Identifying Retailscape Transformations: A Methodological Framework for Spatiotemporal Analysis in Urban Environment

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Abstract. Retail is a dynamic, evolving function that reflects or drives shifts in the social and functional dimensions of cities. The transformation of retail in the 19th and 20th centuries has been widely studied, yet the rise of the internet and mobile commerce has introduced new patterns of change in urban retail presence. However, research on retail transformation at the local scale remains limited, particularly due to the lack of microscale datasets with temporal data. This study proposes a geoprocessing protocol to identify and analyze retail functional changes over time in urban environments. Using spatiotemporal point pattern analysis over the street network, the approach provides a robust framework for identifying and describing the nature of shifts in the *retailscape*. We test this methodology to official time-series datasets from some metropolitan areas in France, spanning 2008–2022. Preliminary results demonstrate the protocol's effectiveness in detecting retail transformations in terms of nature, intensity, and spatial distribution across urban areas. This research contributes to a deeper understanding of urban retailscape evolution, offering insights into retail dynamics, urban planning, and the resilience of urban systems in response to changing economic and social contexts.

Keywords: Retailscape · Spatio-Temporal Patterns · Urban Functions

1 Introduction

Retail systems in urban environments are undergoing profound transformations due to management or technological advancements, challenging competitive environments and evolving consumer behaviors. The rise of the internet and mobile commerce (e/m-commerce) has significantly altered how goods and services are distributed and consumed, impacting not only the functional aspects of retail but also its spatial distribution within cities [1–3]. Digital technologies have catalyzed and accelerated shifts in both the morphology and functionality of retail spaces, influencing the layout of retail outlets and their relationship with the surrounding urban environment [4–6]. In particular,

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certain retail functions have expanded, while others—particularly traditionally operated retail—have seen significant reductions. These changes are reshaping the urban landscape, affecting not only retail areas but also the broader service sector, with a shift toward services providing or experiential and leisure-oriented businesses.

While there is a growing body of literature that explores the evolution of retail systems through comparative analysis over time [7–9], two significant gaps remain. First, much of the existing research focused on broad geographic areas or administrative boundaries, such as city-wide or regional analyses. If they were to be carried out on a larger scale, these comparative analyses were generally carried out within the framework of predefined commercial centres, leaving aside the smallest aggregates and dispersed businesses. These studies have highlighted overarching trends, such as the decline of traditional retail and the growth of integrated retail (retail chains) or the growth of certain service functions, depending on the urban context (large, average, small-size cities). However, they fail to account for intraurban variations and the localized transformations [10] that may differ depending on the position of retail outlets within the urban structure. Retail functions within different parts of a city may experience distinct changes depending on the configuration and socio-economic characteristics of the underlying urban space.

Second, many studies that compare temporal shifts do so over extended periods, such as comparing the retail landscape of pre-industrial times with the present or examining changes over spans of 50 years or more [10, 11]. This wide temporal gap often makes it difficult to capture contemporary trends or emerging shifts in the retail landscape, particularly those driven by the rapid growth of digital technologies and e/m-commerce. As a result, there is a lack of research that effectively tracks the fine-grained, ongoing transformations in retail systems at the local scale, which are crucial to understanding how the retail landscape is evolving today.

The literature also highlights a methodological gap in the tools used to measure and analyze these transformations. Traditional approaches to understanding retail change, such as large-scale comparative studies, often overlook the nuances of spatial dynamics and temporal evolution within cities [12, 13]. Specifically, there is limited research focused on the identification of spatiotemporal patterns at the microscale level, which would allow a deeper understanding of how specific retail functions evolve in response to shifting socio-economic conditions [13].

Given these gaps, this study aims to introduce a protocol for the identification and analysis of spatiotemporal retail transformations at the local scale. This methodology will employ spatiotemporal point pattern analysis applied to urban street networks, which allows for the examination of retail patterns with respect to both spatial distribution and temporal dynamics.

The following sections of this paper are organized as follows: the next provides a brief overview of the methodological state of the art for identifying intraurban retail patterns on urban street networks, introducing the temporal dimension as a developing frontier in this field. The third section outlines the objectives of the study. The fourth section presents the methodology, detailing the dataset, study area, and the proposed analytical protocol. In the fifth section, we present the results of the analysis, offering insights into the spatial and temporal transformations of retail functions in a selected metropolitan area in France. Finally, the conclusion reflects on the findings and provides

suggestions for future research and practical applications in urban planning and retail management.

2 From Patterns to Processes: Developing Spatiotemporal Point Pattern Approaches in Retail Geography

The analysis of spatial patterns within cities has long been central to urban studies and retail geography. Since Bryan Berry's pioneering work on the identification of the morpho-functional structure of cities [14], spatial pattern analysis has been used to understand the distribution of retail functions and the urban dynamics that shape them. Berry's work laid the foundation for understanding the relationship between urban space and its functions, but the study of retail location at the micro-scale remained largely neglected throughout the 20th century [15–17]. Instead, research focused primarily on broader national, regional, urban and (large) neighborhood scales. With the increasing availability of fine-grained spatial data on retail activities, the focus has shifted towards more granular, intraurban analyses, enabling researchers to explore retail distribution and transformations at a much more detailed level.

A common approach in early retail geography research was the reliance on administrative boundaries, such as city districts or neighborhoods, for spatial partitioning [18]. These broad boundaries often masked the finer, more complex dynamics of retail activity and urban form. When work is carried out outside administrative boundaries, based on field surveys (which makes it difficult to compile time series, which are easier to obtain from administrative sources), the analysis is generally carried out at the scale of commercial nodes and streets [19–21]. The primary aim of these studies was to characterize the nature and hierarchy of predefined agglomerations or administrative units, rather than to investigate the underlying spatial structures and processes driving their evolution over time.

More recent advancements in retail spatial analysis have moved beyond these traditional approaches, with a growing emphasis on spatial point pattern analysis. This approach focuses on the distribution of retail Points of Interest (POI) at the intraurban level, offering new insights into how retail activities are organized. Since the early 2000s, a variety of point pattern analysis techniques—such as k-means, probability density function [16], kernel density estimation (KDE), random walks, and density-based spatial clustering of applications with noise (DBSCAN) [22, 23], accessibility based [24]—have been applied to explore the spatial distribution of retail activities. These methods have proven effective in identifying spatial clusters of retail activities, each based on different spatial logics and underlying assumptions about proximity, density, or accessibility. However, these approaches often overlook the networked nature of public space—a fundamental dimension for understanding the spatial distribution of urban functions [12, 13]. These methods have proven useful in identifying spatial organization of retail activities in cities. Specific network-based solutions for point pattern analysis have been developed [25, 26] and more recently applied to the study of retail landscapes, enabling the integration of morphofunctional properties of retail agglomerations along the street network [27–30]. However, much of this research continues to rely on static

snapshots of spatial configurations, often overlooking the dynamic temporal processes that drive the evolution of retail landscapes over time.

While studies examining the temporal evolution of retail do exist, they are typically conducted at aggregated administrative levels, neglecting intraurban variation [9, 11]. When fine-scale data is considered, the analyses are often limited to diachronic comparisons between a few distant temporal snapshots, rather than exploring continuous spatiotemporal processes underlying retail agglomeration and transformation.

Meanwhile, spatiotemporal point pattern analysis has advanced considerably in recent decades, especially in disciplines such as epidemiology, ecology, environmental science, and urban studies. Techniques now include non-parametric methods, clustering algorithms, extensions of Ripley's K function, temporal clustering approaches, computational optimizations, and sophisticated statistical models—offering powerful tools for uncovering complex patterns over space and time. Nevertheless, their application to retail geography remains limited. While a limited number of studies have examined spatiotemporal evolution patterns in retail systems at the intraurban scale, these efforts remain relatively underexplored [31, 32]. The scarcity of fine-grained temporal datasets, combined with the inherent heterogeneity and network-based structure of retail systems, presents significant analytical and computational challenges. Additionally, many existing protocols are difficult to calibrate, interpret, or adapt for short time series.

Fine-grained, temporally detailed, and street-network-based studies of retail systems remain rare due to the lack of suitable datasets and the complexity of existing methods. The key challenge is to identify methodological solutions capable of integrating spatial, temporal, and network dimensions into a coherent framework. This paper takes a step in that direction.

3 Objective

While macrogeographic studies provide valuable insights into broad trends, they often overlook the finer, micro-scale dynamics of retail changes—specifically at the level of small retail clusters, streets, and storefronts. This micro-scale is where retail dynamics may directly shape citizens' experiences of urban life, influencing their daily interactions with the city.

The main objective of this paper is to address this gap by focusing on **spatiotemporal transformations of retail functions at the intraurban microgeographic level.**

Detecting Contemporary Spatiotemporal Changes: One of the key goals of this research is to detect contemporary spatiotemporal changes in the urban retail landscape, particularly since the rise of electronic and mobile commerce (e/m-commerce). This period marks a pivotal shift in the way retail functions operate and are distributed across urban environments. By focusing on functional changes—such as the emergence or decline of specific retail categories and shifts in their spatial distribution—this paper aims to provide a refined framework for analyzing urban retail transformations over time at a fine spatial and temporal scale.

Exploring the Spatiotemporal Co-evolution of Retail Functions: Another important objective is to explore the spatiotemporal co-evolution of different retail functions. This

line of investigation aims to understand how various categories of retail activities interact over time within urban spaces, identifying patterns of environmental relationships (synergy, competition, etc.). This will provide a more comprehensive understanding of retail evolution, not just in isolation, but as part of a dynamic and interconnected urban ecosystem.

Considering the Network-Based Structure of Urban Space: Additionally, this paper emphasizes the importance of considering the network-based, structured nature of urban space. Traditional analyses often treat space as continuous, but urban environments in general and retail spaces in particular are inherently constrained by their street networks. These networks shape the distribution and interaction of retail functions, and integrating them into the analysis is crucial for a more accurate representation of retail dynamics [12, 13].

Identifying Meaningful Trends: Lastly, this research introduces a statistical protocol to account for uncertainty in detecting spatiotemporal trends. Many existing studies fail to differentiate between weak, spurious trends and true, meaningful transformations in retail patterns. By incorporating statistical significance tests into the analysis, this paper will enable a more reliable identification of changes and minimize the risk of mistaking short-term fluctuations for long-term shifts.

4 Methodology

4.1 Data

This study relies on two primary datasets to analyze the spatiotemporal patterns of retail activities at the intraurban level. The first dataset is the official register of economic activities provided by INSEE [33], offering a comprehensive record of businesses operating in France. Unlike other datasets used in point pattern analyses of economic activities, this dataset includes temporal information, specifically the dates of opening and closing of retail establishments.

To ensure a robust analysis, the study focuses on metropolitan areas: these spaces present spatial distribution conditions of retail activities enabling a clearer identification of intraurban spatiotemporal patterns. However, some temporal biases must be considered. The official closure date of a business, as recorded in the dataset, may not correspond to its actual closure, as businesses often remain registered for fiscal reasons even after ceasing operations. This may introduce a dissymmetrical time lag of up to one year. Furthermore, although the dataset provides exact closure dates (including day and month), these values are often unreliable, as closures tend to be registered at the end of the fiscal year. To mitigate these inconsistencies, this study aggregates temporal information at the yearly level, considering entire calendar years from January 1st to December 31st.

The study period spans from 2008 to 2022, covering fifteen years. While earlier years could have been included, the starting point of 2008 ensures consistency in functional categorisation, avoiding artificial biases introduced by the restructuring of the NAF[1]

[1] The NAF have equivalence to the NACE (Statistical Classification of Economic Activities in the European Community) system at the European level and are also broadly aligned with the ISIC (International Standard Industrial Classification of All Economic Activities) at the global level.

(*Nomenclautre d'Activités Française*, French industry classification) codes. Moreover, this period is particularly relevant for the study, as it coincides with the diffusion of online and mobile commerce (m-commerce) and the subsequent transformation of retail systems. The economic crisis in 2009 also accelerated certain changes in the behavior of consumers and traders. The dataset is already geolocated, although some spatial biases exist, particularly for liberal/self-employed professions (such as lawyers, medical professions, etc.) where the registered address may not correspond precisely to the store's physical location. However, this bias is significantly less pronounced for brick-and-mortar stores selling goods, which are the focus of this research. The study retains a subset of NAF codes corresponding to retail establishments and reorganizes them into fifty-two categories. Since this paper is primarily methodological, the classification of retail categories is not the focus; rather, the emphasis is placed on the analytical framework. The final dataset includes the geolocation of retail activities, the corresponding NAF codes, and their grouping into functional retail categories.

The second dataset used in this study is the street network retrieved from OpenStreetMap [34]. This dataset provides a detailed representation of the urban public space and serves as the spatial domain through which retail activities are analyzed. Unlike Euclidean-based approaches that measure spatial proximity in straight-line distances, all distance calculations in this study are performed over the street network. This ensures a more realistic representation of accessibility and spatial relationships, as retail activities operate within the constraints of the built environment rather than in an abstract, isotropic space.

The availability of both datasets at the national level makes the entire methodological framework easily applicable to other urban areas across France. Their integration in this study establishes a methodological foundation that enables a fine-grained analysis of spatiotemporal retail dynamics while accounting for the structured nature of urban space.

4.2 Methodological Framework

The methodology developed in this study follows a three-step process to analyze the spatiotemporal evolution of retail functions at the intraurban scale. First, the local composition of retail activities is measured at multiple points uniformly distributed along the street network. For each point, the presence of different retail functions is computed within a given network-based radius for each year from 2008 to 2022, creating a temporally and spatially fine-grained dataset. Second, local statistical tests are applied to identify statistically significant trends in the evolution of each retail function and the overall retail landscape. These tests allow for the detection of increasing, decreasing, stable and non-significant patterns within localized areas over time. Third, the results are synthesized into two complementary visual representations: a radar plot illustrating the co-evolution of individual retail categories in relation to their overall retailscape at the local scale and a spatial map depicting the geographical distribution of identified local trends. This combined approach ensures a comprehensive representation of retail transformations by integrating both statistical trend analysis and spatial visualization, allowing for a nuanced interpretation of functional changes in the urban retail fabric. The entire analytical protocol is implemented in a Python environment, ensuring full

reproducibility and openness. The use of open-source libraries allows for easy adaptation and replication of the methodology across different urban contexts, facilitating further research and practical applications. We now proceed with a detailed explanation of each of these three steps.

Measuring the Local Composition of Retail Functions Along the Street Network. A uniform set of sampling points is distributed along the street network to ensure a consistent spatial resolution and a nuanced description of retail transformations across urban space. At each sampling point, the methodology identifies the presence and distribution of categories of retail functions within a defined local radius Υ , measured along the street network rather than in Euclidean space. In this study, we consider 52 retail categories, but the classification is fully customizable, allowing for the replication of this procedure for any point pattern analysis over the street network. The choice of spatial radii is also user-defined. Here, we employ four distances—75 m, 150 m, 300 m, and 600 m—selected based on established thresholds in retail geography for identifying spatial structures of retail systems (e.g., linear street segments, retail clusters, and neighborhood centers). Additionally, these distances align with pedestrian accessibility measures commonly used in urban studies, particularly within the framework of x-minute distance models for assessing the distribution of retail and services. This alignment ensures that the proposed protocol can be seamlessly integrated into contemporary urban research on accessibility and service provision. This step is executed using the Python library cityseer [35], which offers specialized functions for analyzing the distribution of points of interest (POIs) over a street network at given distances. We employ an unweighted count-based approach, capturing the number of retail establishments by category within each specified radius. This process is repeated for each year from 2008 to 2022, generating a temporal sequence of local retail compositions for every sampled point. The resulting dataset reflects the fine-scale evolution of functional patterns within the urban retail landscape. It is important to note that sampling points along the network that remain beyond the defined radius Υ from any store throughout all years are excluded from further analysis. Consequently, subsequent analyses do not refer to the entire street network but rather to the subgraph within Υ meters of at least one retail establishment at any time during the period under review. This subgraph represents the effective footprint of the urban retail system, within which functional temporal patterns are systematically examined.

Local Test to Detect Significant Trends in the Evolution of Retail Functions. To assess trends in the temporal evolution of retail functions, we apply the Mann-Kendall [36–38] and the Theil-Sen [39, 40] tests. The Mann-Kendall test is a non-parametric statistical method designed to evaluate the presence of monotonic trends over time. This test is particularly suited for analyzing retail distributions, as it does not assume a specific functional form of change and is robust to non-normal distributions. The test is performed independently for each sampling point and for each n-retail function category, as well as for the overall retail presence. The associated p-value allows us to determine whether a detected trend is statistically significant. The Mann-Kendall test presents several advantages in this context. Since it is non-parametric, it does not require assumptions about the underlying data distribution. It is also robust to outliers, making it more stable compared

to polynomial fitting methods, and is straightforward to interpret, providing clear outputs that identify whether a trend is increasing, decreasing, or stable. However, the test also has some limitations. It is inherently insensitive to non-monotonic trends and does not distinguish between linear and non-linear patterns of change. Moreover, its power is limited when applied to short time series, meaning weak trends may remain undetected when the dataset consists of relatively few observations. Although alternative methods such as polynomial fitting, ARIMA models, temporal clustering and time-series decomposition were considered, the relatively short and coarse-grained dataset made these approaches highly sensitive to variations; some of these protocols also require extensive parameter tuning, introducing further complexity in interpretation. A specific methodological choice in this analysis was to not apply pre-whitening procedures to correct for temporal autocorrelation prior to the Mann-Kendall test. While temporal autocorrelation can lead to inflated significance in trend detection, pre-whitening also poses the risk of suppressing true underlying signals, particularly in short series like ours. In the context of neighborhood-level retail patterns—where persistence over time is a meaningful part of the trend itself—autocorrelation may not represent spurious statistical noise but rather reflect real temporal inertia in urban economic processes. Moreover, pre-whitening techniques such as trend-free pre-whitening can reduce the power of the test in short or noisy datasets by overcorrecting for dependencies. Given the exploratory nature of this study, the limited temporal depth of the data and the absence of seasonal effects, the unadjusted Mann-Kendall test offers a transparent and interpretable assessment of retail dynamics. For these reasons, this test was chosen as a more robust and interpretable method, well-suited for both academic research and practical applications. While the Mann-Kendall test is used to assess the presence and significance of monotonic trends, it does not directly quantify their magnitude. For this reason, we complement the Mann-Kendall analysis with the Theil–Sen estimator, a robust, non-parametric method that calculates the median slope of all pairwise combinations in the time series. This allows us to describe not only whether a trend exists (via the Mann-Kendall p-value), but also its strength and direction (via the Theil–Sen slope). Using both indicators provides a clearer and more interpretable characterization of local retail dynamics across space. This step is performed using the Python library pymannkendall [41], which provides robust tools for spatial statistical analysis, including the implementation of the Mann-Kendall and Theil–Sen tests for trend detection. The outcome of this step provides a statistically robust identification of increasing, decreasing, or stable trends in local retail compositions across the retailscape domain defined in the previous section.

This second step already provides an intermediary result, offering a crucial comparison between the overall trends observed at larger spatial scales—such as national, regional, or municipal levels—and those identified at local scales. By applying the Theil–Sen test to the local retail functions, we can not only quantify the significant trends in retail distributions at a fine spatial resolution but also assess how these local trends align or diverge from broader patterns observed in wider areas. The combination of these tests provides a richer, more nuanced picture of retail dynamics, which will be further explored and discussed in the results section.

Identification of Different Natures of Retailscape Transformations in Space. The final step of the analysis involves the integration of the results into a dual graphical representation designed to capture the co-evolution of retail functions across space and

time. The first visualization employs a radar plot, which illustrates the relative trend of each retail function in comparison to the overall retail presence. This approach allows for an intuitive understanding of how individual retail categories evolve in relation to the broader retail landscape. The primary objective of this representation is to assess how the evolution of a specific retail function compares to the overall retail context. To construct this plot, we calculate the Theil–Sen slope (S) for each retail function category k, as well as for the overall retail presence excluding category k. These two slope values, which can be positive or negative, represent the direction and intensity of trends for the retail category k and the rest of the retail composition. The two slopes are then transformed into polar coordinates where the first axis represents the slope for category k, while the second axis represents the slope for the overall retail presence minus category k. The distance from the center of the plot indicates the magnitude of each trend, while the position across the plot reflects the combination of positive and negative trends. For example, when both slopes are negative, they are positioned in the bottom-left quadrant, while positive slopes are positioned in the top-right quadrant. Points closer to the center reflect weak, stable, or non-significant trends, while those farther from the center correspond to more pronounced changes. The position of each point in the radial plot also indicates the nature of the trend, which we categorize into 16 distinct combinations of local retailscape transformations. This process provides an intuitive visual representation of the relationship between the trends in the individual retail category and the overall retail landscape$k$ (Table 1 and Fig. 1).

In addition to the radar plot, a second visualization is produced, providing a geographical representation of the 16 identified combined trends. In this map, the various typologies are differentiated using color coding, while the intensity of each trend is represented by the size of the corresponding points. This spatial map serves to highlight the heterogeneous nature of retail transformations across the urban area, allowing for a clearer visualization of how different regions of the city are experiencing diverse retail trends. Furthermore, the same methodology is applied to pairs of retail function categories, enabling the exploration of co-evolutionary trends. The interpretive logic remains consistent, although the analysis of bivariate trends introduces a layer of complexity (Table 2 and Fig. 2).

In both the univariate and bivariate analyses, the significance value derived from the Mann-Kendall test serves as a filter, enabling the identification of the most statistically robust and relevant patterns. Together, these two groups of visualizations—the radar plot and the spatial map—offer a comprehensive analytical framework that allows for the detailed exploration of the diversity and spatial distribution of functional transformations within the urban retail landscape. This dual approach provides valuable insights into the evolving dynamics of the retailscape at a fine-grained, local scale.

Table 1. Local Spatiotemporal Trends: Retail Categories vs. Overall Retailscape Trends. This table categorizes the growth and decline of a specific retail category (K-category) in relation to the overall retailscape at the local scale. It outlines different spatial dynamics, highlighting how K-category stores perform within the evolving retail environment.

Trend name	Trend of k-retail	Trend of other retail categories	Short explanation
1. Background Growth	Stability	Growth	K-retail stores remain stable while the surrounding retailscape expands, leading to a diminished relative presence in a growing local retailscape.
2. Underperforming Growth	Weaker Growth	Stronger Growth	K-retail stores are increasing in number but at a slower rate than the broader retail sector, resulting in a reduced functional presence in a rapidly expanding local context.
3. Concordant Growth	Growth	Growth	K-retail stores are expanding at a rate similar to their surrounding retail functions, maintaining their relative position within the local retailscape.
4. Outperforming Growth	Stronger Growth	Weaker Growth	K-retail stores are increasing at a higher rate than the broader retail sector, leading to an enhanced functional presence within a slower-growing local retail environment.
5. Exclusive/Dominant Growth	Growth	Stability	K-retail stores are growing while the broader retailscape remains stable, allowing them to gain greater local and functional significance.

(*continued*)

Table 1. (*continued*)

Trend name	Trend of k-retail	Trend of other retail categories	Short explanation
6. Adaptionist Growth	Stronger Growth	Weaker Decline	K-retail stores are expanding despite a broader local retail decline, demonstrating resilience and adaptability to changing conditions.
7. Equilibrium Shift	Growth	Decline	K-retail stores are growing while the broader retail sector contracts, driving a shift in the functional structure of the local retailscape.
8. Defiant Growth	Weaker Growth	Stronger Decline	K-retail stores continue to grow modestly despite a significant contraction in the surrounding retailscape, suggesting a functional shift or substitution.
9. Defiant Stable Presence	Stability	Decline	K-retail stores remain stable while the broader retail sector declines, making their continued presence more pronounced within a contracting environment.
10. Tolerant/Resilient Decline	Weaker Decline	Stronger Decline	K-retail stores are in decline, but at a slower pace than the surrounding retail environment, indicating relative resilience in a broader downturn.
11. Uniform Decline	Decline	Decline	Both K-retail stores and the broader retail sector are contracting at similar rates, reflecting a synchronized local-scale downturn.

(*continued*)

Table 1. (*continued*)

Trend name	Trend of k-retail	Trend of other retail categories	Short explanation
12. Excessive Decline	Stronger Decline	Weaker Decline	K-retail stores are declining more rapidly than the broader retailscape, suggesting heightened vulnerability within this specific retail function.
13. Singular Decline	Decline	Stability	K-retail stores are decreasing in number, while the surrounding retail sector remains steady, pointing to challenges specific to this functional retail category.
14. Divergent Decline	Stronger Decline	Weak Growth	K-retail stores are shrinking while the surrounding retail sector expands slightly, indicating a loss of functional significance.
15. Surrendering Decline	Decline	Growth	K-retail stores are disappearing as the broader retail sector expands, suggesting a transformation in the functional composition of the local retailscape.
16. Lagging Decline	Weaker Decline	Stronger Growth	K-retail stores are declining while the broader retail sector expands more rapidly, highlighting an increasing disparity in local growth dynamics.

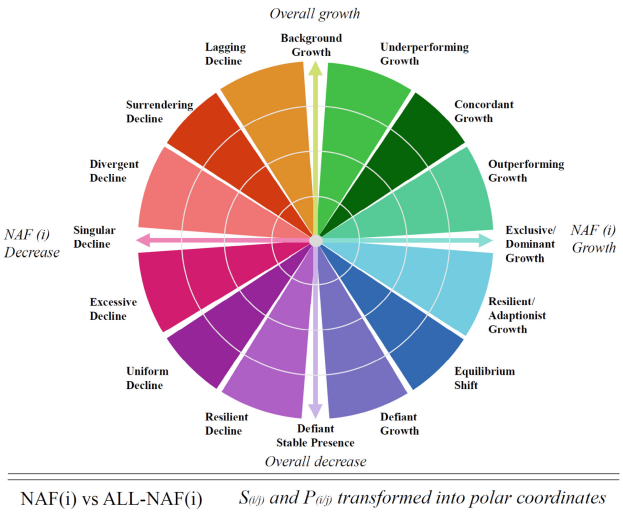

Fig. 1. The compass of retailscape transformation: local spatiotemporal dynamics of K-category retail function within its broader local context.

Table 2. Local Spatiotemporal Trends: Retail Categories Bivariate Trends. This table compares the trends of two different retail categories (A-Retail Categ. and B-Retail Categ.) within the same local retailscape. It describes the possible combinations of growth and decline scenarios, illustrating how one retail category expands or contracts relative to another, shaping the functional composition of the local retail environment.

Trend name	Trend A-Categ.	Trend B-Categ.	Short explanation
1. Stable *A* vs. Growth *B*	Stability	Growth	*A*-Category stores remain stable while *B*-Category stores expand, leading to a shift in the relative balance between the two retail categories.
2. Dominating Growth of *B* over *A*	Weaker Growth	Stronger Growth	*A*-Categ. stores are increasing at a slower pace than *B*-Categ., resulting in a declining relative presence of *A*.

(*continued*)

Table 2. (*continued*)

Trend name	Trend A-Categ.	Trend B-Categ.	Short explanation
3. Concordant Growth	Growth	Growth	*A*-Category and *B*-Category stores are expanding at similar rates, forming a synchronized growth pattern.
4. Dominating growth of *A* over *B*	Stronger Growth	Weaker Growth	*A*-Category stores are expanding faster than *B*-Category stores, indicating a lead in local proliferation.
5. Independent Growth of *A*	Growth	Stability	*A*-Categ. stores are expanding while *B*-Category stores remain unchanged, signaling a localized shift toward *A*
6. Collapsing *B* vs. Emerging *A*	Stronger Growth	Weaker Decline	*A*-Category stores are expanding as *B*-Category stores contract at a slower rate, creating a shift in dominance.
7. Fading *B* vs. Surging *A*	Growth	Decline	*A*-Category stores are expanding while *B*-Category stores shrink, driving a transformation in local spatial organization.
8. Modest Growth of *A*, Sharp Decline of *B*	Weaker Growth	Stronger Decline	*A*-Category stores are still growing slightly as *B*-Category stores decline rapidly, indicating *A*'s resilience amid a contracting of *B*-Category.
9. Independent Decline of *B*	Stability	Decline	*A*-Category stores remain unchanged while *B*-Category stores decline, marking an isolated contraction of *B*.

(*continued*)

Table 2. (*continued*)

Trend name	Trend A-Categ.	Trend B-Categ.	Short explanation
10. Faster Decline of *B* than *A*	Weaker Decline	Stronger Decline	*A*-Category and *B*-Category stores are both declining, but *B*-Categ. is decreasing at a more pronounced pace.
11. Synchronized Contraction	Decline	Decline	Both *A*-Category and *B*-Category stores are declining at similar rates, reflecting a simultaneous contraction
12. Faster Decline of *A* than *B*	Stronger Decline	Weaker Decline	*A*-Category and *B*-Category stores are both in decline, but A-Category stores are contracting at a higher rate.
13. Withdrawing *A* vs. Static *B*	Decline	Stability	*A*-Categ. stores are in decline while B-Categ. stores remain unchanged suggesting isolated contraction of *A*
14. Collapsing *A* vs. Emerging *B*	Stronger Decline	Weak Growth	*A*-Category stores are declining rapidly, while *B*-Category stores are expanding slightly, signaling a dynamic functional shift.
15. Receding *A* vs. Advancing *B*	Decline	Growth	*A*-Category stores are shrinking while *B*-Categ. stores are expanding, indicating a contrasting local dynamic.
16. Fading *A* vs. Surging *B*	Weaker Decline	Stronger Growth	*A*-Category stores are declining slightly, while *B*-Category stores are expanding significantly, showing opposite local trends.

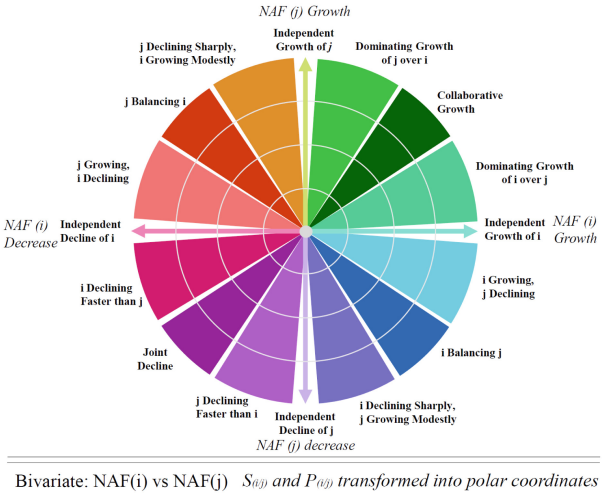

Fig. 2. The compass of retailscape transformation: local bivariate spatiotemporal retail dynamics.

5 Results

The specific description and analysis of the various retail trends identified in this study go beyond the scope and objectives of this paper. The primary aim here is to present a robust and replicable protocol for detecting spatiotemporal patterns of retail transformations along the urban street network. Accordingly, this section presents preliminary findings for two selected retail functions—fast-food outlets and home-related stores—as illustrative examples. These categories have been chosen for their contrasting market dynamics and spatial behaviors, and to highlight the potential of the proposed methodology compared to traditional approaches that rely on administrative units or aggregated regional data.

The following three figures outline key outputs from the application of the protocol to the French Riviera Conurbation. Figure 3 presents the local spatiotemporal patterns of Fast-Food establishments, and for Home-Related Retail, analyzed at 150-meter and 300-meter radii to reflect hyperlocal and neighborhood-scale transformations. Maps and histograms are shown with and without statistical significance filtering, providing a comparative view of general versus robust patterns.

Regarding Fast-Food retail, the overrepresentation of fast-food outlets in certain neighborhoods reflects urban dynamics like income inequality, restructuring, and entrepreneurial opportunities in lower-income areas. This growth is also tied to the rise of take-away and delivery services, which cater to the demand for convenience in high-traffic areas. At both spatial scales (150 m and 300 m), the most dominant pattern is *Outperforming Growth*, which becomes even more pronounced when only statistically significant changes are considered. This trend is especially concentrated in the historic city center and port area, which are major tourist destinations in the Nice urban region, as well as areas around the main train station, universities, hospitals, and key urban facilities. In contrast, the main high street of Nice and its surroundings—as well as luxury

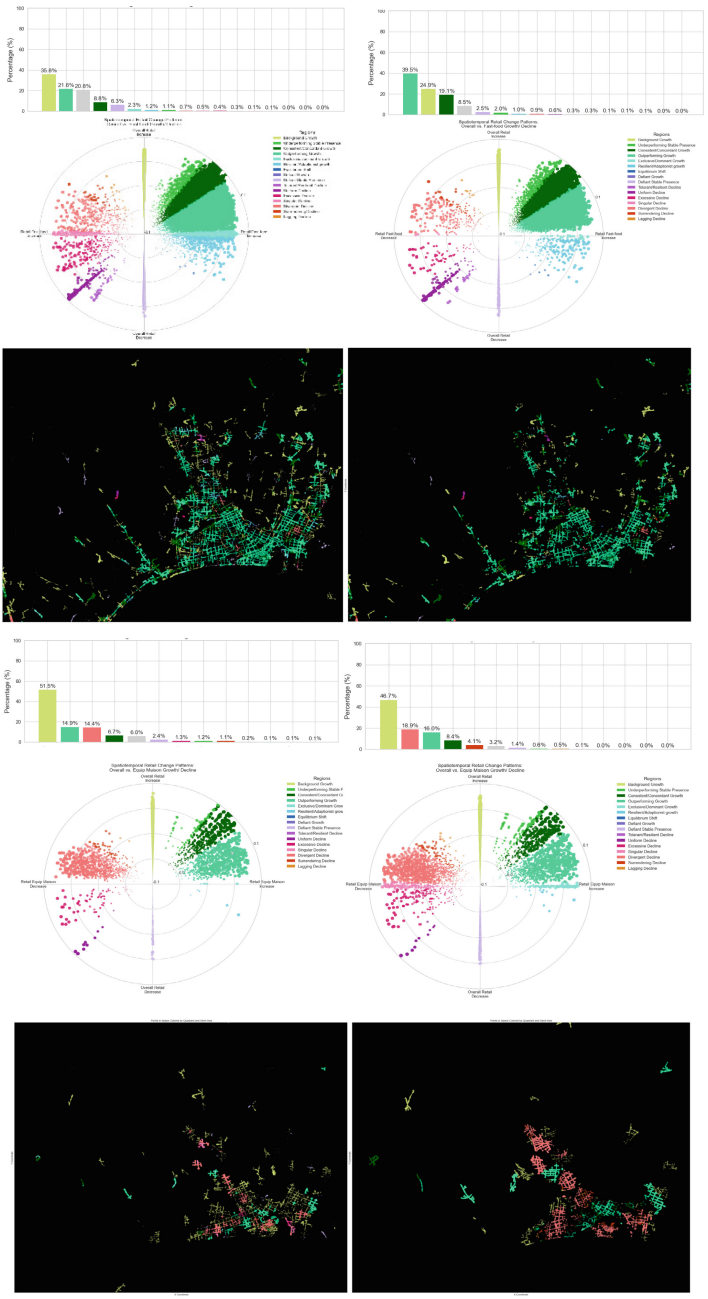

Fig. 3. Top: local spatiotemporal patterns for fast-food (56.101) at 150 radii without (left) and with statistical significance filtering. Bottom: local spatiotemporal patterns for home related (47.59) at different scales: 150 (left) and 300 (right) radius.

and fashion-oriented districts—exhibit little or no presence of fast-food transformation, suggesting either functional resistance due to the local retail specialization or the strong stability of these retailscapes. The second and third most frequent patterns are *Background Growth*, which occurs often at the transitional zones between high-density and residential areas, where fast-food is not the primary driver of growth, and *Concordant Growth*, where fast-food increases proportionally alongside surrounding retail functions. Peripheral zones show a more heterogeneous mix of trends, with pockets of functional contraction suggesting spatial withdrawal or market saturation.

In the case of Home-Related Retail, the dominant trend across both scales is *Stability within a Background Growth*, indicating that this function remains relatively unchanged while surrounding retail areas are expanding. The second and third most common trends are Divergent Decline and Outperforming Growth. These patterns reveal a highly localized and fragmented structure, particularly evident at the 150-meter radius. The alternating nature of these trends suggests micro-level reorganizations, possibly due to shifts in demand, repositioning of commercial spaces, or localized redevelopment efforts. Interestingly, when the analysis scale shifts to 300 meters, these patterns are largely smoothed out. Main commercial axes become less prominent, and a general decline emerges in dense residential areas. This suggests that different retail functions may operate across distinct spatial scales, and transformations may manifest differently depending on their spatiotemporal footprint.

Figure 4 presents local bivariate spatiotemporal patterns at a 150-meter radius for three retail function pairings: Fast-Food vs. Restaurants, Restaurants vs. Clothing, and Clothing vs. Health & Beauty. From the analysis, we observe distinct interactions between retail functions. The main high street and historical city center show a decrease in clothing-oriented stores while restaurants and health & beauty outlets are increasing, reflecting shifts in urban commercial activity, particularly in response to changing consumer preferences and spatial demand. Many streets experience an increase in fast-food outlets without corresponding changes in restaurants or clothing, suggesting the wider spatial impact of fast-food retail relative to these other categories. Health & beauty establishments tend to concentrate in densely residential areas and around suburban centralities, sometimes coupled with a decline in clothing stores. In interpreting these patterns, the size of the points in the maps and histograms can offer insight into the statistical significance of the trends. Many of these observed transformations might appear as stable or non-significant patterns upon closer examination. While the current analysis presents just a few of the most notable pairings, there are many other potential combinations that warrant further research to fully capture the spatiotemporal dynamics and interactions between diverse retail categories.

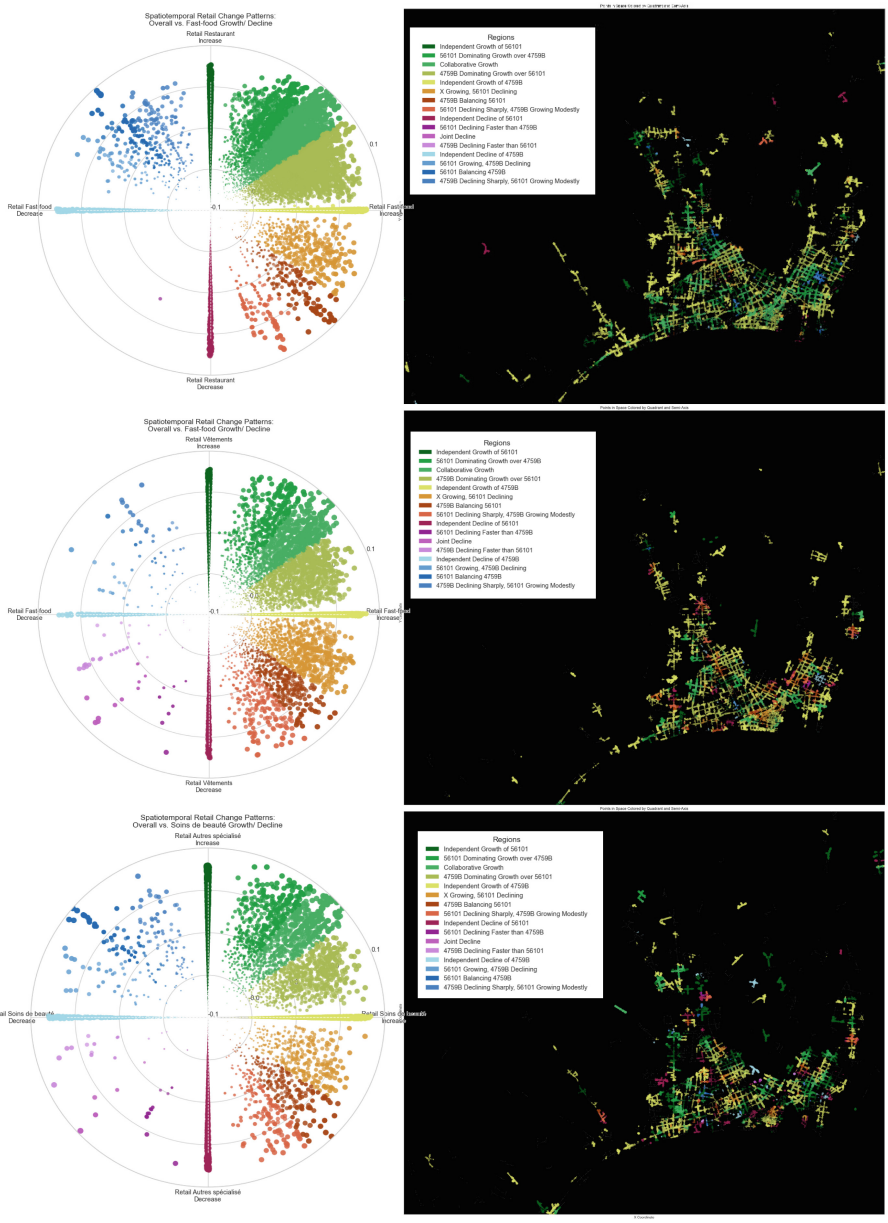

Fig. 4. Local bivariate spatiotemporal patterns at 150 meters for Fast-food vs. Restaurants (upper) Restaurant vs. Clothing (center) Clothing vs. Health&Beauty (lower image).

6 Discussion and Perspectives

This paper presents a methodological protocol designed to detect spatiotemporal patterns of retail transformation at the intraurban level, with a specific focus on functional changes in the retail landscape. The methodology relies on uniform spatial sampling points along the street network and follows a three-step analytical framework to explore changes in retail functions over time.

The first step measures the local composition of retail functions, enabling a fine-grained analysis of how different retail categories evolve across urban locations. This step uses customizable radii and classifications, making the method adaptable to different cities and research contexts. The second step applies the Mann-Kendall test to identify significant trends—whether increasing, decreasing, or stable. Although the test is limited to monotonic trends and may not capture more complex, non-linear changes, it remains a practical and interpretable option suited to the nature of the dataset. The third step synthesizes the results into radar plots and geographic maps, offering both spatial and functional insights into the co-evolution of retail activity across the urban fabric.

A key strength of this approach is that it avoids the use of parametric models or clustering methods. These techniques often require extensive parameter tuning and lack objective validation benchmarks, particularly in urban studies where a definitive "ground truth" is difficult to establish. By bypassing these constraints, the protocol provides a more flexible and transparent way to detect retail patterns.

The protocol also incorporates statistical significance as a threshold for identifying strong trends. At the same time, it retains non-significant patterns, which may reflect weak or emerging changes in retail dynamics. These early indicators can offer important clues about potential shifts that deserve further monitoring, thus enhancing the proactive capacity of the methodology.

Another advantage lies in the high customizability of the approach. Researchers can define parameters such as radii and POI classifications to suit specific urban contexts and analytical goals. This makes the method broadly applicable across different cities and study areas with diverse spatial and temporal configurations.

While the protocol provides a detailed analysis of functional transformations, one ongoing challenge is integrating these results with retailscape morphological changes to better understand retail spatial transitions. Future research could pursue comparative studies across various regions to reveal both generalizable patterns and context-specific dynamics.

Overall, this methodological contribution supports two key directions. First, it could help uncover the spatial conditions—such as accessibility, street network configuration, and sociodemographic factors—that shape retail transformations. Second, it offers a practical decision-support tool for urban planners and policymakers. By identifying intraurban retail trends, the protocol can inform zoning decisions, guide economic development, and improve the adaptability of retail systems to changing consumer behaviors and technological advancements.

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