is among the most dynamic cities in Europe. It has demonstrated remarkable economic development over the past decades. After its destruction at the beginning of WWII, it has been in a permanent transition process in search of a new 'face'. The built environment – especially in the central parts of the city – shows evidence of radical transformation and rejuvenation, while the emerging new socio-ethnic climate shows clear signs of cultural-economic diversity. Rotterdam comprises a great variety of

distinct districts and neighbourhoods, each with its own history, culture, demography, and social economy. These strong contrasts make it an ideal testbed for the proposed data-based neighbourhood planning framework. Building an equilibrated, sustainable, and inclusive urban future is an enormous challenge. This paper therefore presents a methodology for a novel geo-design approach (Steinitz 2012) to data-based neighbourhood planning, exemplified by systematic image creation (micro-scenario design) and evidence-based assessment of Rotterdam's neighbourhoods, while taking into consideration their cohesiveness and connectivity, as advocated in Clark (2024). The main challenge for integral multi-scalar urban sustainability is to ensure the material and immaterial prerequisites (e.g., amenities) for resilient future-oriented strategic planning of the city. Strengthening community sense and neighbourhood love demands proactive strategies from both residents and urban planners (Kitchen et al. 2012, Clark 2024). This resilience challenge, while exemplified by Rotterdam, is shared by many other cities in the world.

The notion of urban resilience is nowadays expanding beyond its traditional macro- and meso-scales to encompass the granular level of neighbourhoods (Batty 2008). Data-based research on urban neighbourhoods has in recent years become very popular in the urban sciences (see e.g., Clark 2024, Kourtit et al. 2024). Recognizing the essential role neighbourhoods play as the building blocks of urban life, we aim to explore and reimagine the future of cities by examining alternative states of neighbourhoods within a city. Embracing the concept of spatially dependent neighbourhood images, we address in this paper the spatial structure of diverse districts and communities in cities. By doing so, we explore the complex multi-scalar force field that shapes multi-faceted urban development and assess strategic pathways to urban resilience (Folke 2006, Droin et al. 2026).

Our study follows the spirit of geo-design principles by emphasizing the role of space in exploring and planning urban futures (Steinitz 2012). The research task is to empower cities – and their neighbourhoods – to address the future with solid, data-based evidence and foresight (van den Bergh et al. 2011, Vergragt, Quist 2011, Carpenter et al. 2012, Klijn, Koppenjan 2012, Wang et al. 2023).

Geo-design has emerged in recent years as an important vehicle for developing realistic future images of cities (see Steinitz 2012). In the dynamic and rapidly shifting landscape of urban development, geo-inspired scenario design serves as a valuable decision-support tool for policy under uncertainty, guiding planners through the labyrinth of unpredictable forces that shape the urban fabric.

Citizen engagement and policy foresight are vital components of our scenario-development process. By combining citizen-derived wellbeing scores with hypothetical local futures, we can provide a multidimensional view of each scenario. Furthermore, policy-oriented strategic-choice approaches offer a roadmap for embracing regulatory systems and resilience strategies (Nijkamp, Blaas 1994). Resilience – in the context of urban wellbeing – has both a spatial and temporal dimension. Thus, a differentiated focus on geography and adjustment speed is a critical element. Consequently, it is also pertinent to address resilience in cities from a sub-local, particularly neighbourhood, perspective. In recent literature,

several studies have been published on neighbourhood resilience, especially from a social-ecological angle (Larimian et al. 2020).

To cultivate urban resilience at the sub-local scale, we must address the intrinsic fabric of local economies (e.g., the portfolio of amenities) and socio-cultural communities (bonding and bridging), exploring the profound dynamics that intertwine internal urban development with connectedness to surrounding neighbourhoods. This focus aligns with the central objective of our study: understanding how local wellbeing and attachment translate into resilient urban futures. Emphasizing the significance of community sense and neighbourhood love, our study seeks to lay the groundwork for the creation of spatially dependent, inter-linked neighbourhood images (Angelidou 2015, Clark 2024, Kourtit et al. 2024).

Redefining urban resilience calls for a transformative shift towards spatially dependent, data-driven neighbourhood micro-scenarios that systematically show the developmental patterns of each district and their intricate interconnections with surrounding neighbourhoods. This shift propels us into a data-informed exploration of potential futures for urban areas, illuminating the pathways that lead towards urban prosilience at the sub-local scale. Multi-actor evaluation frameworks can provide structured ways to incorporate heterogeneous stakeholder perspectives into planning decisions (Macharis et al. 2010a, b). Micro-scenarios in a place-based urban planning context seek to map, interpret, and provoke reflection on residents' perceptions and engagement regarding their daily living environment. They capture not only the essence of local livability but also show new opportunities for improvement and transformation. Moreover, they can be used as communication and co-creation tools in participatory urban planning (see e.g., Carmona et al. 2003, Carpenter, Horvath 2022).

To understand the impact of spatially dependent neighbourhood scenarios, we evaluate each micro-scenario's implications across multiple dimensions of urban resilience – ranging from the social fabric that binds communities to the economic dynamics that drive prosperity, and from environmental sustainability that safeguards ecosystems to the robustness of infrastructural systems (Folke 2006, Marcotullio 2007, Alberti 2008, Grimm et al. 2008, Zhao et al. 2022). This multidimensional analysis acknowledges that resilience is not isolated but embedded in a complex, interdependent spatial system. Our analysis, therefore, extends beyond individual neighbourhoods, recognizing the interplay between micro-level dynamics and the broader cityscape (Carpenter et al. 2001, Walker et al. 2004, Hunt, Watkiss 2011, Reckien et al. 2014, Lei et al. 2024, Ye et al. 2025). It serves as a visual synthesis of how subjective wellbeing data translate into spatially defined scenario outcomes. This requires the availability and use of individual survey data on the appreciation of urban amenities at the neighbourhood level.

The empirical analysis is guided by three research questions:

1. How can Rotterdam's neighbourhoods be decomposed into cubic livability regimes based on the three micro-scenario axes?
2. Do different cubic regimes correspond to different levels of neighbourhood happiness, as measured by the Smiley Index?

3. Are cubic regimes spatially and temporally stable, or do neighbourhoods move between different regime positions over time?

These questions will be addressed in the remaining part of the study.

A Cubic Regime Validation for Rotterdam

Dataset

The empirical analysis uses a neighbourhood-year panel for Rotterdam, the Netherlands, covering 2014, 2016, 2018, and 2020. The database combines survey-based resident perceptions with register-based neighbourhood statistics. The perception indicators are used to construct the three micro-scenario axes of the urban happiness cube: *Community Oasis*, *Vibrant Hub*, and *Eco-Urban Haven*. *Community Oasis* captures perceived maintenance, local support, belonging, and community attachment. *Vibrant Hub* captures cultural, commercial, and activity-based vitality. *Eco-Urban Haven* captures green, mobility, and environmental comfort. The three micro-scenario axes are treated as analytically distinct dimensions of neighbourhood livability. However, their observed values may still display spatial dependence because perceptions and neighbourhood conditions are geographically structured. Nearby neighbourhoods often share similar built environments, housing-market conditions, accessibility patterns, socio-economic profiles, reputational images, and public-service environments. To examine whether the configurational structure of the urban happiness cube is spatially clustered, we use Moran's I statistic, the classical global measure of spatial autocorrelation (Moran 1950, Anselin 1988, Cliff, Ord 1970). In this paper, Moran's I is used as a descriptive spatial diagnostic rather than as a full spatial econometric model. It indicates whether similar values of cubic strength or cubic imbalance tend to be located near one another, but it does not estimate spatial spillover effects or causal spatial dependence. In addition to Moran's I, we estimate a spatial-context robustness model. The model regresses the Smiley Index on cubic regime membership, year indicators, a spatial lag of neighbouring Smiley values, and neighbourhood random intercepts. The spatial lag is computed using the same five-nearest-neighbour weights used for Moran's I. This specification is not intended as a full spatial econometric model. It is used as a robustness check to assess whether the descriptive regime pattern persists after accounting for local spatial context and repeated observations of the same neighbourhoods. The results are reported in Appendix Table A3.

The database also includes objective neighbourhood indicators, such as housing quality, crime levels, educational and income composition, housing tenure, home values, access to schools, access to daycare, access to general practitioners, trade and catering amenities, and business locations. These indicators are not used to construct the cubic regimes. They are reported descriptively in Appendix Table A1 to provide contextual information on the structural conditions associated with each regime.

Operationalizing the Urban Happiness Cube

The urban happiness cube is operationalized through three perception-based micro-scenario axes: Community Oasis, Vibrant Hub, and Eco-Urban Haven. These axes represent different ways in which neighbourhood livability may be experienced by residents. Each neighbourhood-year observation is positioned within this three-dimensional micro-scenario space. The Smiley Index is not used to construct this position. It is kept outside the classification procedure and used afterward as an external validation measure. This distinction is important because the aim is not to estimate another explanatory model of neighbourhood happiness. Instead, the aim is to identify distinct livability configurations within the urban happiness cube.

The three micro-scenario axes and the Smiley Index are continuous perception-based indicators. To translate the cube into an empirical classification, the three micro-scenario scores are first standardized. The cubic regimes are then created by discretizing the three standardized micro-scenario axes into relatively high and non-high positions. This discretization is used for interpretability and configurational comparison. It inevitably reduces some continuous variation, and the regimes should therefore be read as analytical summaries rather than natural categories. The Smiley Index remains continuous and is used to compare the resulting regimes. A related spatial aggregation issue is the Modifiable Areal Unit Problem (Fotheringham, Wong 1991). The analysis is conducted at the neighbourhood level because this is the spatial scale at which the survey indicators and planning-relevant contextual variables are available. However, the regime distribution, spatial autocorrelation statistics, and transition patterns may be sensitive to the boundaries and aggregation level used. The cubic regimes should therefore be interpreted as neighbourhood-level analytical configurations rather than boundary-invariant spatial entities.

Each neighbourhood-year observation is classified according to whether its Community Oasis, Vibrant Hub, and Eco-Urban Haven scores fall in the upper tertile of the corresponding distribution. Five cubic regimes are defined. Observations with at least two high micro-scenario scores are classified as Integrated high-scenario regimes. Observations with only Community Oasis in the upper tertile are classified as Community-led regimes. Observations with only Vibrant Hub in the upper tertile are classified as Vibrancy-led regimes. Observations with only Eco-Urban Haven in the upper tertile are classified as Eco-led regimes. Observations with none of the three axes in the upper tertile are classified as Weak or transitional regimes. This rule-based classification follows directly from the cubic framework. It is transparent, reproducible, and suitable for identifying alternative pathways of neighbourhood livability. The resulting regimes are validated in four steps. First, we examine the distribution of neighbourhood-year observations across the five regimes. This shows whether Rotterdam's neighbourhood system is dominated by one livability configuration or whether several configurations coexist. Second, we compare the mean Smiley Index across regimes. Since the Smiley Index is excluded from regime construction, this provides an external

validation of the cubic classification. Third, we examine the spatial distribution of regimes and Smiley values using neighbourhood polygon maps. Finally, we assess temporal movement between regimes through transition matrices. As a sensitivity check, we repeat the classification using several alternative upper-tail thresholds, including above-median, upper-40%, upper-30%, and upper-quartile specifications. The aim is not to replace the main upper-tertile classification, but to assess whether the descriptive interpretation depends entirely on a single cut-off. The results are reported in Appendix Table A2.

Empirical Results: Cubic Regimes in Rotterdam

We now apply the rule-based cubic classification to the Rotterdam neighbourhood-year panel. The results are presented in four steps. First, we examine the distribution and micro-scenario profiles of the regimes. Second, we compare Smiley Index values across regimes. Third, we map the spatial distribution of regimes and Smiley values. Finally, we examine spatial autocorrelation and temporal transitions.

Distribution and profile of cubic regimes

Table 1 presents the distribution of cubic regimes. The results show that Rotterdam’s neighbourhoods are not concentrated in a single regime. The largest group is the Weak or transitional regime, representing 28.21 percent of observations, followed by the Integrated high-scenario regime, with 26.43 percent. The Community-led, Vibrancy-led, and Eco-led regimes account for 16.79, 17.14, and 11.43 percent, respectively. This distribution confirms the pluriform character of Rotterdam’s neighbourhood system.

Table 2 reports the standardized micro-scenario means by regime, and Figure 4 summarizes these regime profiles. The Community-led regime is strongly positive on Community Oasis, but negative on Vibrant Hub

Table 1. Distribution of Cubic Regimes

Regime	N	Share (%)
Integrated high-scenario regime	74	26.43
Community-led regime	47	16.79
Eco-led regime	32	11.43
Vibrancy-led regime	48	17.14
Weak or transitional regime	79	28.21

Source: Author’s own work.

Table 2. Standardized Cubic Axis Means by Regime

Regime	N	Community Oasis	Vibrant Hub	Eco-Urban Haven	Cubic strength	Cubic imbalance
Integrated high-scenario regime	74	0.454	0.414	0.772	0.547	0.995
Community-led regime	47	1.061	−0.376	−0.469	0.072	0.952
Eco-led regime	32	−0.426	−0.629	0.918	−0.046	0.937
Vibrancy-led regime	48	−0.513	1.158	−0.401	0.081	1.032
Weak or transitional regime	79	−0.572	−0.613	−0.572	−0.586	0.611

Source: Author’s own work.

and Eco-Urban Haven. The Eco-led regime is strongly positive on Eco-Urban Haven and negative on the other two axes. The Vibrancy-led regime is strongly positive on Vibrant Hub, but negative on Community Oasis and Eco-Urban Haven. The Weak or transitional regime has negative values on all three axes. These profiles show that the classification captures distinct positions inside the urban happiness cube.

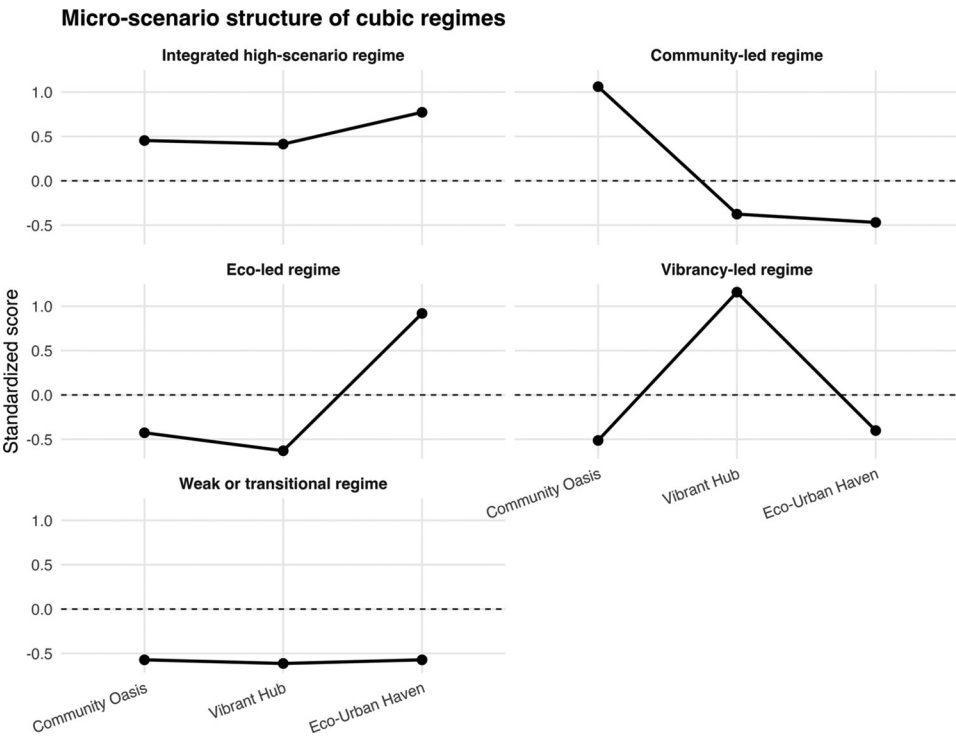


Fig. 4. Micro-scenario structure of cubic regimes
Note: The figure shows the mean standardized scores of each cubic regime on the three micro-scenario axes. Values above zero indicate above-average positioning on the corresponding axis, while values below zero indicate below-average positioning.
Source: Author’s own work.

Objective neighbourhood conditions by cubic regime are reported in Appendix Table A1. These descriptive results are used only to contextualize the regimes; they do not enter the classification procedure.

Smiley Index differences across regimes

Table 3 shows the Smiley Index by cubic regime. The Community-led regime has the highest average Smiley Index, followed by the Eco-led regime. The Integrated high-scenario regime occupies an intermediate position, while the Weak or transitional regime and the Vibrancy-led regime show lower average Smiley values. This is an important result. It suggests that higher neighbourhood happiness in

Rotterdam is not primarily associated with vibrancy alone. Instead, perceived belonging, support, and community attachment appear to be more closely associated with neighbourhood love.

Table 3. Smiley Index by Cubic Regime

Regime	N	Mean Smiley	Std. dev.	Min	Max
Community-led regime	47	0.682	0.115	0.441	0.887
Eco-led regime	32	0.650	0.128	0.383	0.878
Integrated high-scenario regime	74	0.623	0.119	0.412	0.872
Weak or transitional regime	79	0.608	0.123	0.374	0.855
Vibrancy-led regime	48	0.585	0.120	0.395	0.854

Source: Author's own work.

Next, the ANOVA test confirms that Smiley values differ significantly across the main cubic regimes (Table 4). This provides an independent validation criterion within the dataset, since the Smiley Index is not used to construct the cubic regimes.

Table 4. ANOVA Test for Smiley Differences across Cubic Regimes

Term	Df	Sum sq.	Mean sq.	F value	p-value
cubic_regime	4	0.2686	0.0672	4.5956	0.0013
Residuals	275	4.0183	0.0146		

Source: Author's own work.

The threshold sensitivity analysis gives a broadly consistent descriptive pattern (Appendix Table A2). The Community-led regime has the highest mean Smiley Index under all tested threshold specifications, while the Vibrancy-led regime has the lowest mean in four of the five specifications. The Community-led minus Vibrancy-led difference is positive in every case. However, the statistical significance of overall regime differences varies by threshold: the ANOVA is significant for the upper-40%, upper-tertile, and upper-30% specifications, but weaker for the above-median and upper-quartile specifications. This is expected because one is too broad and the other creates smaller/more uneven groups. The main upper-tertile classification should therefore be interpreted as identifying a relatively sharp set of high-intensity livability configurations, rather than as evidence of fully threshold-invariant regime effects.

Figure 5 visualizes the distribution of the Smiley Index across the five cubic regimes. The pattern confirms that the regimes differ not only in their micro-scenario structure, but also in residents' overall appreciation of their neighbourhood. The Community-led regime has the highest average Smiley Index, followed by the Eco-led regime. The Integrated high-scenario regime occupies an intermediate position. By contrast, the Vibrancy-led regime has the lowest average Smiley value. This suggests that neighbourhood happiness is more closely connected to belonging, support, and community attachment than to vibrancy alone.

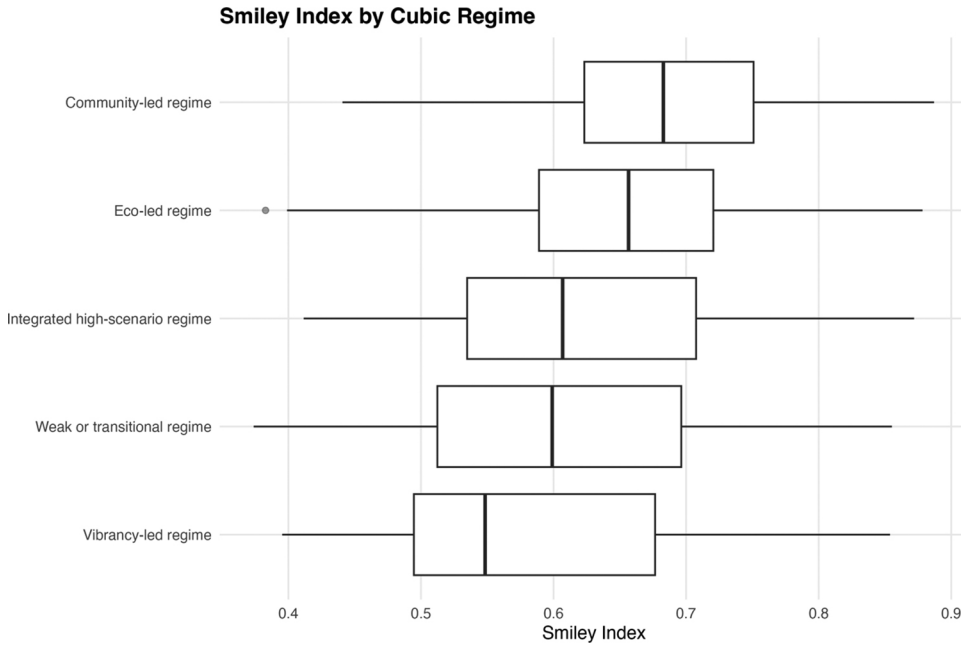


Fig. 5. Smiley index by cubic regime
Source: Author’s own work.

This result is central to the empirical contribution of the paper. The cubic framework shows that a neighbourhood does not need to score highly on all three livability dimensions to be associated with high resident appreciation. A more specialized community-led configuration may be more favourable than a broadly integrated but less socially anchored configuration. Conversely, a vibrant urban profile may not translate into neighbourhood love when it is not accompanied by community attachment or environmental comfort.

Spatial distribution of cubic regimes

Figure 6 maps the cubic regimes across Rotterdam for 2014, 2016, 2018, and 2020. The maps show that livability configurations are spatially differentiated and change over time. In 2014, integrated and vibrancy-led regimes are more visible. By 2016 and 2018, the spatial pattern becomes more mixed, with community-led, eco-led, integrated, and weak/transitional regimes appearing in different parts of the city. By 2020, the weak or transitional regime becomes more prominent.

This spatial pattern supports the idea that the urban happiness cube is not a fixed typology. It is better interpreted as a dynamic spatial configuration. Neighbourhoods may move between different positions in the cube as perceptions of community, vibrancy, and eco-urban comfort change.

Next, Figure 7 maps the Smiley Index across the same years. The Smiley map confirms that perceived neighbourhood happiness is spatially differentiated.

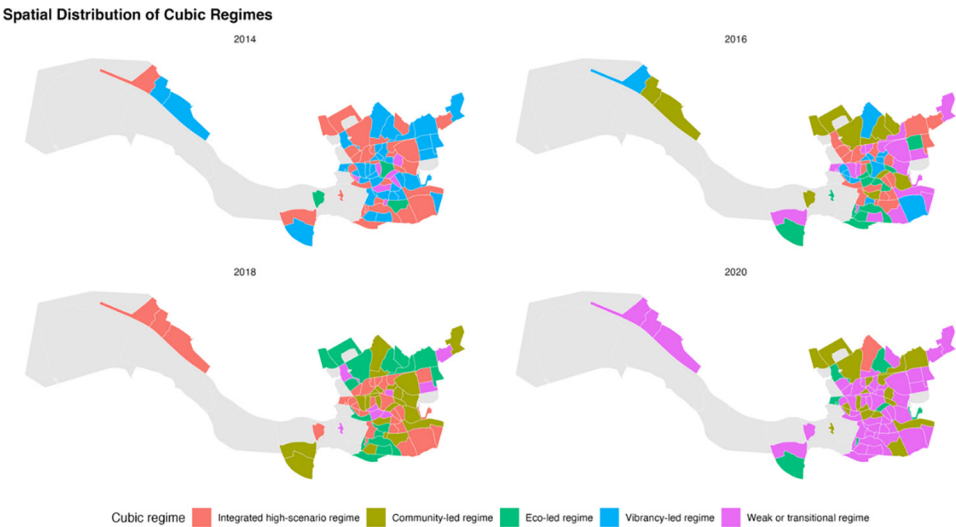


Fig. 6. Spatial distribution of cubic regimes, 2014–2020
Source: Author’s own work.

High and low Smiley values are not evenly distributed across Rotterdam. However, high Smiley values do not coincide perfectly with the integrated high-scenario regime. This supports the central empirical finding: community-led and eco-led configurations are also associated with comparatively favourable Smiley Index values.

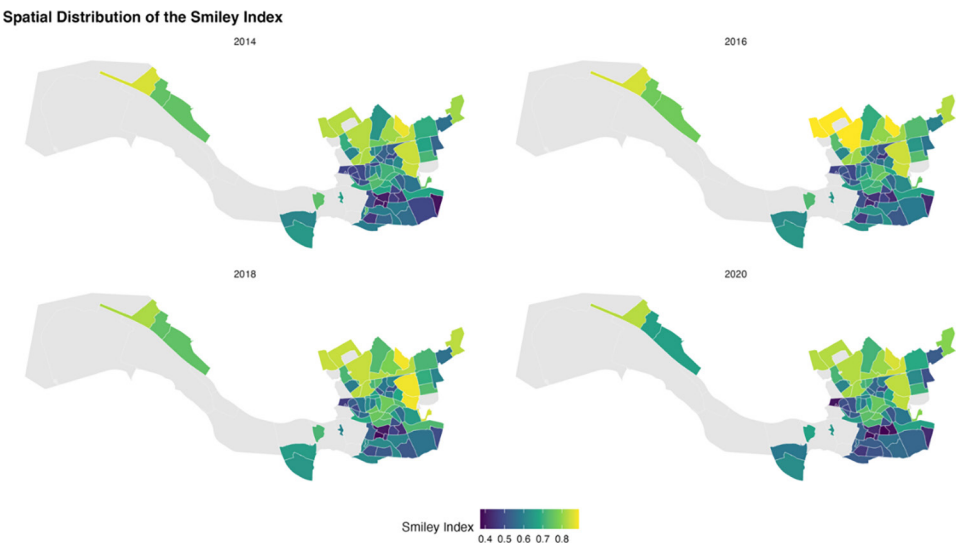


Fig. 7. Spatial distribution of the Smiley Index, 2014–2020
Source: Author’s own work.

Spatial autocorrelation and regime dynamics

Table 5 reports Moran’s I statistics for two derived cubic measures: cubic strength and cubic imbalance. Cubic strength captures the overall intensity of the three micro-scenario axes, while cubic imbalance captures the extent to which a neighbourhood is dominated by one or two axes rather than evenly positioned across the cube. The results indicate that the spatial pattern of the cubic structure is not stable across all years. Most Moran’s I values are weak and statistically insignificant. The clearest exception is 2018, when cubic imbalance displays a positive and statistically significant spatial autocorrelation. This suggests that, in that year, more specialized or uneven micro-scenario configurations were spatially clustered in Rotterdam.

Table 5. Spatial Autocorrelation of Cubic Regime Measures

Year	Measure	Moran I	Expected I	p-value
2014	Cubic strength	−0.0918	−0.0145	0.8784
2014	Cubic imbalance	0.0327	−0.0145	0.2371
2016	Cubic strength	0.0795	−0.0145	0.0786
2016	Cubic imbalance	0.0546	−0.0145	0.1495
2018	Cubic strength	0.0111	−0.0145	0.3465
2018	Cubic imbalance	0.2951	−0.0145	0.0000
2020	Cubic strength	−0.0155	−0.0145	0.5062
2020	Cubic imbalance	−0.0754	−0.0145	0.8362

Spatial weights are based on five nearest neighbours using neighbourhood coordinates.
Source: Author’s own work.

This result helps clarify the spatial interpretation of the cubic framework. The evidence does not point to a permanent city-wide spatial dependence pattern. Instead, it suggests that the geography of livability configurations is time-specific. In some years, neighbourhoods with similar cubic profiles are more spatially concentrated; in other years, the cubic structure is more dispersed. Spatial clustering in the cubic measures may arise from several mechanisms. Neighbouring areas often share similar built environments, access to amenities, housing-market conditions, transport connections, socio-economic profiles, reputational images, and public-service environments. Residents’ perceptions of community, vibrancy, and environmental comfort may therefore be spatially structured. However, the present analysis does not identify the causal sources of spatial dependence. It only shows whether micro-scenario configurations are spatially concentrated in particular years.

To further examine this issue, we estimated a spatial-context mixed model as an additional robustness check. The model regresses the Smiley Index on cubic regime membership, year indicators, a spatial lag of neighbouring Smiley values, and neighbourhood random intercepts. The spatial lag is computed using the same five-nearest-neighbour weights used for Moran’s I. This specification is not intended as a full spatial econometric model. It is used to assess whether the descriptive regime pattern persists after accounting for local spatial context

and repeated observations of the same neighbourhoods. The results, reported in Appendix Table A3, show that the spatial lag of neighbouring Smiley values is positive and statistically significant. This confirms that neighbourhood appreciation is spatially structured. After including this spatial-context term, year indicators, and neighbourhood random intercepts, the Community-led regime remains the highest estimated regime profile. However, the differences between regimes become smaller than in the descriptive means. The result therefore supports a cautious interpretation: community-led configurations remain associated with higher neighbourhood appreciation, but part of the observed variation in Smiley values is also related to broader spatial context.

Table 6 adds a temporal perspective. It reports the transition matrix between cubic regimes as row percentages. A considerable share of observations in the Integrated high-scenario, Community-led, and Eco-led regimes move to the Weak or transitional regime in the following period. At the same time, observations that start in the Weak or transitional regime most often move toward the Integrated high-scenario regime. This two-way movement reinforces the dynamic interpretation of the urban happiness cube. Cubic regimes should therefore not be treated as permanent labels attached to neighbourhoods. They are better understood as changing configurations of perceived livability. A neighbourhood may move from an integrated or specialized position to a weaker or more transitional position, but movement in the opposite direction is also possible. The cube, therefore, captures not only differences between neighbourhoods, but also shifts in the way residents experience community, vibrancy, and eco-urban comfort over time.

Table 6. Transition Matrix between Cubic Regimes, row percentages

Origin regime	Integrated high-scenario regime	Community-led regime	Eco-led regime	Vibrancy-led regime	Weak or transitional regime
Integrated high-scenario regime	19.18	17.81	15.07	6.85	41.10
Community-led regime	9.68	25.81	19.35	0.00	45.16
Eco-led regime	12.00	32.00	8.00	4.00	44.00
Vibrancy-led regime	33.33	16.67	12.50	12.50	25.00
Weak or transitional regime	39.39	30.30	12.12	3.03	15.15

Source: Author's own work.

Discussion and Conclusions

This study has presented a multiscalar approach to urban wellbeing, by employing the concept of a Smiley index associated with three types of neighbourhood scenarios for the city of Rotterdam. This urbanometric approach is based on an amalgam of various quantitative research techniques and appeared to offer actionable insights for intra-urban planning directions. Of course, we recognize

some limitations in our quantitative approach; the field of quantitative geographical research is vast and comprises numerous research techniques, such as spatial econometrics, spatial autocorrelation theory, spatial regression, spatial filtering methods, clustering techniques, spatial syntax, MAUP analytics, computational neural network analysis, urban scaling analytics, latent class modeling, and many more. Clearly, all such quantitative techniques could not be employed in one and the same case study. We have to leave this methodological challenge for future research.

This paper has introduced the notion of a neighbourhood wellbeing – through a Smiley index – in urban happiness cube for modelling pluriform livable urban spaces. The framework starts from the idea that cities are not uniform spatial systems. They are composed of neighbourhoods with different combinations of social, cultural, commercial, environmental, and infrastructural qualities. The empirical analysis translated this idea into a cubic regime classification based on three underlying micro-scenario axes: Community Oasis, Vibrant Hub, and Eco-Urban Haven. The Rotterdam application shows that neighbourhood livability is not arranged along a single gradient from low to high quality. Instead, it appears as a set of distinct configurations. Community-led regimes show the highest average Smiley Index, followed by eco-led regimes. Vibrancy-led regimes show the lowest average Smiley value. This finding is important because it questions the assumption that cultural or commercial vibrancy automatically creates neighbourhood happiness. In Rotterdam, belonging, support, and community attachment appear to matter more for neighbourhood love than vibrancy alone.

The spatial maps confirm that cubic regimes are geographically differentiated and temporally changing. The transition results also show that neighbourhoods are not locked into fixed livability types. They move between integrated, community-led, eco-led, vibrancy-led, and weak/transitional positions. The urban happiness cube should therefore be understood as a dynamic configurational space. It helps identify alternative pathways through which liveable places may be formed. The study also has methodological implications. Instead of estimating another regression model in which happiness is explained by neighbourhood characteristics, the paper treats micro-scenarios as the axes of a configurational system. The Smiley Index is used afterward as an external validation measure. This approach offers a different contribution to urbanometrics: it shifts attention from marginal effects to livability constellations.

For policy purposes, the results suggest that neighbourhood strategies should not rely only on creating lively commercial or cultural hubs. Such interventions may be valuable, but they do not automatically generate neighbourhood love and thus a higher Smiley index. Policies that strengthen belonging, local support, maintenance, community attachment, green comfort, and environmental quality may be more directly connected to residents' perceived happiness of livability. The cubic framework can help urban planners identify contrasting neighbourhood profiles and inform discussion of which planning priorities may be most relevant in different contexts.

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Conflict of interest / authors' input

The authors declare that they have no conflict of interest and assures that the work is the result of their own creation. The division of work on the article was as follows:

- conceptualisation: KK, PN
- methodology: KK, PN, UT
- research organisation: KK, PN, UT
- formal analysis: KK, UT
- writing: KK, PN, UT

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Modelowanie różnorodnych przestrzeni miejskich, przyjaznych do zamieszkania

Zarys treści: Artykuł rozwija podejście konfiguracyjne do modelowania różnorodnych przestrzeni miejskich sprzyjających życiu. Wykorzystuje ono mikroszenariusze, kształtowane przez oparte na preferencjach ludzi mapy jakości życia w dzielnicach, jako analityczne filary ilościowego planowania urbanistycznego. Dobrostan mieszkańców w danym miejscu mierzy się za pomocą wskaźnika szczęścia miejskiego („Smiley”). Analiza ilościowa została przetestowana na przykładzie Rotterdamu w Holandii. W artykule wprowadzono sześcián szczęścia miejskiego wykorzystujący trzy osie percepcji: oaza społeczności, tętniące życiem centrum oraz ekologiczna oaza miejska. Wyniki ilościowe pokazują, że dzielnice Rotterdamu nie są rozmieszczone wzdłuż jednego gradientu jakości życia. Mapy przestrzenne i macierze przejść wskazują, że systemy te charakteryzują się zróżnicowaniem geograficznym i dynamiką czasową.

Słowa kluczowe: jakość życia w mieście, mikroszenariusze, urbanometria, dekompozycja, sześcienny system jakości życia

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Table A1. Objective conditions by Cubic Regime

Regime	Variable	Mean
Integrated high-scenario regime	Housing quality	40.516
Integrated high-scenario regime	Crime/ safety burden	62.605
Integrated high-scenario regime	Highly educated share	0.276
Integrated high-scenario regime	Low-income share	0.527
Integrated high-scenario regime	Average home value	150.635
Integrated high-scenario regime	Owner-occupied homes	0.334
Integrated high-scenario regime	Rental properties	0.647
Integrated high-scenario regime	Distance to school	−0.003
Integrated high-scenario regime	Distance to daycare	0.032
Integrated high-scenario regime	Distance to GP	−0.010
Integrated high-scenario regime	Schools within 3 km	0.078
Integrated high-scenario regime	Trade/catering amenities	−9.713
Integrated high-scenario regime	Business locations	−144.730
Community-led regime	Housing quality	48.957
Community-led regime	Crime/ safety burden	57.829
Community-led regime	Highly educated share	0.357
Community-led regime	Low-income share	0.472
Community-led regime	Average home value	183.809
Community-led regime	Owner-occupied homes	0.344
Community-led regime	Rental properties	0.641
Community-led regime	Distance to school	0.003
Community-led regime	Distance to daycare	−0.040
Community-led regime	Distance to GP	0.005
Community-led regime	Schools within 3 km	−0.569
Community-led regime	Trade/catering amenities	27.819
Community-led regime	Business locations	266.250
Eco-led regime	Housing quality	44.764
Eco-led regime	Crime/ safety burden	66.044
Eco-led regime	Highly educated share	0.294
Eco-led regime	Low-income share	0.509
Eco-led regime	Average home value	165.062
Eco-led regime	Owner-occupied homes	0.369
Eco-led regime	Rental properties	0.623
Eco-led regime	Distance to school	0.002
Eco-led regime	Distance to daycare	−0.038
Eco-led regime	Distance to GP	0.004
Eco-led regime	Schools within 3 km	0.023
Eco-led regime	Trade/catering amenities	5.312
Eco-led regime	Business locations	43.516
Vibrancy-led regime	Housing quality	39.505
Vibrancy-led regime	Crime/ safety burden	54.363
Vibrancy-led regime	Highly educated share	0.262
Vibrancy-led regime	Low-income share	0.558

Regime	Variable	Mean
Vibrancy-led regime	Average home value	147.146
Vibrancy-led regime	Owner-occupied homes	0.336
Vibrancy-led regime	Rental properties	0.640
Vibrancy-led regime	Distance to school	−0.003
Vibrancy-led regime	Distance to daycare	0.070
Vibrancy-led regime	Distance to GP	−0.009
Vibrancy-led regime	Schools within 3 km	0.828
Vibrancy-led regime	Trade/catering amenities	−48.411
Vibrancy-led regime	Business locations	−465.573
Weak or transitional regime	Housing quality	46.078
Weak or transitional regime	Crime/ safety burden	56.382
Weak or transitional regime	Highly educated share	0.302
Weak or transitional regime	Low-income share	0.501
Weak or transitional regime	Average home value	171.886
Weak or transitional regime	Owner-occupied homes	0.336
Weak or transitional regime	Rental properties	0.654
Weak or transitional regime	Distance to school	0.002
Weak or transitional regime	Distance to daycare	−0.033
Weak or transitional regime	Distance to GP	0.010
Weak or transitional regime	Schools within 3 km	−0.247
Weak or transitional regime	Trade/catering amenities	19.810
Weak or transitional regime	Business locations	242.421

Table A2. Threshold sensitivity of cubic regime classification

Threshold specification	High-est-mean regime	Highest mean Smiley	Low-est-mean regime	Lowest mean Smiley	Community-led mean	Vibrancy-led mean	Community – Vibrancy	ANOVA p-value
Above median	Community-led	0.641	Weak/transitional	0.589	0.641	0.601	0.040	0.122
Upper 40%	Community-led	0.664	Vibrancy-led	0.592	0.664	0.592	0.072	0.043
Upper tertile/main	Community-led	0.682	Vibrancy-led	0.585	0.682	0.585	0.097	0.001
Upper 30%	Community-led	0.669	Vibrancy-led	0.593	0.669	0.593	0.076	0.042
Upper quartile	Community-led	0.669	Vibrancy-led	0.596	0.669	0.596	0.073	0.063

Note: Thresholds define the cut-off above which each standardized micro-scenario axis is treated as “high.” The main specification uses the upper-tertile threshold. ANOVA p-values refer to differences in Smiley Index across the five regimes under each threshold.

Table A3. Spatial-context mixed model: estimated marginal Smiley Index by cubic regime

Cubic regime	Estimated marginal mean	SE	Lower CI	Upper CI
Integrated high-scenario regime	0.628	0.012	0.604	0.653
Community-led regime	0.642	0.013	0.617	0.668
Vibrancy-led regime	0.628	0.013	0.602	0.654
Eco-led regime	0.614	0.013	0.588	0.640
Weak or transitional regime	0.614	0.012	0.590	0.639

Note: Estimated marginal means are based on a mixed model with cubic regime membership, year indicators, a spatial lag of neighbouring Smiley values, and neighbourhood random intercepts. The spatial lag uses five-nearest-neighbour weights. The coefficient of the spatial lag is positive and statistically significant.