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Multi-Level Street-Based Analysis of the Urban Fabric: Developments for a Nationwide Taxonomy

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Multiple fabric assessment (MFA) is a computer-aided procedure designed for identifying and characterizing urban fabric types (morphotypes) from a street-based perspective. Nonetheless, the original MFA presents some limitations: it relies on surface-based descriptors, conceived as proxy variables for the pedestrian perspective in urban form analysis, rather than direct sight-based measurements. It also uses building footprint classes as proxies for building types. The spatial statistics on the street network concentrate on patterns of over- and under-represented values, which often results in a limited number of morphotypes. Furthermore, the morphotypes are typically valid only for a specific study area. This article presents the latest methodological advancements in MFA overcoming these four limitations. Its implementation over the eight largest French metropolitan areas successfully distinguishes approximately 20 distinct place-specific morphotypes, which are further aggregated into a comprehensive multi-level nested taxonomy. The new MFA procedure allows a nationwide comparative analysis of contemporary urban forms, laying the groundwork for a comprehensive understanding of morphologically regionalized metropolitan areas. Through detailed algorithmic improvements and nationwide implementation, integrating traditional urban morphology with streetscape analysis, MFA provides insights into the analogies and differences of the urban fabric in contemporary metropolitan areas, enabling interoperability with other domains of urban research.

Keywords: morphotypes; streetscape morphometrics; urban fabric

Introduction

When exploring urban space, city users encounter a diverse array of cityscapes, ranging from vernacular centers and modernist developments to sprawling suburbia and distinct exurbs. These various forms of the urban fabric strongly influence city functionality, human perception, practices, and uses, and they pose unique challenges for urban technological and environmental transitions. The identification and description of the morphological properties of cities are

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central to multiple domains of urban studies, including geography, architecture, urban planning and design, and environmental psychology. Historically, urban morphology focused on the identification and characterization of urban fabric and the morphological regionalization of cities (Oliveira & Yaygın, 2020): a complex task, relying on in-depth but qualitative assessments limited to specific cultural and historical contexts and hindering reproducibility and scalability (Fleischmann et al., 2022).

In recent years, the increasing availability of fine-grained geospatial data and advancements in computational spatial analysis and artificial intelligence (AI) have paved the way for a data-driven approach to urban morphology, referred to as urban morphometrics (e.g., Araldi & Fusco, 2019; Bobkova et al., 2021; Dibble et al., 2019; Fleischmann et al., 2022; Gil et al., 2012; Oliveira & Medeiros, 2016). Urban morphometrics, enriched by constant dialogue with traditional urban morphology frameworks, offers innovative data-driven, computer-aided methods for analyzing urban form and fabric. This approach provides new insights into the internal morphological structure of cities (Araldi & Fusco, 2019; Berghauer Pont, Stavroulaki, Bobkova, et al., 2019; Berghauer Pont, Stavroulaki, & Marcus, 2019; Fleischmann, 2021).

Within this recent stream of research, the Multiple Fabric Assessment (MFA, Araldi & Fusco, 2019) stands out as a computer-aided urban morphometric procedure that integrates a series of analytical techniques for morphological regionalization. MFA encompasses three primary techniques in the following order: (i) morphometric analysis of streetscapes through geoprocessing, (ii) detection of statistically significant network-constrained patterns of streetscape descriptors using local spatial statistics, and (iii) identification of morphological regions via multivariate clustering based on machine learning techniques. MFA is unique in its kind: it distinguishes itself from other urban morphometric procedures due to its street-based perspective, which allows for a multiscale description of the built environment as observed from the public space of the street. This perceptible-based framework facilitates the convergence of urban (typo)morphology traditions with streetscape analysis and, in some respects, with the configurational approach of Space Syntax, within a complementary and coherent analysis of urban form. Importantly, MFA does not overlap with configurational approaches but remains complementary to them. Additionally, the pedestrian-based modeling approach is crucial in light of the renewed interest in the perception, use, and design of public spaces (e.g., walkable cities, post-pandemic cities). MFA is designed to easily interface with other domains of urban studies providing a coherent human-centered multilevel analysis of the urban form (Gehl, 2010). MFA has already been applied to various urban areas across different sociocultural contexts and geographical scales (Erin, Araldi, Fusco, et al., 2024; Fusco & Araldi, 2017a, 2017b; Guyot et al., 2021; Perez et al., 2019), assessing the relationship between urban morphological characteristics and socio-economic factors such as residential satisfaction, sociodemographic distribution, retail spatial organization (Araldi, 2019; Erin & Cubukcu, 2022).

Despite its strengths, MFA has certain limitations that this work aims to address. First, the original MFA relies on surface-based descriptors conceived as proxy variables for the pedestrian perspective in urban form analysis, instead of direct sight-based measurements. Second, the inclusion of building types descriptors are reduced to a segmentation of building footprint surfaces considered as proxies of building types within a given case study, thus overlooking the three-dimensional properties that contribute to the definition of a proper building typology. Third, the ILINCS (Integrated Local Indicators of Network-Constrained Spatial Patterns) spatial statistics method within MFA focuses on detecting patterns of morphological descriptors as over- or under-represented values, overlooking the difference between patterns resulting from

heterogeneous and homogeneous intermediary values, each one corresponding to specific urban morphological characteristics. As a consequence of these limitations, the clustering outcomes of MFA often result in relatively few groups (often between 8 and 12 classes).

A fourth point concerns the possibility of generalizing outcomes. In MFA, like in all morphological analytical procedures relying on clustering, results are typically valid only for the data on which the analysis was performed. When analyzing multiple regions for comparative purposes, it could be tempting to look for a unique optimal clustering solution for all of them. Contrary to this, we see MFA capacity to reflect local specificities, when applied independently to each case study, as an asset more than a limitation. What is needed here is a further phase of the analysis, to obtain generalization by combining MFA results from different case studies.

This article presents the latest advances in the MFA methodology to address these points. The three identified limitations will need the development of: (i) geoprocessing techniques for sight-based direct measures of streetscape, derived from visibility studies; (ii) a more appropriate definition of building types through inductive multivariate analysis of a national building database; (iii) street-network constrained spatial statistic of urban morphometrics, beyond hot-/cold-spot analysis. The generalization of MFA outcomes will need (iv) a new double clustering procedure preserving each region's unique characteristics but resulting in a global taxonomy for multiple study areas. All these developments necessitated efficient, reproducible Python algorithms in a unified environment, replacing proprietary software and enabling nationwide implementation. The improved procedure is tested over the eight largest French metropolitan areas, paving the way for a multiscale comparative analysis of contemporary urban forms in France and beyond. We highlight that the main goal of this methodological article is to present these improvements/developments of MFA and the rationale behind them. As their need was particularly felt in addressing the production of a taxonomy of forms of the urban fabric for France's largest metropolitan areas, and as the improved methodology was indeed applied to the data describing these case studies, we propose a quick overview of how the place-specific morphotypes detected in each case study can be organized in an overarching taxonomy. However, a thorough geographical analysis of the morphological regionalization of France's largest metropolitan areas goes beyond the scope of this article and will be the object of a future thematic article.

The article is organized as follows. Section 2 provides the literature review utilized in this article to address the highlighted limitations. This section is divided into three parts, each focusing on a critical aspect: *visibility*, *urban fabric*, and *spatial patterns* – a threefold literature review essential for understanding the MFA procedure, its limitations, and the proposed new version. Following this, the original MFA procedure is outlined, highlighting its main conceptual and methodological features as well as its limitations. Section 3 presents the three improvements to the MFA procedure, allowing for better results in urban fabric analysis. The new computational solutions are described, and their intermediary outcomes illustrated. Section 4 presents the development and the implementation of the additional procedure to generalize MFA outcomes, enabling the transition from place-specific to nationwide morphotypes, organized in nested taxonomies following AI-driven multivariate clustering. The new version of MFA is implemented in the eight largest metropolitan areas of France, resulting in a general nested taxonomy for all of them. Section 5 concludes the article by highlighting issues of results validation, specificities, and potential of the MFA outcomes and perspectives of methodological developments.

Computer-Aided Methods for the analysis of the urban Form: visibility, urban fabric, and spatial patterns

As introduced in the previous section, MFA is a computer-aided procedure for the analysis of the urban form, from the public space perspective, ranging over multiple scales, from the street to the metropolitan area. This work lies at the crossroad between three aspects of urban studies traditionally developed by three specific research domains: the notion of *visibility* from urban design and architecture, the one of *urban fabric* from urban morphology and the one of *patterns* from spatial analysis. Providing a whole comprehensive literature specific to each of these three aspects goes beyond the limits of this article. Instead, this section outlines the main notions underlying these concepts and how they have been differently combined in the broad domain of urban science, and finally, how they converge in the street-level analysis of the urban form proposed by MFA.

Visibility

Vision plays the dominant role among sensory perceptions involved in space experience (Thiel, 1961). The way built-up elements are arranged can modulate city users' experience, not limited to how those elements are perceived but also influencing how people move about and inhabit urban space (Benedikt, 1979; Gehl, 2010). Visibility analysis represents the fundamental step for both understanding public space and developing good urban design (Batty, 2001). Perception of urban space based on visibility is also at the origin of Lynch's notions of legibility and imageability of the city (Lynch, 1960). From these same theoretical premises, Benedikt (1979, expanded from Tandy 1967) developed the "isovist theory." The concept of 2D isovist is defined as the set of all points visible from a given viewpoint in space with respect to an environment. Each point in space can be thus defined by a set of quantitative measures derived from the geometrical properties of its corresponding isovist (ibid.; Batty, 2001). Computational advances of the last decades allowed urban design and architecture to largely explore and expand the theoretical concepts of isovists and convex spaces, with different methodological extensions (i.e., dynamic visibility analysis in Yosifov & Fisher-Gewirtzman, 2024).

Visibility is not only limited to *how far/much can we see* and *how much space is enclosed* but also concerns *what we can see*. Besides the specific stream of research stemming from isovists theory, urban design literature has been also studying the role of further qualities of urban spaces on human perception and consequently on the social functioning of cities. More specifically, the importance of the street-edges and public/private interfaces has remained current in most mainstream urban design theories (Carmona, 2021; Gehl, 2010). Based on these works, urban design has attempted to objectively measure perceptual qualities, rather than simply assert their importance (Ewing & Handy, 2009). While the reinterpretation of urban design qualities in quantitative terms is not always possible, some aspects of urban design are more easily measurable. Ewing et al. (ibid.) propose a systematic approach to operationalize design notions through quantitative measures: five main notions (Imageability, Enclosure, Human scale, Transparency, Complexity) are operationalized through 28 indicators and investigated in relation to walkability. Similarly, other authors operationalized streetscape measures from GIS data sources, to identify objective and theoretically-grounded indicators aiming at quantifying physical descriptors of the streetscape (Araldi & Fusco, 2017, 2019; Harvey et al., 2017; Usui, 2023, 2024a, 2024b; Yosifov & Fisher-Gewirtzman, 2024). In Harvey et al., 2017, streetscape description is divided into *skeletal* and *skin* components. The former is defined as the spatial distribution of volumes of buildings along the street, providing spatial

proportions that may be elemental to perceptions as comfortable urban spaces. Skeletal streetscape descriptors are easily retrievable by vector representation of buildings and street centerlines (i.e., facades set-back, façade frequency, etc.). The latter embellishes the former with visual texture (ibid.). Distinguishing the two components is not always clear nor adapted, especially when considering the public-private interface where both aspects are inherently related and need to be studied conjointly (Dovey & Wood, 2015; Pafka & Dovey, 2017). A more recent stream of research focuses on street-based images proposing a human-centric study of the urban landscape through deep-learning approaches applied to photo-based segmentation (Biljecki & Ito, 2021). Street-level images enable higher precision in the description of more qualitative aspects of the streetscape (i.e., façade colors, tree canopy) and in the quantification of human perception of streets (Seiferling, Naik, Ratti, et al., 2017) yet at the cost of an informative loss about the plastic three-dimensional compositional properties of the visual shed.

Regardless of the specific methodological approach, the implementation of computer-aided procedure enables the production of high volumes of data. Confronted with the challenge of organizing and synthesizing large data sets, researchers often propose the implementation of classificatory systems. Most of the aforementioned works, also propose different approaches of classification/clustering of cityscapes (Thiel, 1961), isovists (Batty, 2001), streetscapes (Harvey et al., 2017), street-level images (Ibrahim et al., 2020). These studies proposed static fine-grained detailed characterization of the urban space, potentially reproducible to large spatial extents (technical limitations of large-extent implementations will be progressively removed by increasing processing power). Other limitations are related to the very hyper-local/ intrinsic description of space overlooking the spatial relationship between urban elements at higher(global) scales (Batty, 2001; Turner & Penn, 1999).

To overcome this limitation, Space Syntax (SSx) proposes to characterize urban forms through descriptors of the topological organization of axial lines defined as the longest visual axis in convex spaces within the network of public space (Hillier, 1996). SSx approach takes as a starting point the relative positions of the parts within the network as a whole, making assumptions about the behavior of the “agents” who use the system (Kropf, 2011), ultimately allowing for understanding the influence of spatial configurations on social life (Oliveira, 2016). The perceptual framework in the analysis of the urban form together with a parsimonious, fast and objective methodological approach, represents the reasons underlying both the success of SSx and its main limitations. Indeed, after a wide development and dissemination in the last 20 years, SSx has more recently been acknowledged by the urban morphology scientific community (ibid.). Nonetheless, SSx focuses on the spatial organization of empty spaces leaving aside key considerations of three dimensional geometry and the composition of the urban fabric (Netto, 2016; Ratti, 2004), which is an essential aspect of the urban morphological approach. Similarly, a rich literature on street network configurational methods has been also proposed (Marshall et al., 2018; Porta et al., 2010) dropping the SSx cognitive framework and focusing more on mobility aspects, but still overlooking the urban fabric.

The urban fabric

Typo-morphology is a specialized field within urban studies that emerged from the need to understand building typologies, the urban fabric and the spatial structure of settlements, with an historical perspective, focusing on their compositional features, that is, how elements are assembled together to produce wholes (Çalışkan et al., 2022). The urban fabric is the finest scale of analysis of urban form, considering the morphological composition of coherent urban

fragments, generally a few blocks or interconnected streets. Below this scale, the analysis of the single building, its internal organization and its relation to its plot, its neighboring buildings and its street belongs more specifically to typological analysis. Although some differences are observed among the traditional analytical school of urban morphology (Moudon, 1997), they all follow several common methodological steps. First, the components of the urban fabric are identified: streets, buildings, and plots. Next, the analyst produces a geometrical description of the components of the urban fabric. The compositional relations of the urban fabric are then analyzed, within each component and among them as well as their evolution over time. Mapping the different forms of the urban fabric which define morphological regions allows for both a comparative analysis of their specific morphological features and for the study of the overall structure of settlements.

Knowledge-based approaches of urban morphology are being superseded by a rising deployment of more sophisticated quantitative computer-aided methods, stimulated by the increasing computing power, and the availability of spatially fine-grained data. As observed for urban design, computer-aided procedures in urban morphology also rely on the use of classificatory algorithms (Fleischmann et al., 2022). A wide variety of urban form classification/clustering methods have been developed considering different urban form elements locally (i.e., intrinsically) or averaged at different scales: buildings (Araldi, Emsellem, Fusco, et al., 2023; Hecht et al., 2015; Steadman et al., 2000) and building patterns (Hecht et al., 2015; Schirmer & Axhausen, 2016), streets (Boeing, 2019; Gil et al., 2012) and street patterns (Louf & Barthelemy, 2014; Marshall, 2004; Moosavi, 2022), street-blocks (Berghauser Pont & Haupt, 2010) and street-block patterns (Berghauser Pont, Stavroulaki, Bobkova, et al., 2019; Berghauser Pont, Stavroulaki, & Marcus, 2019), neighborhood (Thomas et al., 2012) and settlements (De Bellefon, Combes, Duranton, et al., 2021). While graph-based methods use very few variables (Berghauser Pont & Haupt, 2010; Marshall 2004), the increasing number of descriptors require the use of more sophisticated algorithmic approaches (k-means: Gil et al., 2012; Louf & Barthelemy, 2014; data mining/AI: Hecht et al., 2015). These works come from a large variety of theoretical backgrounds, each one with specific research objectives, going beyond the study of the urban form as defined by the urban morphological discipline. Two main shortcomings can be detected.

Firstly, most of these studies propose classification/clustering of urban elements (or group of elements) based on their intrinsic descriptors providing types of elements. The spatial organization of these elements at higher scales is often reduced to the simple projection in space of the individual descriptors and types. Despite the relevance of these studies for many research goals, they should not be understood as a pertinent description of the urban fabric. Urban morphology defines the urban fabric as an identifiable pattern that is formally similar over multiple places and made up by specific spatial combinations of blocks, streets, and building types (Scheer, 2017). Therefore, the shift from the study of types of urban form elements to types of the urban fabric (morphotypes) and morphological regions requires a methodological switch from local-intrinsic to local-based analysis of the urban morphometrics, where space gains a key role not limited to a cartography task. Although this aspect is recognized in the theoretical and knowledge-based approaches of urban morphology, this is not often the case in quantitative studies.

The second shortcoming relates to the notion of the urban fabric defined by the coexistence of (at least) three elements: streets, buildings, and plots (Moudon, 1997). While some of the aforementioned works include procedures for the analysis of the spatial distribution of built-up forms, they are still focused only on one element at the time, ultimately proposing a piecemeal

vision of the urban morphological system. Identifying and characterizing urban morphotypes requires a common, comprehensive framework of urban morphometrics considering the three constitutive components of the urban fabric and their spatial relationship (Çalışkan et al., 2022; Scheer, 2017).

A third aspect stems from the two mentioned above: the spatial relationship between urban form elements could vary depending on the perspective from which the urban fabric is analyzed. Traditionally, urban morphology adopts the aerial point of view from the urban planning and geographic tradition (Oliveira & Yaygın, 2020). To our knowledge, only MFA propose a street-based, therefore human-centered point of view. Despite the absence of this perceptive approach in traditional urban morphology, the role of the street as an organizing factor of urban form is not overlooked as witnessed, for example, by the concept of “pertinent strip” from the Muratorian morphological tradition. Kropf (2009), too, identifies the street as the possible element to bridge different aspects of urban morphology. The interface between the street and the built-up form is also at the core of computer-based procedures for the analysis of street edges (or parcel face) in Vialard (2013). More recently, the Paris Region Institute proposed a morphological analysis of the Paris region based on a classification of street-based landscapes within a specific spatial partition, defined as the set of parcels facing the same street¹. Still, as previously observed, this work, too, provides an intrinsic classification of one-side-streetscape types, mapped over a region, but its spatial organization remains overlooked.

Spatial patterns

Spatial patterns are essential to inject spatial organization in the analysis of the urban fabric. Landscape analysis and spatial statistics developed several methodological approaches for pattern analysis based on location-based methods (Fotheringham, 1997, 1998). Two location-based methods can be distinguished: smoothing techniques and local spatial statistics, both iteratively applying a mathematical or a statistical process, respectively, over a geographical moving window. Windows are allowed to overlap (McGarigal, Cushman, Ene, et al., 2012). The results of moving window analysis maintain the same spatial units used as input, producing a description of the neighborhood of each spatial unit in regard to a chosen metric (Hagen-Zanker, 2016). Within location-based studies, the definition of the spatial unit, its size, the extent of the window (metrical, topological, etc.) profoundly influences the scale of the result (ibid.). While these approaches have been widely implemented in raster-based analysis of ecological landscapes, they have been adopted only more recently by urban morphology for vector-based descriptions of morphological elements. In urban studies, the moving window is often referred to as *catchment area* (Pafka & Dovey, 2017), *walkable shed* (Hess, 1997), *pedshed* (Thadani, 2010). While some works use Euclidean or topological radius over an administrative/gridded/morphological-based partition, others use street-network-constrained moving windows, reflecting human movement on the street, especially in urban design and transportation studies.

Within urban morphometrics, the use of location-based techniques is even more recent. These works are organized in three steps: (i) choosing a spatial unit, (ii) defining contextual indicators within the moving window, (iii) clustering indicator values to obtain typologies of local environments. For example, in Song and Knaap (2007) several indicators (of physical form and accessibility) are collected within several distances from a set of points; a classification allows for the identification of typologies of location-based neighborhoods. In this work, urban form measures are captured only for a sample of locations, rather than through a moving window applied on all the spatial units of the analysis. In Fleischmann et al. (2022) after producing

morpho-functional descriptors over a building-based complete spatial tessellation, each indicator is discretized over a moving window defined by topological distances. Four contextual indicators are collected as measures of locally smoothed primary descriptors (interquartile mean and range, inter-decile Theil Index and Simpson’s diversity Index). This operation results in a multiplication of the original number of features from N to $4N$ locally smoothed descriptors: despite the richness of the descriptors, their higher numerosity arises questions about the collinearity between variables derived from the same original descriptor and leading to issues of higher complexity, computational time and legibility of the resulting cluster profiles (Arribas-Bel & Fleischmann, 2022). In Berghauer Pont and Marcus (2014) a location-based network-constrained approach to measure and classify built-form context is proposed, also named as *accessible density*: traditional built-up density measures are implemented over a set of parcels selected within a network-constrained catchment area. A moving window is also used to smooth street interface measures in Pafka and Dovey (2017).

Spatial smoothing methods present two issues: first, the mathematical function redistributes values within neighboring units erasing intrinsic specificities corresponding to, for instance, urban barriers or punctual/linear structures within the urban fabric. Second, the resulting smoothed morphometric pattern might result from a random process, therefore corresponding to a spurious pattern, instead of a significant one (Xie et al., 2022). The notion of significant pattern in urban morphology is traditionally undertaken by the expert-based work of morphologists, seldom questioned, subjective, and non-reproducible. Smoothing approaches, despite their reproducibility, still do not assess the significance of the observed distribution.

Local spatial statistics, known as Local Indicator of Spatial Association (LISA) and derived as local versions of global indicators of spatial association, represent a methodological solution to overcome these limits. These indicators allow us to verify the connectedness or relationship of values over space, namely spatial autocorrelation (Ord & Getis, 2001). Differently from the smoothing techniques, LISA assess the statistical relationship between the intrinsic value of each spatial unit, and those observed in a close distance (as in the moving window technique) considering the overall statistical distribution over the study space. Moreover, the use of street-network constrained LISA, ILINCS (Yamada & Thill, 2010) has been shown to outperform traditional LISA when studying street-based phenomena such as traffic accidents. The equation for local spatial association is as follows:

$$L_i = \frac{\sum_{j \in N(i)} w_{ij} \cdot S(X_i, X_j)}{D_i \sqrt{\sum_{j \in N(i)} w_{ij}^2}} \quad (1)$$

where: (i) X_i and X_j are the values of the variable X at locations i and j , respectively; (ii) $N(i)$ represents the set of neighboring locations or spatial units around location i ; (iii) w_{ij} is the contiguity matrix on the street network; (iv) $S(X_i, X_j)$ is a function or statistic that compares the values of X at locations i and j : for Moran’s I , $S(X_i, X_j) = (X_i - \underline{X})(X_j - \underline{X})$, where \underline{X} is the mean of X across all locations; (v) D_i is a normalizing factor: for Moran’s I D_i is the standard deviation of X .

Despite the large success of LISA in geographical studies, this approach has been hardly used in urban studies and even less in urban morphometrics. Moran’s I has been implemented in its global version in Tsai (2005) with the goal of quantitatively characterizing the overall urban form of metropolitan cities, while its local version in Torrens (2008) and, more recently, in Serra et al. (2018). Nonetheless, these three works implement Moran’s I statistics on population

distributions. To date, the implementation of LISA in urban morphometrics remains unexplored. The first utilization of ILINCS for street-based urban morphometric descriptors was instrumental in formulating the initial version of the MFA (Araldi & Fusco, 2019; Fusco & Araldi, 2017a, 2017b).

Multiple fabric assessment, the urban fabric from the street perspective

While several authors attempt to translate visual-perception research into architectural and urban design (Morello & Ratti, 2009), Leduc et al. (2011) observed that fewer works have attempted to introduce aspects of pedestrian visually-perceived space into urban morphology. As we discussed, the convergence of visual perception with urban morphology should not be reduced to the mere implementation of isovist/street-level morphometrics descriptors on large urban extents. At the same time, configurational analysis of non-built spaces is no substitute for the morphometric study of the urban fabric from a visual point of view.

MFA took up this challenge, aiming at bridging the tradition of urban fabric analysis by urban morphology with the tradition of the streetscapes perceived by pedestrians walking on the street network (Lynch, 1960; Harvey & Aultman-Hall, 2016). The street is the key element for the analysis of the urban form in its different facets (Kropf, 2009) and the starting point on which spatial analysis procedures are implemented (Araldi & Fusco, 2019; Simons, 2021). The street network is here used both as a set of spatial units and as a spatial constraint, at every step of the procedure.

MFA is a data-driven procedure. Since the goal is to study large urban areas, the use of exhaustive data describing streets, buildings, and plots is of paramount importance. As with most computer-aided morphometric procedures, the basic inputs of MFA are a vector-based database of plots, buildings, and streets, including building heights and specialization (LOD0+ of the CityGML data model in Biljecki et al., 2016). The most developed versions of OSM in many countries provide such a database. A digital terrain model of the study area is a further input of MFA. However, the input data and the resulting morphometric descriptors might also vary depending on the availability of data or the specific goal of the study. MFA has thus been applied without plot data in Erin et al. (2024), while Guyot et al. (2021) added two indicators describing urban vegetation.

MFA, as described in Araldi and Fusco (2019), is a three-step procedure, as follows:

1. *Proximity band and morphometric indicators*: MFA uses morphometric descriptors of the urban fabric as perceived by pedestrians walking on the street. Its basic elements are descriptors of the skeletal streetscapes (Harvey & Aultman-Hall, 2016) in proximity bands around each street segment, the latter being a computational operationalization of Caniggia's pertinent band of the street. MFA uses a limited number of theory-driven morphometric descriptors, describing buildings, plots, street network, site, and the mutual relations among these components of the urban fabric.
2. *Identification of patterns of urban form*: ILINCS are implemented to understand whether the spatial distribution of the values of a given morphometric descriptor produces statistically significant patterns or not, network-constrained local spatial statistics. For each morphometric indicator, the value calculated on each street segment is assessed together with the values of the surrounding streets with a topological lag of three units. High, low, and non-significant patterns of each indicator are thus identified transforming each morphometric descriptor in a set of statistically significant network-constrained spatial patterns. Specific corrections are required when implementing local statistics: symmetrical assumptions and, in the case of

rate variables, homoskedasticity assumptions, are not often met, especially when studying fine-grained descriptor over large urban areas such as morphometric descriptors (Fusco & Araldi, 2017a, 2017b). This spatially explicit method is able to identify patterns of connected streets which are hot and cold spots where local intensities diverge from the underlying distribution. The use of street network-constrained local statistics reflects some important constraints of visible forms: a pedestrian walking within a given urban fragment can easily compare a street segment only to adjacent ones. For each urban morphometric variable, each street segment is associated with a categorical variable corresponding to high, low, and non-significant patterns.

3. *Clustering*: Urban morphotypes are identified through the spatial cooccurrence of morphological patterns over the different descriptors, using unsupervised clustering algorithms. Naïf Bayes Classifier (NBC), an inference method based on conditional probabilities (Duda et al., 2001), was implemented due to two main distinctive qualities. First, Bayesian AI is particularly fit for this task because it allows detecting morphotypes which share a few key characteristics, allowing for some diversity in other less important descriptors (and the key characteristics vary from one morphotype to the other). This aspect represents a profound difference from the aforementioned urban fabric procedures proposed in the literature where clustering algorithms seek homogeneity among all morphometric descriptors. Second, it has the advantage of using the probabilistic framework of Bayesian reasoning, producing probabilities that a morphotype has a specific property, or that a street segment belongs to different morphotypes, given the observed data.

In conclusion, MFA allows the analysis of the urban fabric from the street perspective. Unlike Space Syntax (Hillier, 1996) or Multiple Centrality Assessment (Porta et al., 2010) it is not a configurational analysis of the centrality properties of the elements of the street-network. The concept of the urban fabric lies at the core of MFA and results from a geometrical and compositional description of the built fabric, of the plot fabric, and of the street network, taking into consideration what elements are visible from the street. MFA is thus a distinctly morphological procedure which (paraphrasing Kropf, 2011) considers the local relative values of morphometric properties (streetscapes) of each part (street segment) on the network, relatively to the statistical distribution of the same morphometrics as a whole (see section 3.3), making assumptions about the behavior of the “agents” who visually explore the morphological system thought the network of public spaces (perceptive approach).

Improving MFA: streetscape morphometrics, building types, and geostatistical analysis

The high potential of MFA is accompanied by certain limitations that have emerged from its use. The specific goal of this article is to present the most recent developments of the MFA. In this section, we discuss the limitations of the original MFA outlined in the introduction, providing the rationale for the methodological innovations proposed in this article. The following three subsections address: the development of new pedestrian-based streetscape morphometrics (Section 3.1), the inclusion of the typological nexus between building types and the urban fabric (Section 3.2), and the identification of street-constrained morphological patterns beyond hot- and cold-spot analysis (Section 3.3). The proposed developments aim to overcome these limitations, enabling the new MFA (Fig. 1) to achieve greater precision in extracting morphological content

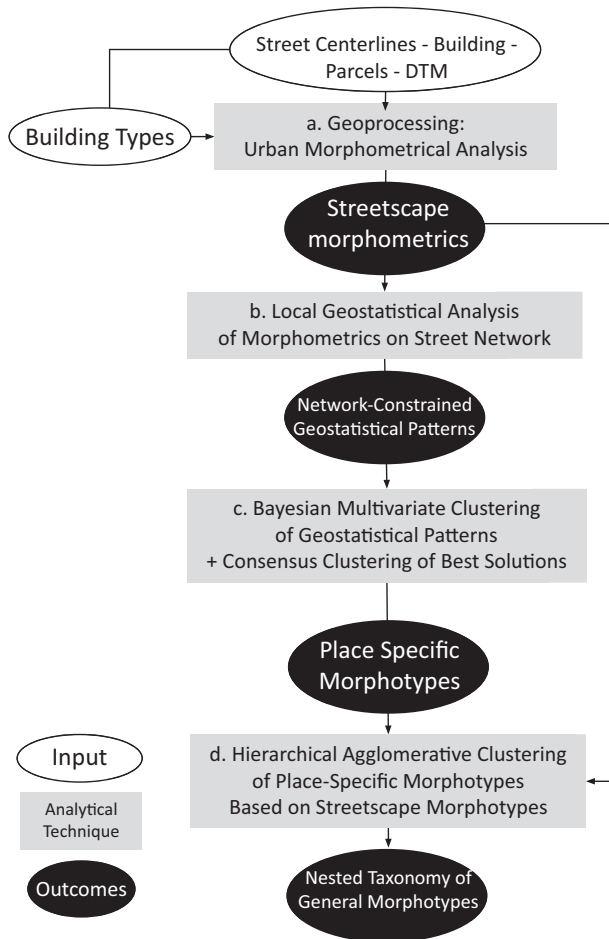


Figure 1. Flowchart of the Multiple Fabric Assessment (MFA) protocol.

from available databases, as well as improved robustness and scalability for analyzing larger study areas.

The new version of MFA was conceived to be applied to each of the 101 departments (administrative divisions) of France. Except for the Paris region, where eight departments must be merged to cover the huge metropolitan area of the capital city, departments are practical and appropriate study areas for urbanization in France. Established since the French Revolution, they were hardly modified over more than two centuries, have comparable spatial extent (between 3 and 10 thousand square km outside of the Paris region) and were defined around a main city that serves as department capital. Some departments roughly correspond to metropolitan areas; others, in more rural regions, contain several small cities that are not connected within a functional area (as defined, for example, by journey to work trips). However, geography of metropolitan and functional areas is evolving considerably over the years (Aguilera, 2005), at a pace which is not comparable to the morphological processes which produced the different observed morphotypes. The whole of France is covered by an official vector database of metric precision (BD TOPO by the National Institute of Geographic and Forest Information, IGN 2020), which is also structured at the department level.

In this article, we will rapidly present the results obtained by the application of the MFA to the eight largest metropolitan areas in France: Paris, Marseille-Aix-en-Provence, Lyon, Lille-Roubaix-Tourcoing, the French Riviera, Bordeaux, Toulouse, and Nantes. A forthcoming article will be devoted to the geographical analysis of French largest metropolitan areas as revealed by MFA.

The skeletal streetscape

The first improvement concerns the definition of new skeletal streetscape morphometrics from the pedestrian point of view. As seen before, proximity bands, street-facing parcels, street edge buffers, and so on, regardless of the specific computational definition, often propose a surface-based method focusing on a subspace of the urban fabric surrounding streets (or, more specifically, public space edges). Measures of densities, ratios, and counts are implemented over these subspaces, sometimes considered as *artificial* (Pizzo Diniz et al., 2023) and often interpreted as proxy variables of visible elements for city users, although no visual-based approach is used to determine what can actually be seen. To overcome these critical aspects and inspired by the ray casting/tracing approach from visual analysis studies we developed a computational approach providing point-based measures of the skeletal streetscape.

First, a uniform distribution of Sight Points SPs is placed along each street segment S . The number of SPs , proportional to the street Length L , is defined by the interspace I , chosen by the analyst (in this work, 3 m). As in Harvey et al. (2017), a junction offset JO is used to separate SPs from street junctions. The number of SPs of a given street nSP and their observed interspace I are thus defined as follows: $nSP = \text{int}[(L - 2 * JO)/I] + 1$; $i = (L - 2 * JO)/nSP$. The whole street network (minus the JO) is then covered by a uniform distribution of SPs at a distance of approximately I .

Second, for each SP four sightlines SL (rays) are drawn: two perpendicular (left and right, SL_{lr}) and two tangent lines (front and back, SL_{fb}) to the street centerline, limited at 50 and 300 m, respectively (Fig. 2). The four SLs capture the main view directions of a pedestrian walking along a street. When SPs lay over bends of winding streets, the concave side of the street is enriched by an additional number of SLs to further explore the widening horizon perceptible by pedestrians (orange sightlines in Fig. 2, left). The number of additional SLs for a SP laying on a bending street $nSL'_{SP(lr)}$ is defined as proportional to the bending angle – BA – equal to: $nSL'_{SP} = \text{int}(BA/A)$, where A is the minimum angle for which the enrichment of concave street is needed (in this work 5°). The four SLs (or more, on the concave side of bends) is an extreme reduction of the number of sightlines used in isovist analysis; yet, they allow us to calculate sightlines every few meters (3 m in our application) keeping the essential visual information for the pedestrian walking on the street, and to enhance its computational feasibility over the several thousand km of a metropolitan street network.

Thirdly, SP and SL are then used to capture point-level measures of cross-section of the skeletal streetscape. A first set of perpendicular 50 m- SL_{lr} is then used to study the street-building relationship. For each SL the following measures are collected: (i) open space os – the distance between the street center-line and, building façades, if present within a 50 m distance; (ii) set back sb – the distance between street edges² and the building façade³; (iii) h – the building height of the first intersected building; (iv) hw – the height-width ratio, obtained as the ratio between the two previous measures; (v) perceived coverage ratio cr – as the ratio of SL intersected by building footprint over the total SL length (50 m); (vi) building identifier $b.id$, (vii) specialized building type prevalence $bt.s$ – the ratio between the SL length intersecting specialized buildings

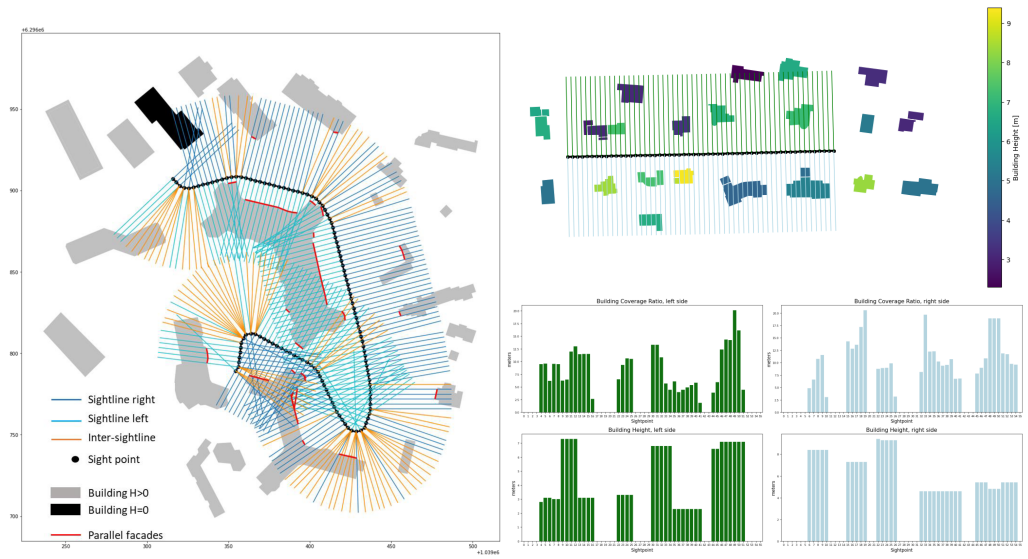


Figure 2. Computational protocol for the skeletal streetscape obtained through left/right sightlines, enriched over street bends (orange sightlines). On the left, identification of the street parallel façades subsegments in red. On the right, sight-point level morphometrics of building coverage ratio (cr) and building height (h) along the street.

and the overall length of the SL crossing built-up surface (viii) $bt.t$ – the ratio between the SL length intersecting each building type t intersected ($n = [0:16]$) (defined in Araldi et al., 2023, see Section 3.2) and the overall length of the SL crossing ordinary built-up surface. A more sophisticated method has been conceived and implemented for the (viii) Parallel Façade measure pf – at the SP level: for each SL we measure the angle between a 3 m segment centered on SP on one side, and, on the other, the segment of building façade within the 3 m distance from the intersection point with the SL (only when a building is intersected within the first 15 m from the street edge). When lower/higher than a certain threshold, the portion of building façade assessed is considered as parallel/non-parallel and a Boolean value is assigned to the SP (Fig. 2, left). A second set of perpendicular SL_{lr} is used to study street-plot relationship. For each SL the following measures are collected: (ix) $p.id$ – the plot ID, when intersected, and (x) pd – the plot depth measured as the distance between the front and back plot face intersected by the SL (defined as the distance between the intersection point of each SL with the plot perimeter). A third set of 300 m- $SL_{f/b}$ tangent to the street centerline at each SP , is used to measure the (xi) sv – street view depth along the street as the street-tangent distance between SP and the first intersected building. To study the relationship between street and site morphology, (xii) the local slope angle sa – is assigned to each SP retrieved from a 1 m-raster DTM (IGN 2020).

Before proceeding to the last step, one further operation is still required: where the SL enrichment has been implemented, measures are summarized in one final metric averaging values observed over the nSL of each SP .

Finally, the SP -level measures (Fig. 2, right), describing local cross-sectional compositional properties of the street every 3 m, are summarized into 28 street-level descriptors of the skeletal streetscape of each junction-to-junction street segment. Street-level Open Space, Set-Back, Building Height, Height-Width Ratio, Coverage Ratio, Building type Prevalence, Specialized

Building type Prevalence, Street View Depth and Street Acclivity are obtained as the average value observed over the SP-level measures along the street segment. Relative⁴ Parallel Façades is implemented as the ratio of sightlines intersecting a parallel facade within the first 15 m from the street edges (*pf*) and the overall number of *SL* intersecting a building footprint. Building and Plot Frequencies are obtained as the number of unique *p/b.id* found along the street, divided by its length.⁵ (Table 1). Five additional measures describing the street geometry and layout are directly defined at the street segment level: street length, tortuosity, and topology of intersections (cul-de-sac, crossroads, bifurcations and star-like junctions, corresponding to degree 1, 4, 3, and 5 or more, respectively, as in Araldi & Fusco, 2019).

The definition of point-based streetscape measures can easily be adapted to different network modeling approaches both in terms of aggregation (named streets, axial streets, etc.) and distances (metrical, topological, angular, etc.) thus opening to further methodological comparative studies considering different models of the network of public space beyond the one used in this article.

The typo-morphological nexus

Before proceeding with identifying street-based morphometric patterns, a second innovative aspect has been introduced in MFA. As remarked by Italian urban morphologists (Caniggia & Maffei, 1979), the typo-morphological nexus must be integrated in any analysis of the urban fabric: building types must be known beforehand in order to understand their contribution to the assemblage of the urban fabric.

From the computational point of view, the typo-morphological nexus results in a first work of identification of building types attributed to each building of the study area and subsequently introduced as input variables in the analysis of the urban fabric. The identification of a building typology prior to the implementation of the MFA has been tested in Perez et al. (2019) and Erin et al. (2024). In these works, the labeled output of a NBC of building types replaces the subset of raw building descriptors within the original MFA.

Following these works, a general building typology from morphometric descriptors of simplified building hulls was produced for the entire stock of ordinary buildings in France by Araldi et al. (2023). A combined Bayesian and Hierarchical Ascendent Clustering approach has been specifically developed and implemented over a limited number of morphometric descriptors of the building hulls (footprint surface, elongation, convexity, number of floors, number of adjoining neighbors, and number of dwellings). Sixteen basic building types (bt.*t*), making up six more general groups, were thus identified among the 28.8 million ordinary buildings (Fig. 3). The remaining 10.5 million specialized buildings were considered as an additional category for MFA, but no specific typology was proposed for them. The resulting building typology can be briefly described as follows.

A first group is made of *compact single-family townhouses* (bt.1) and *very small contiguous buildings* (bt.2) of a few dwellings (up to 8), low-rise (1–2 floors) the former and mid-rise (3–5 floors) the latter, but both with a very small and compact footprint surface (<150 m²).

A second group is made of articulated buildings and mid-sized townhouses, with mid-sized (150–300 m²) and more complex footprints. Within this group, we can distinguish *mid-rise multifamily articulated buildings* (bt.3) characterized by 3–5 floors and accommodating several dwellings; *large articulated townhouses* (bt.4), adjoining buildings of two stories, mainly of one or sometimes a few dwellings; and finally *low articulated single-family townhouses of one story* (bt.5).

Table 1. Skeletal Streetscape Morphometrics

Indicators		Equation	UM	Range
Urban form	SP-level	Street-level		
Street–building relationship	os	OS – open space	(m)	[0:50]
	sb	SB – set back	(m)	[0:50]
	h	H – building height	(m)	[0:+∞)
	hw	HW – height/width ratio	(–)	(0:+∞)
	pf	PF – relative parallel façades (10 m)	%	[0:1]
	cr	CR – coverage ratio (50 m)	%	[0:1]
	b.id	BF – building frequency	(–)	[0:+∞)
Building types	sv	SV – street view depth (bidirectional up to 300 m)	(m)	[0:600]
	bt.t	BT.t – building type <i>t</i> (<i>t</i> = [1:16]) prevalence (50 m)	%	[0:1]
Street–plot relationship	pd	PD – specialised building type (<i>t</i> = [0]) prevalence (50 m)	%	[0:1]
	p.id	PF – plot frequency	(m)	[0:50]
Street–site phology	sa	SA – street acclivity	(–)	[0:+∞)
Street	–	ST – street tortuosity	%	[0:1]
	–	SL – street length	(m)	[0:+∞)
	–	N1 – nodes of degree 1	%	[3:+∞)
	–	N4 – nodes of degree 4	%	[0, 0.5]
	–	N35 – nodes of degree 3 or 5+	%	[0, 0.5, 1]

* *N* represents the number of sightpoints homogeneously distributed over the street segments.

† *edgeA* and *edgeB* correspond to the two edges of each street segment.

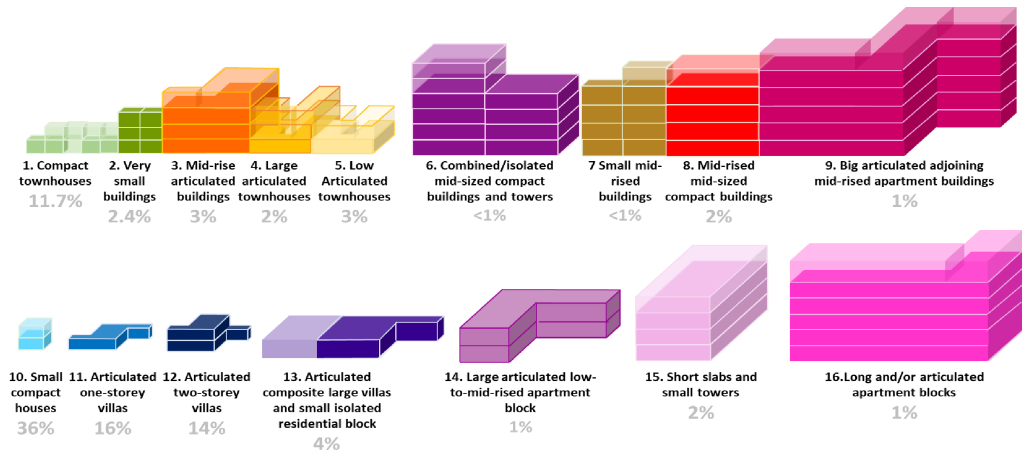


Figure 3. Simplified graphical representation of the general typology of residential buildings in France with their weight in the national building stock.

Source: (Araldi et al., 2023)

A third group of building types gathers three forms of multi-family mid-rise buildings (4–7 floors): *small adjoining mid-rise buildings* (bt.7), characterized by a compact small footprint and several dwellings (2–24); *mid-rise mid-sized compact buildings* (bt.8), characterized by complex and large footprint surfaces (150–600 m²), accommodating a larger number of dwellings (>8) and with a more variable building height, even if always more than 4 floors; finally a specific type of *mid-sized compact buildings* that can be both *isolated or combined* in little groups of 2 or 3 (bt.6).

Big articulated adjoining mid-rise apartment buildings (bt.9) constitute a specific group characterized by very distinctive features: large (surface over 600 m²) and very complex footprint, with few adjoining buildings and with varying building heights, always over 4 stories.

Three types of building made the group of detached single-family houses and villas: *small compact houses* (bt.10) are, indeed, by very compact one-floor or two-floor single-family houses (exceptionally duplexes), with a small footprint surface (75–150 m²); *articulated villas of one and of two stories* (bt.11 and bt.12, respectively), both combine large villas and some semidetached houses with a footprint surface mainly between 150 and 300 m², with more complex shapes than bt.10. These three types are particularly important: over 65% of the French ordinary building stock is associated with bt.10, bt.11, and bt.12, making (semi)detached houses and villas the most common building types in France. A fourth type of *articulated composite large villas and small isolated residential blocks* (bt.13) is also characterized by detached (80%) or semidetached (20%), low-rise buildings with one or a few dwellings, but with a very large footprint (over 300 m²) of very complex shape, with values beyond those observed for the previous three types.

Finally, a group of isolated mid-sized and large collective buildings: *short slabs and low-rise towers* (bt.15) and *long and/or articulated apartment blocks* (bt.16) are both isolated mid-to-high-rise apartment buildings, mainly between 4 and 6 floors with a high number of dwellings. While the former have a smaller footprint (between 300 and 600 m²) with a more compact footprint shape, the latter has a very large footprint (from 600 to over 1200 m²) with a very elongated/articulated shape. *Large articulated low-to-mid-rise apartment blocks*

(bt.14) present large and complex footprint shapes like bt.16, but differ from both bt.15 and bt.16 for their limited number of dwellings (mainly between 2 and 8) and lower height (2–3 floors).

The building types presented here are then used as a categorical variable associated with each building intersected by a sight-line in MFA (resulting in the variables “Prevalence of building type n ” following the sight-line and street-segment averaging, as explained in the previous section 3.1).

Patterns of urban form: Beyond hot- and cold-spots

One of the distinctive aspects of MFA is the implementation of ILINCS (network-constrained Local Moran's I) to explicitly identify statistically significant spatial patterns of urban morphometrics on the street network. Two main considerations further stimulated our research interest. First, local statistical approaches focus on the study of spatial non-stationarity of variables allowing for differentiating pockets of high or low values (also known as hot- and cold-spot analysis) and non-significant zones. However, as observed in Anselin and Li (2019) if a pattern of values is higher than the average, although not considerably higher, they are still classified as hot spots. Moreover, what is categorized as non-significant might encompass subspaces of heterogeneous (combining high and low) values together with subspaces of homogeneous values close to the average of the overall statistical distribution. Second, the statistical distribution of the underlying variable is assumed to be the product of a single generative process. Nonetheless, different urbanization processes (preindustrial, industrial, and present-day metropolitan) have been characterized by different forms of the urban fabric, with more or less important consequences on the spatial patterns of each morphometric variable. What we observe and measure today, corresponds to the overlapping of these different phases with different generative processes. To overcome these two aspects, a specific four-step geostatistical workflow has been developed and implemented for each morphometric indicator.

- i. Empirical Bayesian (EB) correction is implemented to adjust row indicators instability due to the variability of the underlying spatial unit dimension (Anselin et al., 2006; Fusco & Araldi, 2017a, 2017b) (Fig. 4).
- ii. A unidimensional Gaussian Mixture Models (GMMs) segmentation (Duda & Hart, 1973) is then applied to the adjusted variable distribution to identify low, intermediary, and high values. The three-level segmentation is thus transformed into three binary variables (the observed values for a street segment falling within or outside of a given interval of values).
- iii. For each binary variable, local statistics for binary variables are implemented. More specifically we use the Local Join Count Statistics (LJCS), the so-called BB join count (Anselin, 2019; Anselin & Li, 2019). LJCS can be potentially implemented for any discretization of a continuous variable (Anselin, 2019) and it is specifically adapted for empirical contexts where the number of events is small while the size of the data set is large (Anselin & Li, 2019). This approach is particularly appropriate for our distributions of segmented morphological descriptors where a given discretization level is associated to a (sometimes extremely) low number of street segments. LJCS are here implemented considering a street-network topological adjacency matrix (similarly to ILINCS, Yamada & Thill, 2010), with a spatial lag of three (as in the previous version of MFA). Thus, in Equation (1), $S(X_i, X_j)$ represents the local join count of similar measure (observations with value 1) while no normalizing factor D_i is used. The outcomes of the local statistics consist in three variables for each street segment: the local BB join count indicator, a

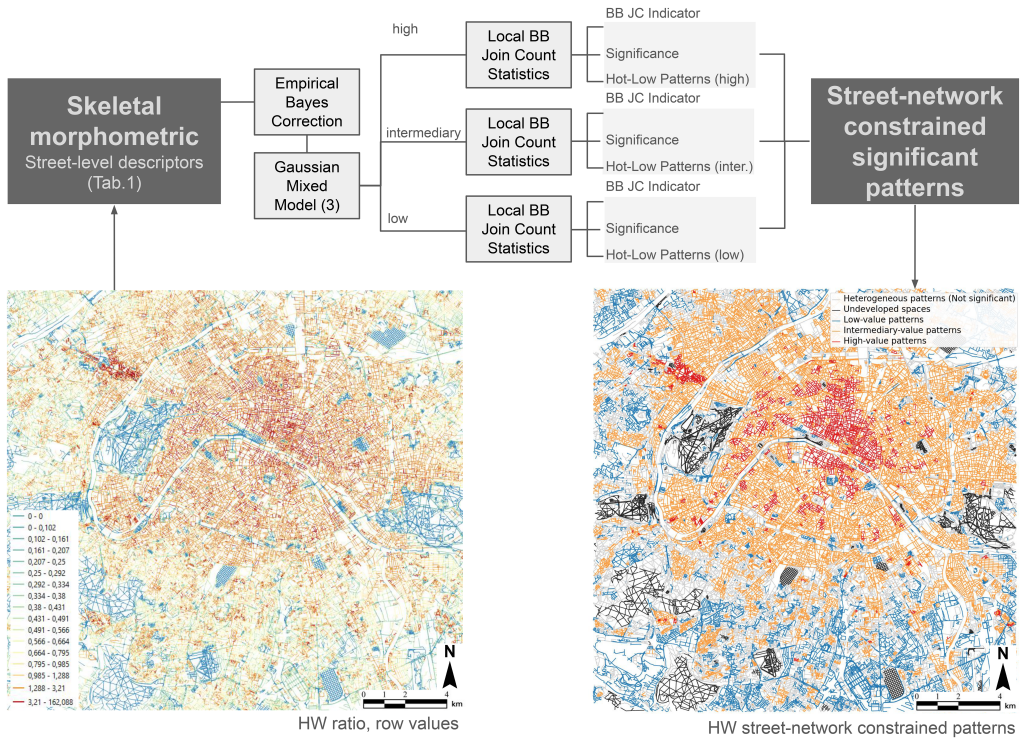


Figure 4. From street-level morphometric description to the identification of significant network-constrained patterns of urban form: implementation of Local Join Count Statistics on three-level GMM segmentation on Building Height/Street Width Ratio in Paris.

pseudo significance p-value resulting from the 999-fold permutation procedure (Monte Carlo randomization process), and a categorical descriptor identifying hot/cold-spot and non-significant values (significance threshold $p = 0.01$) for low, intermediary and high values, respectively.

- iv. Each street segment is finally associated with a pattern of high, intermediate, and low values depending on the hotspot with the highest statistical significance. If equal p values are observed, the highest level is selected (high and intermediate levels might be considered as more informative than intermediate and low levels, respectively). When no significant hotspot is detected, the street segment is categorized as belonging to an heterogeneous pattern.

This four-step geostatistical workflow is implemented at first over the coverage ratio values CR and the specialized building type BTs; patterns of low CR values and patterns of high BTs, correspond mainly to empty spaces and industrial/logistical/commercial zones. They are classified as undeveloped areas and as specialized fabric, respectively. These two patterns are used to further delineate our study area. Filtering undeveloped land from the study area removes extreme values of other morphometrics and allows GMM to identify three non-null intervals. The spatial statistic workflow is then implemented a second time over all the morphometric descriptors (including CR) over the filtered subspace.

This specific geostatistical workflow represents a major conceptual development of MFA. The combination of GMM and LJCS allow us to disengage from the notions of *average value*, of *single generative process* of the urban morphometric descriptors as well as from the assumptions underlying the application of local Moran's I which are hardly met when analyzing the empirical distributions of morphometric descriptors (Fusco & Araldi, 2017a, 2017b). It also enables the discrimination of patterns between heterogeneous and homogeneous distributions of intermediary values, and allows for a clearer delineation of patterns between high and low values. Finally, the geostatistical workflow allows us to move from a continuous descriptor to a discrete contextual variable (whose modes describe statistically robust spatial patterns of homogeneously high, intermediate, low values, and heterogeneous values). We also avoid multiplying *primary* descriptors by using a set of *contextual* sub-variables as in Fleischmann (2021). We can thus reduce the correlation between variables that would affect the subsequent clustering step (Section 4) and keep a manageable number of variables in the clustering interpretation phase. To conclude, local spatial statistical approaches seem a much better option than traditional segmentations of spatially smoothed variables.

A taxonomy of urban fabrics: from place-specific to national morphotypes

Improving the morphometric description of the urban fabric was not the only goal of the new version of MFA. This section presents both the implementation of a combined probabilistic and hierarchical clustering to produce more robust clustering solutions (Section 4.1) and the development of a further step allowing comparative quantitative analysis between different study regions (Section 4.2). Both were necessary to produce a morphological understanding of French metropolitan areas combining place-specific and a nationwide taxonomy of morphotypes.

Place-specific urban fabrics

As previously introduced (Section 2.4), NBC of spatial patterns represents an important step of MFA. The new version of the procedure improved the efficiency of the NBC to produce a larger number of clustering solutions. It also allows for the combination of different best clustering models and produces a nested taxonomic description of morphotypes (like in Fleischmann et al., 2022), not limited to one (sub)optimal clustering solution at a given number of classes.

More specifically, an unsupervised clustering algorithm has been developed combining Bayesian approach, namely Iterative Naive Bayesian Inference Agglomerative Clustering – INBIAC algorithm (expanded from McCaffrey, 2013), with Agglomerative Hierarchical Clustering – AHC. The new IBIAC algorithm and its further combination with AHC is detailed by Araldi et al. (2023) in their research on building types.

After a preliminary phase of seed optimization given a chosen number of clusters k , INBIAC replaces recursive batch inference of cluster assignments for all records (typical of the Expectation–Maximization algorithm normally used in NBC) with an iterative assignment of individual records; it randomly extracts records from the database assigning them to the cluster with highest posterior probability at that given moment of the clustering procedure. This operation changes cluster composition incrementally while updating clustering priors in the process used in the Bayesian calculus. Within INBIAC, the local optimization of log-likelihood in record assignment to clusters produces a global log-likelihood improvement for the whole model. The higher speed of the INBIAC algorithm can be used to perform a higher number of clustering solutions. A limited number of best models is then selected and further combined, as follows.

From the 33 morphological patterns, weighted according to their normalized mutual information, we produce 1100 models for each French metropolitan area (exploring k between 10 and 20 cluster solutions with 100 models each). The best models (in terms of log-likelihood) are selected for each cluster solution. Subsequently, 4 to 6 models are selected in each study area, with a different number of clusters using the elbow method on the log-likelihood of the models. The next step is a combination of these selected best models.

Urban fragments which are always together in the same clusters in these best models become kernels that constitute the starting point of a final hierarchical clustering algorithm (AHC). The latter is performed on a distance matrix between kernels using the Gower dissimilarity measure and centroid-linkage clustering, while weighing each kernel by the number of street segments it represents. This approach shares the same underlying hypothesis of consensus clustering algorithm (Monti, Tamayo, Mesirov, et al., 2003), where several cluster solutions are combined (in our case we use a “controlled” subset of n optimal clustering solutions at different levels k) to achieve a more robust solution. The result is a nested taxonomy – the dendrogram – of morphotypes specific to a given study area. The selection of most informative cuts of the HCA dendrogram are defined by higher gaps between levels. The most detailed of the pertinent cuts defines the sought-for urban morphotypes, that is, typical forms of the urban fabric within a given study area. Higher pertinent informative cuts allow for understanding their nested grouping. Finally, the characterization and interpretation of the urban morphotypes and of their grouping at any given level are based on quantitative data-driven probabilistic profiles produced by the MFA. It should be remarked that in the new MFA, specialized urban fabric is identified at an early stage of the analysis as the space of significant overrepresentation of specialized buildings. As such it constitutes a specific morphotype without going through the INBIAC algorithm and the successive HCA of the best clustering models. Discriminating different specialized fabrics (e.g., industrial areas, business or educational campuses, transportation hubs, etc.) would require more specific specialized building types together with the analysis of the compositional properties of their assemblages with streets and plots.

The new MFA was applied to the eight largest metropolitan areas in France: Paris, Marseille-Aix-en-Provence, Lyon, Lille-Roubaix-Tourcoing, the French Riviera, Bordeaux, Toulouse, and Nantes. The study areas were defined within the department borders of the central city (except for Paris, where the borders of a wider region is considered), by eliminating undeveloped space through geostatistical analysis as explained in Section 3.3.

The new MFA was able to differentiate around 20 morphotypes in each of the eight largest French metropolitan areas. The previous version of the procedure had been applied to the metropolitan areas of the French Riviera (Fusco & Araldi, 2017a, 2017b) and of Marseille (Fusco, Araldi, & Perez, 2021) producing 9 and 8 morphotypes, respectively. The new procedure has thus a higher discriminating power than the old one. In the case of the Paris metropolitan area, the largest of our sample (12 million inhabitants over 12 000 km²), 23 morphotypes could be identified (including specialized space). However, when applied to the city of Paris proper (2.1 million inhabitants over 105 km²), the number of morphotypes was reduced to 14, with finer distinctions being made among compact urban forms but with the loss of many suburban types which are not observable within the homogeneously dense capital city. The application of the old MFA to Marseille, both at the metropolitan scale and for the central municipality, had always produced 8 morphotypes (even if with slight differences among them) suggesting that more than the spatial extent, it is the inner diversity of the study area that limits the number of pertinent morphotypes identified by MFA.

In conclusion, at this stage of the analysis we have produced a set of place-specific morphotypes for each French metropolitan area. MFA is particularly well suited to produce place-specific types because the spatial patterns of the morphometric indicators are calculated with reference to average values which are specific to each study area.

A taxonomy of urban fabrics for French metropolitan areas

The place-specific approach was essential in the geostatistical analysis and in the determination of the local morphotypes. The choice of implementing MFA at the scale of each metropolitan area is based on the underlying hypothesis of the presence of different regionalization factors influencing the built-up forms. Urban fabric analysis should indeed acknowledge and consider the presence of different regional planning traditions, historical, geographical, environmental conditions which lead to a large variety of urban fabrics.

Implementing MFA at the national scale (beyond the technical issues of computational feasibility) would oblige the identification and definition of very general morphotypes, overlooking regional specificities, and making its results less pertinent to the understanding of local morphological regionalization. However, the place-specific results beg the question of their comparative analysis. Thus, a further methodological step has been specifically developed, with the goal of combining MFA outcomes from different study areas in an overarching hierarchical clustering model. To achieve this goal, we need to go back to the values of the original 33 morphometric descriptors in order to lose the reference to the place-specific averages of the geostatistical analysis and consider their morphometric similarity/dissimilarity.

First, the statistical distributions of the morphometric descriptors of each morphotype are discretized over the ranges of the n quantiles (with n varying between 2 and 30) obtained from the cumulative distribution of all the study areas. Not all descriptors are discretized in the same way and with the same number of intervals: indeed, the number and dimension of the intervals depend both on the nature (continuous/categorical) and on the statistical distribution (strong skewness and/or bimodality) of each variable. Thus, specific intervals for each statistical distribution of each morphological descriptor are obtained.

Afterward, a dissimilarity matrix between place-specific morphotypes is calculated through the Gower distance by weighting each interval of each descriptor by the frequency of appearance over the set of all the study areas. This specific matrix of weights offers two main advantages. Firstly, it allows to equally assess all morphometric descriptors (and not proportionally to the number of intervals); regardless of the number of the chosen intervals, each indicator assumes a unit value when calculating the distance matrix between different urban fabrics. Secondly, and more importantly, for each morphometric descriptor, intervals that are relatively rare count less than those which are more frequent in the overall study areas, thus giving more importance to the most representative content of each indicator in terms of nationwide shared characteristics.

Once the dissimilarity matrix is obtained, we apply, here again, an agglomerative hierarchical clustering analysis (AHC) algorithm (using centroid-linkage agglomerative principle among clusters). As for the AHC performed for each study area, we weight each place-specific morphotype by the number of street segments it represents. Next, we identify dendrogram cuts with long branches corresponding to the most stable levels of the aggregations produced by the AHC. Performing this second hierarchical clustering of place-specific morphotypes produces a shared nested taxonomy of general morphotypes for all the eight study areas (and in the future for the whole of France), thus making morphotypes comparable across study areas at larger scales while still preserving the local specificities of the urban form.

Fig. 5 shows the results for the combined AHC on France’s eight largest metropolitan areas. Input for the combined AHC was Gower’s dissimilarity matrix among the 163 place-specific morphotypes: 22 for Paris and Lille, 21 for Nantes and Bordeaux, 20 for Toulouse, 19 for Lyon, Marseille and the French Riviera. As previously explained, an additional morphotype corresponding to specialized space, had already been identified in all study areas and is also extremely similar in terms of morphometric descriptors.

Our hierarchical agglomerative algorithm shows that place-specific morphotypes in French metropolitan areas can be meaningfully grouped in a multi-level nested taxonomy allowing for generalization. Fig. 5 shows several levels of aggregation: from 80 very specific clusters, corresponding to a single place-specific morphotype or to a couple of extremely similar ones, to a very simple yet pertinent distinction of two broad classes: the compact city vs. all other forms of non-compact urbanization. The cut at 36 classes is a particularly relevant compromise between specificity and generalization. Within this article, we will only show how these 36 classes converge into more general groups, without analyzing their specificities.

The first general observation is that the forms of the compact city are much more place-specific within French urbanization, as they developed from vernacular forms or from early traditions in urban planning from the 18th and 19th centuries. Today they characterize urban cores within metropolitan areas and some early peri-central expansions. Although they make up only for 6.9% of the analyzed street-network length (12.3% of street segments), they account for 22 of the 36 classes. More specifically, 9 classes account for the different forms of the grid-based compact city, with more specific morphotypes characterizing, for example, the more homogenous classical planned forms observable in Lyon and the French Riviera (namely in

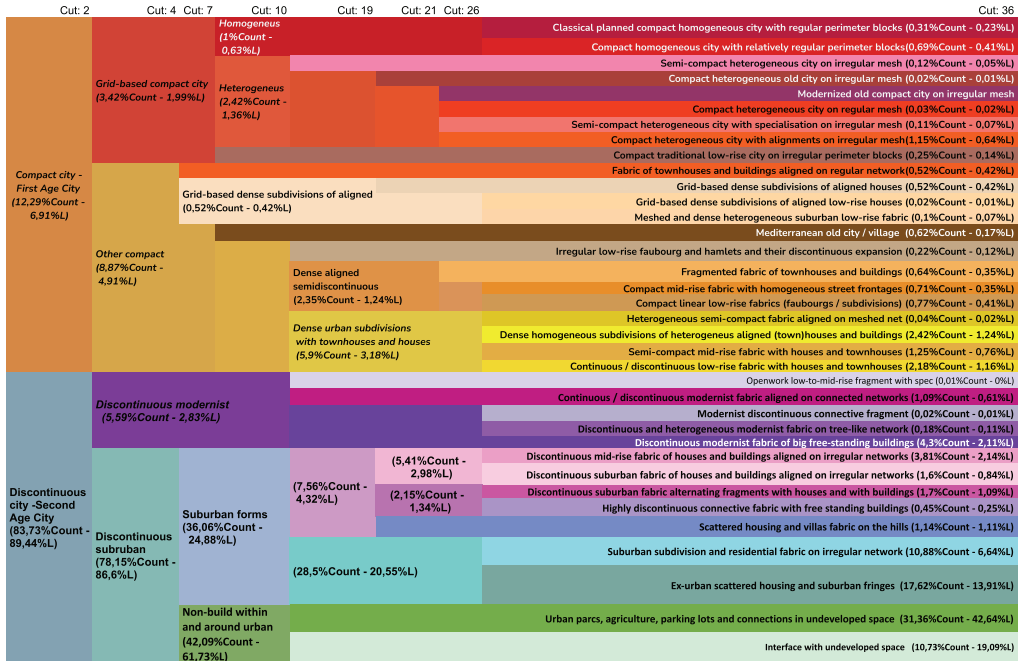


Figure 5. Nested taxonomy of morphotypes in French metropolitan areas at different levels of the dendrogram (Cuts: 2, 4, 5, 7, 10, 19, 21, 26, 36).

Nice), the relatively homogeneous forms of Paris and Marseille, the compact traditional low-rise compact cities of central Bordeaux and Nantes, and more heterogeneous morphotypes observable in all study areas. Thirteen classes account for other forms of the compact or semi-compact city: dense urban subdivisions with or without townhouses, extremely important in northern and western France, compact linear mid-rise structures (like the traditional faubourgs) or more place-specific fragmented ones, but also the highly compact mediterranean old city fabric observable in Marseille and on the French Riviera.

In comparison, the forms of non-compact urbanization are more similar across France, revealing the influence of more nationwide models in later urbanization. They make up most of the peripheral and suburban areas around the urban cores. Several important subgroups can be identified. Discontinuous modern fabrics account for five very peculiar morphotypes that characterize the vast housing projects of the second half of the 20th century. The most typical form of this morphotype exists in almost all metropolitan areas. A more specific morphotype with more continuity of modernist buildings aligned on the street network is particularly relevant in Paris and on the French Riviera.

Suburban forms account for seven morphotypes. The first two regroup very early in the AHC algorithm the different forms of contemporary low-rise suburban subdivisions, whose differences in style are overlooked by our 33 morphometrics, and the different forms of ex-urban scattered housing and suburban fringes. The second is articulated in 5 morphotypes of discontinuous suburban fabrics mixing individual houses and multi-family buildings in different ways. A final aggregate accounts for two morphotypes of non-built-up areas within or around urban and suburban space. This picture is completed by adding the morphotype of specialized space.

Fig. A1 shows the importance of each morphotype within each metropolitan area (left) and the importance of each metropolitan area for each morphotype (right). The latter breakdown is influenced by the larger spatial extent of the Paris metropolitan area (IdF). However, it also confirms that many forms of the compact city are extremely specific to one or two metropolitan areas. Conversely, the same modernist and suburban morphotypes are shared by many metropolitan areas, reflecting the diffusion of the same urban models during the 20th century. Fig. B1 shows how MFA morphotypes can be projected in geographic space (as shown for Paris) to produce a meaningful regionalization of urban space at different scales. This will be the subject of a future article, comparing present-day urbanization in French metropolitan areas.

Discussion and conclusion

This article showed the methodological underpinnings of a new version of MFA, a street-based computational procedure for the identification and characterization of the forms of the urban fabric, applicable to large study areas. The new MFA was able to distinguish around 20 different place-specific morphotypes within each of the eight largest metropolitan areas of France. Embedded within a further phase of agglomerative clustering, the 163 morphotypes could be aggregated within a meaningful multi-level nested taxonomy. The 36-class partition seems particularly relevant, and provides the foundation for a harmonized atlas of urban forms in French cities. However, the specificities of each of the 36 morphotypes, the morphological regionalization that they produce in French metropolitan areas and their contribution to the understanding of contemporary French urbanization will be the object of a future article. The first results presented in this article already point to a more diverse and place-specific morphological

landscape of French compact urbanization, as opposed to more nation-wide forms of modernist and suburban expansion.

In this article, we tried to ensure the internal validity of the clustering through the theoretical coherence and robustness of the results. This includes theory-driven selection of the morphometrics, tests involving Monte Carlo randomization in defining morphological patterns, randomization of seeds, generation of a large number of solutions in optimum clustering search, and the application of consensus clustering approaches. As for the final hierarchical clustering allowing the production of a nested general taxonomy of morphotypes from the 163 place-specific morphotypes, the internal validity could be assessed through the cophenetic correlation coefficient (Haldiki et al., 2001), whose value of 0.742 shows a high correlation between the original Gower distance matrix between the place-specific morphotypes and the distances implied in the nested general taxonomy.

The external validation of the clustering results produced by MFA is a work in progress. A complete external validation for each of the eight series of place-specific morphotypes is impossible to carry out in the absence of recognized “ground truths” for them. However, some of the morphotypes have been produced in very specific historical contexts, allowing for a comparison with historical maps. This is the case for the vernacular forms of the compact city, although the specificities of the local urban history must be considered for fragments that have undergone reconstruction over time. These partial external validations have been carried out on all the case studies.

Fig. 6 shows the MFA results for the sector around the old city center of Marseille. What remains of the medieval city is correctly assigned to the morphotype of the traditional Mediterranean old city, whereas the 18th-century expansion and the 19th-century Haussmannian breakthrough are assigned to the compact homogeneous city structured by perimeter blocks. The port premises are rightly identified as specialized space, and the waterfront of the old port, completely reconstructed after the destruction of WW2, is correctly identified as a mixture of two different types of modernist fabric. For the case of the French Riviera, this kind of external validation has been carried out also for other morphotypes, namely the different modernist forms and those of suburban subdivisions, in good agreement with the available knowledge on the genesis of these different morphotypes (Fusco et al., 2024). More general validations of the place-specific morphotypes of the French Riviera and of the Nord department have been carried out by presenting the morphological regionalization they produce to the local planning agencies in Nice and Lille. Interestingly, the Lille planning agency had carried out a more classical classification of morphotypes based on block morphometrics (ADULM, 2017). In the central areas of the Lille conurbation, the results of the two approaches are relatively consistent, whereas a similar comparison in peripheral and suburban areas is less meaningful, as huge blocks between arterial roads could contain several street-based morphotypes according to MFA.

The interpretability and meaningfulness of the clusters contribute to external validation: clusters should not only be validated in comparison to a “ground truth,” but also be understandable and useful in the real-world context. The results briefly presented in this article are a first proof of the interpretability and meaningfulness of the outcomes of the new MFA. The capacity of these outcomes to produce a meaningful geographical analysis of the urbanization of France’s metropolitan areas will be further proof of their utility. This will be the endeavor of a forthcoming article, although Fusco et al. (2024) already show that this is the case for the French Riviera. Further proof of utility could come from cross-analysis of the identified morphotypes with different human phenomena to which they could be connected. These indirect validations of the

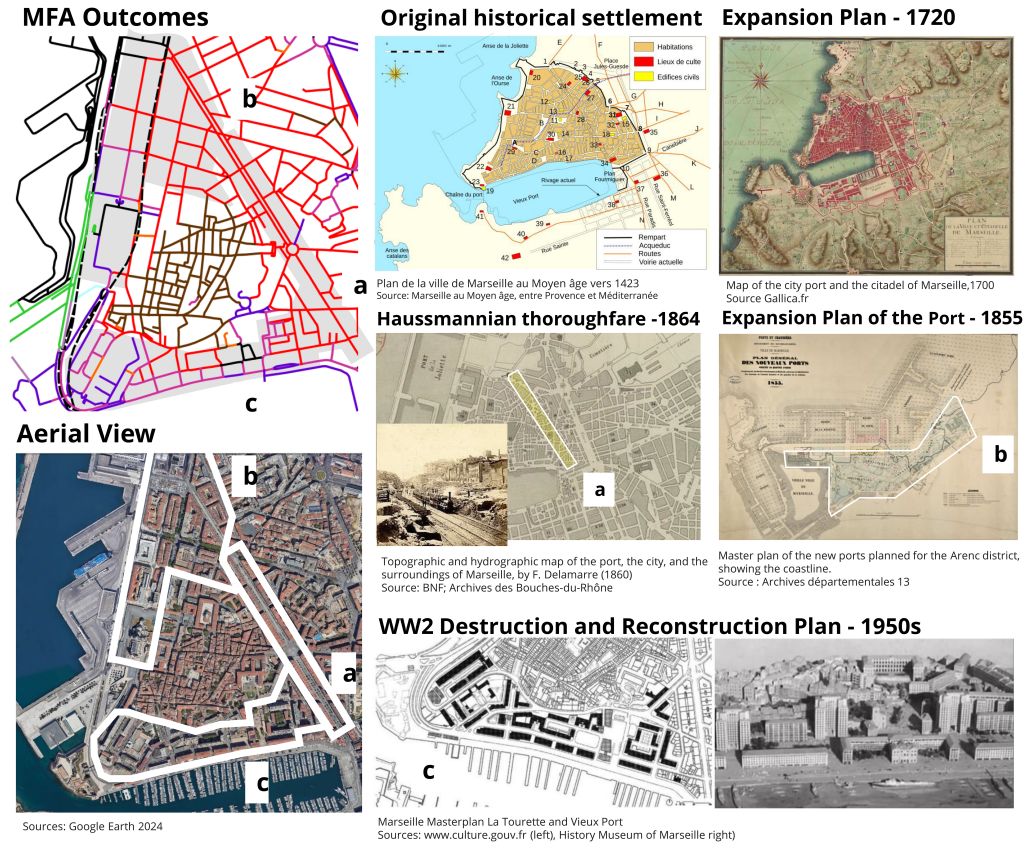


Figure 6. Comparison of MFA morphotypes with historical maps for the old city center of Marseille.

usefulness of identified morphotypes have already been carried out on the outcomes of the old MFA, namely in the analysis of retail activity on the French Riviera (Araldi, 2019) or of residential satisfaction in Izmir (Erin & Cubukcu, 2022), already mentioned in Introduction. Additionally, the results of the new MFA on the French Riviera and in the Aix-Marseille metropolitan area were compared to those of the old MFA, showing overall consistency while further identifying several more specific morphotypes within the more general ones of the previous analyses.

A few methodological specificities of MFA should be highlighted. Unlike other automated morphometric procedures, MFA is street-based, that is, it describes urban forms as they can be perceived by a pedestrian walking on the street. As such, it allows combined analyses with other street-based approaches (i.e., configurational analysis), but does not aim at including them. Both street-based observable forms of the urban fabric and configurational properties of the street network can be relevant factors for urban phenomena (mobility flows, retail, services, crime, residential satisfaction, etc.), whenever these phenomena are linked to perception and usage of the network of public space within a given built environment. It will thus be possible to differentiate the combined role of being on the foreground or on the background street network (in terms of configurational analysis) within a given vernacular compact, modernist high-rise discontinuous or suburban residential openworked fabric.

Another specificity of our method is the geostatistical filtering of non-developed space (natural or rural land) lying clearly outside of urbanized space. This passage is both of methodological and of conceptual importance. Geographical analysis has long strived to delineate the urban agglomeration before characterizing it with urban morphometrics. We acknowledge that present-day urbanization is not just a dichotomy between city and non-city but a more complex assemblage of the agglomerated city, of urban space (which is not agglomerated city proper) and of surrounding rural areas. It is extremely difficult to distinguish *ex ante* what the exact limits of the city are, above all in the presence of forms of sprawled or diffused urbanization. We thus opt for a *via negativa* (Taleb, 2014): it is much easier to rule out in advance what is clearly neither city nor urban space. This is done precisely with the identification of significant hotspots of low values of coverage ratio, which are filtered out of the analysis. Subsequently, MFA application on the remaining space will be able to characterize the different forms of urban, suburban and ex-urban streetscapes, including some rural space with scattered buildings. Careful selection and assemblage of pertinent forms will allow delineating *ex post* the agglomerated city and the larger urban space: delineation comes after characterization.

Beyond improving morphometric descriptors, geostatistical analysis on the street network, and multivariate Bayesian clustering of morphometric patterns, the new method introduces hierarchical clustering at two different phases of the analysis. First, to identify place-specific morphotypes, and later to produce a more general national taxonomy. The object and the purpose of these two applications of hierarchical clustering is distinctly different. The first one is carried out on clustering kernels, that is, on combinations of clustering results of street-constrained spatial patterns of streetscape morphometrics. It integrates the spatial dimension because an urban fabric is by definition an assemblage of connected streetscapes sharing common properties. The resulting dendrogram is based on the consensus between different clustering models. The second one is a clustering based on the statistical distribution of the morphometric descriptors within each morphotype; the dendrogram in this case shows the actual similarity between place-specific morphotypes. That is to say, the spatial arrangement of morphotypes is not considered in the resulting taxonomy; but as we are combining characteristics of place-specific morphotypes, we know that these already define patterns in space. At the same time, two morphotypes of two different regions with a very high similarity value, might be differently located within their relative metropolitan context.

Considerable progress has been achieved in this study; still, some limitations remain unexplored and many research possibilities are open. From a theoretical standpoint, further investigation is necessary to delve into the implications of various network/metric modeling approaches, encompassing the utilization of diverse adjacency matrices. Methodologically, while sensitivity analyses have been conducted at the individual step level, comprehensive assessments of the entire procedure's variability hinge upon resolving technical issues relative to the reduction of the computational time costs. Future research endeavors should bring new elements for the external validation of the MFA clustering results, beyond those already presented.

In conclusion, MFA outcomes, spanning from street-point to street-level analyses, including geostatistical patterns and typo-morphological insights, offer a great potential for the study of the urban form within various research perspectives. Whether employed individually or combined, the different steps of analysis provide a rich and nuanced understanding of urban morphology, facilitating multilevel and multiscale investigations, transcending conventional simplistic density-based metrics, and enriching the discourse within the broad domain of urban studies. However, their combination in the MFA procedure, including the hierarchical clustering to produce generalized taxonomies, seems to open the most promising research perspective of a

holistic assessment of contemporary urban forms within national or even continental geographical extents.

Endnotes

- 1 <https://www.institutparisregion.fr/nos-travaux/publications/un-nouvel-outil-danalyse-des-formes-urbaines-pour-mieux-anticiper-le-developpement-des-territoires/>.
- 2 Since the precise street width is not available in the IGN database and it would require further dataset such as lidar. In this work we use a proxy variable for the street width measured as the number of carriageways (from IGN BD Topo) multiplied by a constant factor of 3 m.
- 3 If the intersection with a building exists, otherwise NaN is assigned.
- 4 We specify here relative since the proxy value of the parallel façade is related only to the street length facing building facades, rather than the overall street length (as in Araldi & Fusco, 2019).
- 5 Measures obtained as average along each street edge and along the same street. Although not investigated in this article, several other street-level descriptors can be produced from the point-level measure such as median, skewness, standard and median deviation, and so on.

Appendix A

	% morphotypes in Metropolitan Areas (length)							% Metropolitan Areas in Morphotypes (length)								
	IdF	R	BR	AM	HG	N	G	LA	IdF	R	BR	AM	HG	N	G	LA
Classical planned compact homogeneous city with regular perimeter blocks																
Compact homogeneous city with relatively regular perimeter blocks	1.1	0.1	0.6						80.2	2.7	17.1					
Semi-compact heterogeneous city on irregular mesh				0.8								100				
Compact heterogeneous old city on irregular mesh					0.3								100			
Modernized old compact city on irregular mesh						0.1								100		
Compact heterogeneous city on regular mesh		0.2								100						
Semi-compact heterogeneous city with specialisation on irregular mesh		0.9								100						
Compact heterogeneous city with alignments on irregular mesh	1.9			0.5				0.3	90.0			5.3				4.7
Compact traditional low-rise city on irregular perimeter blocks							0.6	0.5							47.4	52.6
Fabric of townhouses and buildings aligned on regular network			0.1								100					
Grid-based dense subdivisions of aligned houses	1.4								100							
Grid-based dense subdivisions of aligned low-rise houses								0.1								100
Meshed and dense heterogeneous suburban low-rise fabric								0.5								100
Mediterranean old city / village			1.0	0.9							64.0	36.0				
Irregular low-rise faubourg and hamlets and their discontinuous expansion					1.8							100				
Fragmented fabric of townhouses and buildings			0.6			1.7		0.8			20.4				51.6	28.0
Compact mid-rise fabric with homogeneous street frontages		0.9				2.7									80.0	
Compact linear low-rise fabrics (faubourgs / subdivisions)					1.4	1.4	0.4	0.6					31.2	35.5	14.8	18.6
Heterogeneous semi-compact fabric aligned on meshed net	0.1								100							
Dense homogeneous subdivisions of heterogeneous aligned (town)houses and buildings	1.8				0.7	4.6	0.7	1.1	41.7				4.7	36.3	7.3	10.0
Semi-compact mid-rise fabric with houses and townhouses	2.3					0.7			92.0				8.0			
Continuous / discontinuous low-rise fabric with houses and townhouses		1.7	1.6		1.3	4.7	0.5	1.5	11.3	15.0			10.3	42.0	6.1	15.3
Openwork low-to-mid-rise fragment with specialized buildings	0.0								100							
Continuous / discontinuous modernist fabric aligned on connected networks	1.8			0.8					91.3			8.7				
Modernist discontinuous connective fragment		0.2							100							
Discontinuous and heterogeneous modernist fabric on tree-like network	4.2			1.0					94.9			5.1				
Discontinuous modernist fabric of big free-standing buildings	4.2	3.1	2.1		1.5	1.8		0.5	59.5	11.1	11.3		6.5	8.7		2.9
Discontinuous mid-rise fabric of houses and buildings aligned on irregular networks	6.0		0.6	2.2	0.4			0.8	83.9			3.3	7.0	1.5		4.4
Discontinuous suburban fabric of houses and buildings aligned on irregular networks			2.0	1.3	1.1		2.5	1.4				23.4	9.9	10.9		38.5
Discontinuous suburban fabric alternating fragments with houses and with buildings			4.4	3.7			2.4					44.7	23.6			31.7
Highly discontinuous connective fabric with free standing buildings		1.1				0.7	0.7								30.1	35.7
Scattered housing and villas fabric on the hills				16.0								100				
Suburban subdivision and residential fabric on irregular network	5.1	3.4	6.5	3.8	9.5	3.5	8.3	7.5	25.4	4.2	11.9	4.3	14.0	6.0	19.6	14.7
Ex-urban scattered housing and suburban fringes	12.8	17.6	14.7	1.7	21.6	15.1	12.4	13.4	27.8	9.7	11.9	0.9	14.1	11.3	12.9	11.6
Urban parcs, agriculture, parking lots and connections in undeveloped space	32.5	49.6	44.2	37.7	44.1	47.9	42.3	54.3	23.0	8.9	11.6	6.1	9.3	11.6	14.3	15.3
Interface with undeveloped space	20.0	15.9	21.7	21.7	13.5	11.0	27.1	13.9	31.5	6.4	12.7	7.9	6.4	6.0	20.4	8.7
Specialized fabrics	5.0	5.0	5.4	3.2	3.9	4.1	2.5	3.3	35.4	9.0	14.2	5.3	8.2	10.1	8.4	9.3

Figure A1. Proportions of Morphotypes (Cut: 36) in French metropolitan areas. Paris, Île de France – IdF; Lyon, Rhône – R; Marseille, Bouches du Rhône – BR; Nice, Alpes Maritimes – AM; Bordeaux, Haute Garonne – HG; Lille, Nord – N; Toulouse, Garonne – G; Nantes, Loire Atlantique – LA.

Appendix B

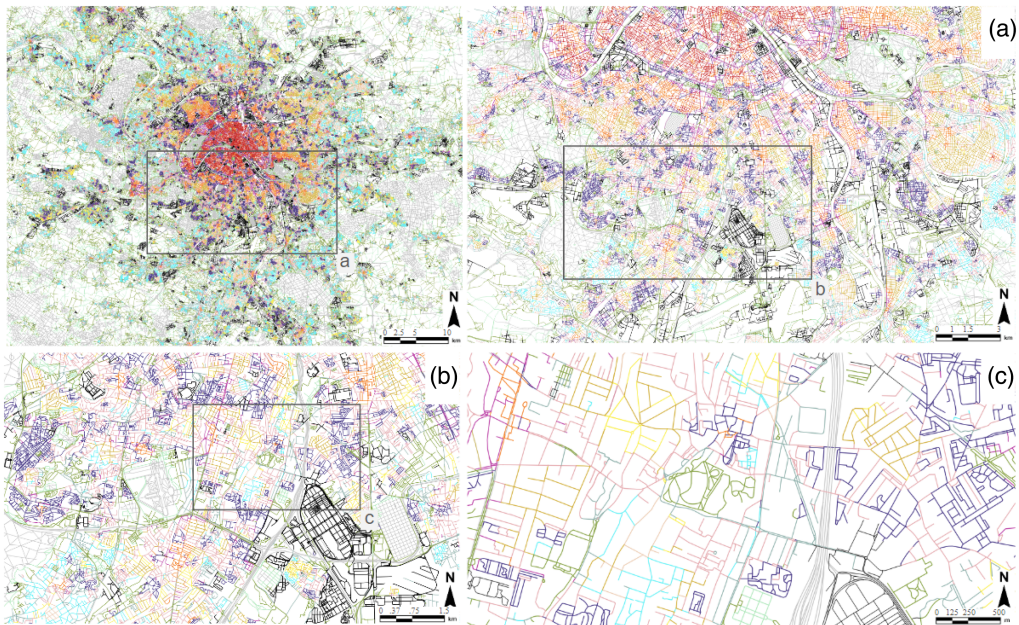


Figure B1. Projection over Paris metropolitan region (visualized at four different resolutions) of the taxonomy of morphotypes in French metropolitan areas (Cut: 36).

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