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Assessing the Landscape of Toolkits, Frameworks, and Authoring Tools for Urban Visual Analytics Systems

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ABSTRACT

Over the past decade, there has been a significant increase in the development of visual analytics systems dedicated to addressing urban issues. These systems distill intricate urban analysis workflows into intuitive, interactive visual representations and interfaces, enabling users to explore, understand, and derive insights from large and complex data, including street-level imagery, street networks, and building geometries. Developing urban visual analytics systems, however, is a challenging endeavor that requires considerable programming expertise and interaction between various multidisciplinary stakeholders. This situation often leads to monolithic and isolated prototypes that are hard to reproduce, combine, or extend. Concurrently, there has been an increase in the availability of general and urban-specific toolkits, frameworks, and authoring tools that are open source and abstract away the need to implement low-level visual analytics functionalities. This paper provides a hierarchical taxonomy of urban visual analytics systems to contextualize how they are usually designed, implemented, and evaluated. We develop this taxonomy across three distinct levels (i.e., dimensions, categories, and tags), juxtaposing visualization with analytics, data, and system dimensions. We then assess the extent to which current open-source toolkits, frameworks, and authoring tools can effectively support the development of components tailored to urban visual analytics, identifying their strengths and limitations in addressing the unique challenges posed by urban data. In doing so, we offer a roadmap that can guide the effective employment of existing resources and chart a pathway for developing and refining future systems.

1. Introduction

In the last decade, the creation of visual analytics systems focused on urban issues has seen a notable surge. These systems simplify intricate urban analysis workflows into intuitive, interactive visual representations, enabling users to explore, understand, and derive insights from large, complex data. Examples of these datasets include street-level imagery, street networks, and building geometries. Developing urban visual analytics systems, however, is a challenging task that necessitates significant programming expertise to handle several critical aspects, such as: (1) visualization to allow for data exploration in urban environments, (2) data management to integrate diverse urban data types and sources, (3) data analytics to highlight patterns and trends, and (4) system performance to ensure interac-

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tive response times. Furthermore, such development requires collaboration between stakeholders from different disciplines, including urban planning, public policy, public health, and climate sciences. The complexity involved and the tendency for these efforts to occur within the framework of one-off collaborations often lead to the creation of monolithic and isolated prototypes that are rarely made publicly available. Such a situation, with a notable lack of emphasis on interoperability as a design requirement, makes it difficult to extend existing systems and integrate discrete components into other tools.

Concurrently, there has been an increase in the availability of general and urban-specific toolkits, frameworks, and authoring tools. While not end-to-end visual analytics systems, they encapsulate visualization and analytics functionalities that facilitate the implementation of these systems (e.g., supporting urban-specific analyses [1, 2] or the creation of map-based visualizations [3]). These toolkits, frameworks, and authoring tools, hereinafter named *construction tools*, vary concerning their expressiveness, accessibility, efficiency, and, therefore, support different applications and users.

While previous studies have reviewed and discussed both areas (urban visual analytics tools [4, 5, 6, 7] and construction tools [8, 9, 10, 11, 12]), none have tried to draw connections between the two. In other words, what the common requirements and features of urban visual analytics systems are, and what construction tools can assist in their implementation. Our goals are then threefold: (1) Gain a more grounded and practical comprehension of typical requirements and features in urban visual analytics systems; (2) Surface functionalities offered by construction tools in light of the previously identified requirements and features; and (3) Identify needs that are not currently covered by existing construction tools, requiring low-level programming efforts by tool developers.

To achieve our goals, in this paper, we first review over 130 relevant urban visual analytics systems to identify their main design needs across 22 categories in four broad dimensions: visualization, analytics, data, and system. We then review visualization and urban-specific construction tools, and discuss how their features match the needs of the systems identified in our work. Finally, we reflect on our findings to identify current shortcomings and directions for future research that we hope will pave the way for new toolkits, tools, and frameworks and help improve the process of designing and implementing urban visual analytics systems.

Our work can be seen from two perspectives. First and foremost, it is a guide for researchers with an in-depth review of urban visual analytics systems. Second, it is a resource for practitioners and tool developers, offering a curated selection of construction tools tailored to streamline the construction of systems. This approach not only aids in bridging recent research and practical gaps but also fosters a synergistic relationship between investigation and application in the urban domain.

2. Background

Urban visual analytics distinguishes itself through several unique aspects rooted in the complex and multifaceted nature

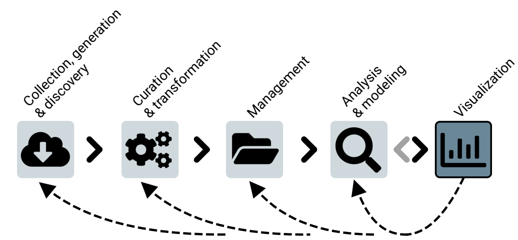


Fig. 1. Typical steps in a workflow for urban data analysis: Collection, generation, & discovery of data; Curation & transformation; Management; Analysis & modeling to derive insights; and Visualization for data exploration and presentation.

of urban environments. First and foremost, urban data is usually large and complex. Datasets such as 311 non-emergency service requests [13, 14] and taxi pickups and drop-offs [15] can contain millions (or even billions) of data points with several attributes. This data size is beyond what is supported by off-the-shelf database systems [9]. Data complexity is also a common characteristic. Typically, urban visual analytics systems leverage various types of data, including mesh data detailing building geometries [16], point cloud data representing diverse built and natural environment features (e.g., sidewalks, benches, trees) [17], imagery data captured at street level [16], and streaming data from sensors [18].

Second, these systems can be tailored to accommodate experts and stakeholders across various domains, each with different levels of data analysis expertise. Consequently, their design may necessitate accounting for varying degrees of data and visualization literacy to facilitate a shared task ecosystem for a heterogeneous user base [19, 20]. For example, an urban accessibility visual analytics system could provide advanced analytical capabilities for urban planners and architects (e.g., the ability to analyze multivariate spatial data) while providing simpler and more direct visualizations and summaries to support decision-making for government officials.

Third, tasks performed by users of these systems might require integrating several data sources at varying spatial resolutions, with different visualization and analytics design choices at each resolution [21]. For instance, an urban planner exploring potential development sites in a city might choose a neighborhood based on aggregated data (e.g., school rating) and then drill down to a particular lot depending on more fine-grained data (e.g., access to public transit stations).

Lastly, urban data analysis workflows might involve several steps to derive insight from data [22]. This iterative process includes the collection, generation, and discovery of data, followed by its curation and transformation, management, analysis, modeling, and visualization (Figure 1). While the goal of a visual analytics system is to distill complex analysis workflows into intuitive, interactive visual representations and interfaces, it must reconcile with the reality that users may already possess components of this workflow. This could manifest through bespoke code (e.g., Python scripts for data cleaning and transformation) or commercially available tools (e.g., ArcGIS Pro for data aggregation). This specificity is particularly salient within the urban domain, given the popularization of data science methodologies for analyzing spatial and urban data. The extent to which an urban visual analytics solution aligns with established practices will decisively influence its sustained adoption and successful integration into existing analytical workflows.

The current landscape of urban visual analytics systems is marked by their intricate complexity. In order to implement them, developers and researchers need to have a deep understanding across several fields within computer science, including visualization, data management, and human-computer interaction. The challenge of replicating and enhancing these systems is magnified by the need to integrate diverse components seamlessly. This often leads to the creation of highly specialized, siloed systems that overlook the importance of interoperability.

In this work, we initiate an examination of urban visual analytics systems, identifying key requirements and features. We explore how existing construction tools can meet these identified needs, aiming to streamline the development process. Our objective is to mitigate the frequent necessity for system developers to *reinvent the wheel*, thereby fostering more efficient and interoperable system development for urban visual analytics.

3. Related works

The literature on urban visual analytics has been the subject of a number of comprehensive reviews. Zheng et al. [4] reviewed over 150 research papers containing contributions to visual analytics in urban computing. Doraiswamy et al. [5] presented a high-level overview of the challenges of urban data. Feng et al. [6] reviewed urban visual analytics contributions, clustering them into four broad groups (descriptive, diagnostic, predictive, and prescriptive analytics). Deng et al. [7] reviewed works along four primary dimensions (domain problem, visualization, integration of visualization, and computational methods). More recently, Miranda et al. [23] surveyed papers with contributions leveraging 3D urban data.

Additionally, other works have reviewed contributions to urban analytics without a focus on visualization dimensions. Yap et al. [11] reviewed the state-of-the-art open-source software in urban planning. Biljecki and Ito [24] reviewed contributions to urban analytics of street-level imagery.

Our work is complementary to the aforementioned surveys and reviews. We focus our efforts on reviewing existing urban visual analytics systems, from which we derive a detailed taxonomy of requirements and features that can be used as a first step towards bridging the gap between bespoke urban visual analytics systems and construction tools. Furthermore, through this comprehensive analysis, we shed light on current gaps and opportunities and provide a curated resource for designing and implementing urban visual analytics systems.

The work presented here is also a comprehensive extension of a previously accepted tutorial at SIBGRAPI 2023 [25]. In the current work, we present a detailed review of urban visual analytics systems and introduce a taxonomy that considers visualization, analytics, data, and system dimensions. Furthermore, we provide a detailed discussion on the availability of construction tools to build urban visual analytics systems.

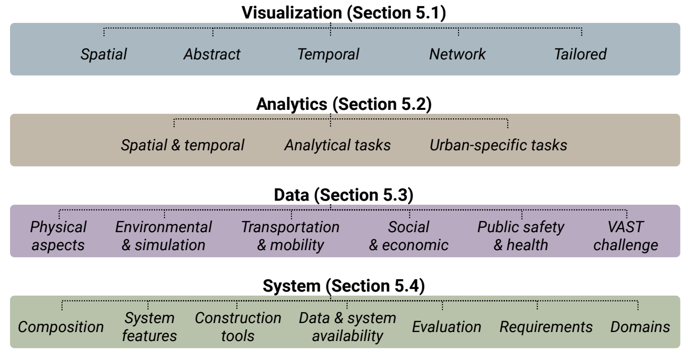


Fig. 2. Overview of the dimensions and categories used in our work. Each category is further broken down into specific fine-grained tags (not shown).

4. Overview

To achieve our goals, this paper is divided in two parts. First, we developed a taxonomy for urban visual analytics systems by examining relevant works to uncover the core requirements and features inherent to this field. This taxonomy is structured around `visualization`, `analytics`, `data`, and `system` dimensions. Within each dimension, we further delineate categories which are then broken down into specific fine-grained tags (see Figure 2). The remainder figures in this paper use a common color scale, with changes in the intensity of colors to indicate different categories. These dimensions and categories were selected to represent important aspects that guide the design of visual analytics systems as well as implementation and usage features. Specifically, using Munzner's analytical framework [26], we analyzed each paper in terms of *What* elements of the urban environment are being visualized (i.e., data dimension); *Why* urban data is being analyzed (i.e., analytics dimension) and *How* urban data is being visualized (i.e., visualization dimension). Additionally, the categories in the system dimension cover practical aspects related to the design, implementation and usage of the tools being proposed. Section 5 describes the categories and tags and their application in classifying each analyzed paper.

In the second part of this paper, we discuss construction tools that can be used to implement the surveyed requirements and features (Section 6). Leveraging our analysis, we delve into the distinctive features of various methods used in implementing urban visualizations. In Section 7, we highlight the principal limitations uncovered through our analysis and pinpoint promising avenues for future development aimed at enhancing the existing construction tools for urban data visualization. Finally, in Section 8, we present the survey's conclusions.

4.1. Methodology

For the selection of the urban visual analytics systems, we have included papers surveyed by Zheng et al. [4], Doraiswamy et al. [5], Feng et al. [6], and Deng et al. [7]. From these surveys, we gathered 78% of the papers used in our work. We supplemented this initial corpus by performing searches on Google Scholar using a set of keywords (visual urban analytics; urban AND visualization; city AND visualization). Table 1 shows the number of papers extracted from each source. Our inclusion

Table 1. Number of papers collected from the sources.

Source	Number of papers
Zheng et al. [4]	13
Doraiswamy et al. [5]	7
Feng et al. [6]	40
Deng et al. [7]	45
Keyword search	30
Total	135

criteria were limited to publications describing urban visual analytics systems, excluding those focused solely on introducing new glyphs or evaluation methodologies. Ultimately, our review encompasses over 130 publications.

For the construction of the taxonomy, we followed a multi-staged approach. First, an initial meeting was held to agree on the main dimensions of urban visual analytics systems that would be considered in our work. After the initial meeting, we agreed on four dimensions: visualization, analytics, data, and system. Subsequently, one co-author went through each one of the papers, extracting relevant fine-grained tags for each dimension. For the tags related to visualization, we considered images and sections related to the visualization interface. For analytics tags, we reviewed the papers' description of system requirements. 55% of the papers explicitly listed all the requirements. For the papers without a list of requirements, the tags were extracted after a careful consideration of the entire text and case studies. We used a similar approach for the data and system tags, focusing on data description and system implementation sections. In a second stage, the co-authors met to finalize the list of tags. Redundant tags were either removed or consolidated into broader ones. Then, one co-author reviewed each paper one more time to ensure that all tags were properly considered.

At the end of the first stage, we obtained more than 190 tags. Some of these tags were too specific, appearing in less than 1% of the reviewed papers. Therefore, we discussed and decided to exclude these tags. At the end of the second stage, after filtering and consolidation of tags, we had over 160 tags. In the third stage, we agreed on a set of intermediate categories to group similar tags. This led to the creation of a hierarchical taxonomy with three levels (dimensions, categories, and tags). Section 5 will discuss the taxonomy in more detail.

For the selection of the construction tools, we included popular visualization toolkits, frameworks, and authoring tools mentioned in previous works. Notably, we considered the following works: McNutt's survey on visualization grammars [12], Mei et al.'s design space of construction tools [8], Qin et al.'s survey on efficient and effective data visualization [9], and Yap et al.'s survey on open-source tools for urban planning [11]. Construction tools were included if they offered features for the construction of urban visual analytics systems. Adopting this criteria, we identified over 30 construction tools.

Limitations. Given urban visual analytics' broad scope, we did not cover all possible venues. Instead, we relied on a mix of previous surveys and keyword searches for our corpus. Additionally, we focused on visual analytics tools proposed in the visualization community – therefore, dashboards and simpler visualization interfaces were not included in our review. While our findings provide valuable contributions and a road map for future research, they should be considered as part of a broader, ongoing discussion about the development and application of urban visual analytics systems.

5. Urban visual analytics dimensions

We reviewed over 130 research works, identifying a spectrum of systems designed to tackle various urban challenges. Some of the systems are devoted to addressing widely-recognized urban issues, offering insights into socioeconomics [27], urban mobility [28, 29, 30], safety [31], noise [32], sunlight access [16], and flooding [33]. Additionally, these systems vary across different spatial scales. Some offer functionalities for building-level analyses [34, 35], while others focus on neighborhood [36] or city-level analyses [37, 16]. Some systems also offer capabilities for multi-scale analyses [38, 21].

Given this broad prospect, we created a hierarchical taxonomy to discern specific traits across this diverse range of systems. At the first level of this hierarchy lies the four dimensions we defined. These dimensions encompass visualization, analytics, data, and system characteristics. The second level of our hierarchical taxonomy introduces 22 different categories, which offer a more nuanced breakdown within each dimension, allowing for a deeper specificity regarding the functionalities of urban visual analytics systems. Figure 2 provides an overview of dimensions and categories. These categories provide an overview through which we can examine the distinct aspects of each system's capabilities. For instance, in the visualization dimension, categories such as spatial and abstract visualizations provide a detailed perspective on the various techniques and methodologies used in the reviewed systems. The final tier of our hierarchy is the tag level, which offers the most fine-grained characterization concerning each system. At this level, over 160 tags were created. These tags serve as detailed descriptors, pinpointing specific attributes or functionalities.

In what follows, we delve into each dimension, exploring the diverse categories within and emphasizing specific tags. Given the extensive number of tags, we will focus our discussion on those that are most frequent, most relevant for discussion, and crucial for understanding the characteristics of the systems. This section is organized as follows: Section 5.1 presents the visualization dimension; Section 5.2 presents the analytics dimension; Section 5.3 presents the data dimension; and Section 5.4 presents the system dimension. To enhance readability, categories, and tags within a dimension are distinctly identified; categories are `marked`, and tags are *underlined*, both utilizing the same dimension color for clarity.

5.1. Visualization

A visualization system must adeptly present information, leveraging well-selected, familiar visual metaphors to ensure the conveyed message is both clear and succinct. The choice of

(a) (b) (c) (d)

Fig. 3. Examples of works with the following tags: (a) 2D map [39], (b) 3D map [40], (c) vector fields [41], and (d) tailored visualizations [42].

visualization techniques is fundamental, requiring a thorough consideration of the data type, the specific analytical tasks the system aims to address, and the intended audience. These considerations are foundational in selecting each scenario's most fitting visualization approach. Beyond merely choosing existing visualization methods, the system should have the flexibility to combine multiple views, offering fresh perspectives on complex urban challenges. Here, we categorize the array of visualization types employed in urban visual analytics, aiming to identify commonly used methods and highlight those adapted for particular types of urban issues.

The visualization dimension has the following categories: spatial, abstract, temporal, hierarchical, and tailored visualizations. We follow Sorger et al.'s [43] definition to differentiate between spatial and abstract visualizations. According to this definition, spatial visualizations map data points to their inherent 2D or 3D spatial coordinates, whereas abstract visualizations lack explicit spatial references or deliberately disregard them. Temporal and hierarchical prioritize time and hierarchical structures, respectively, as their main elements. Meanwhile, tailored visualizations are specifically designed to meet unique requirements. Within these categories, there are a total of 38 tags. Figure 3 shows examples of visualization tags.

`Spatial.` This category includes tags connected to the development of spatial visualization metaphors, which are inherently linked to urban environment analyses. We have found that over 95% of the reviewed systems include spatial visualizations, with only three instances lacking this feature [44, 45, 46]. This category includes 11 tags. 85% of the systems included a *2D map*. For example, Chen et al. [47] used a 2D map to visualize trajectories, and Neto et al. [48] for crime analysis. 50% of the systems used a *heatmap*, often applying kernel density estimation to the spatial data [49, 50, 51]. 40% of the systems used visualizations for *trajectories*, such as graph views [52], color-coded street segments [39], and multi views [53]. In particular, only one reviewed system used *vector fields* to support trajectory analysis [41]. A sixth of the systems used a *3D map*. For example, Cornel et al. [54], Boorboor et al. [55], and Bonadia et al. [56] used 3D maps for flood analysis. Miranda et al. [16] and Moreira et al. [2] used 3D maps for sunlight access and shadow analyses. 7% of the reviewed systems make use of a combination of *multiple maps* [57, 58]. Other spatial visualizations include *choropleth* maps (13%) (e.g., [59, 60]), *contour maps* (7%) (e.g., [61, 57, 48]), *grid* (5%) (e.g., [62]), *voronoi diagram* (3%) [63, 64], and *dorling cartogram* (1%) [65].

`Abstract.` Each tag within this category represents a form of abstract visualization, i.e., where explicit spatial references are either missing or ignored. In this category, we have reviewed systems considering 19 tags. The most popular tag is *bar chart* (48%) (e.g., [66, 67, 68, 69]), followed by *scatterplot* (32%) (e.g., [70, 71]), *line chart* (31%) (e.g., [18, 72]), and *heat matrix* (22%) (e.g., [60, 73]). Fewer than 20% of the systems used *area chart* (17%) (e.g., [54, 53]) and *parallel coordinates* (14%) (e.g., [28, 74, 75]). The other abstract visualizations were used in fewer than 10% of the systems: *radar chart*, *parallel set*, *donut chart*, *box plot*, *violin chart*, *pie chart*, *dot plot*, *polar coordinates*, *word cloud*, *gauge chart*, and *spectrogram*.

`Temporal.` Just as the spatial category is focused on visualizations designed for spatial analysis, this category is directly connected to the analysis of temporal data. We created tags related to the visualization of time-varying data, yielding three tags across all analyzed papers. *Time series* was the most popular temporal visualization, present in 37% of the systems. For example, Miranda et al. [18] and Wei et al. [73] used time series to visualize sensor data. 17% of the systems used *timelines* (e.g., [33, 76]). Deng et al. [77] used timelines for cascading exploration. Only 2% used *streamgraph* (e.g., [78]).

`Network.` Similar to how the spatial and temporal categories are tailored for spatial and temporal analyses, this category is linked to the visualization of networks and hierarchical data structures. Recognizing this, we have identified five tags representing network visualization techniques used across the surveyed papers. The most popular technique was the *node-link* diagram (25%) (e.g., [79, 80, 81]). Krueger et al. [81] and von Landesberger et al. [80] used node-links for mobility data and employed an aggregation scheme to reduce visual clutter. Fewer than 10% of the systems used the following techniques: *tree diagram* (e.g., [82]), *sunburst* (e.g., [83, 84]), *chord diagram* (e.g., [85]), and *treemap* (e.g., [86]).

`Tailored.` In this category, we considered custom visualizations specifically created for urban visual analytics system. Typically, these visualizations aim to address more specific analytical problems, such as flow analysis [87], route analysis [67, 88, 89], and distribution analysis [42]. Often, these new designs are built upon or utilize combinations of existing ones; for example, Zheng et al. [74] extended parallel coordinates for origin-destination analysis, and Wu et al. [75] based their new design on tree maps. In total, 25% of the works reported the implementation of a new visualization (e.g., [28, 57, 90, 91, 92, 93, 64, 94, 87]).

5.2. Analytics

We have also characterized urban visual analytics systems concerning their analytical requirements. In this section, we report on the most frequent analytics tags across three categories.

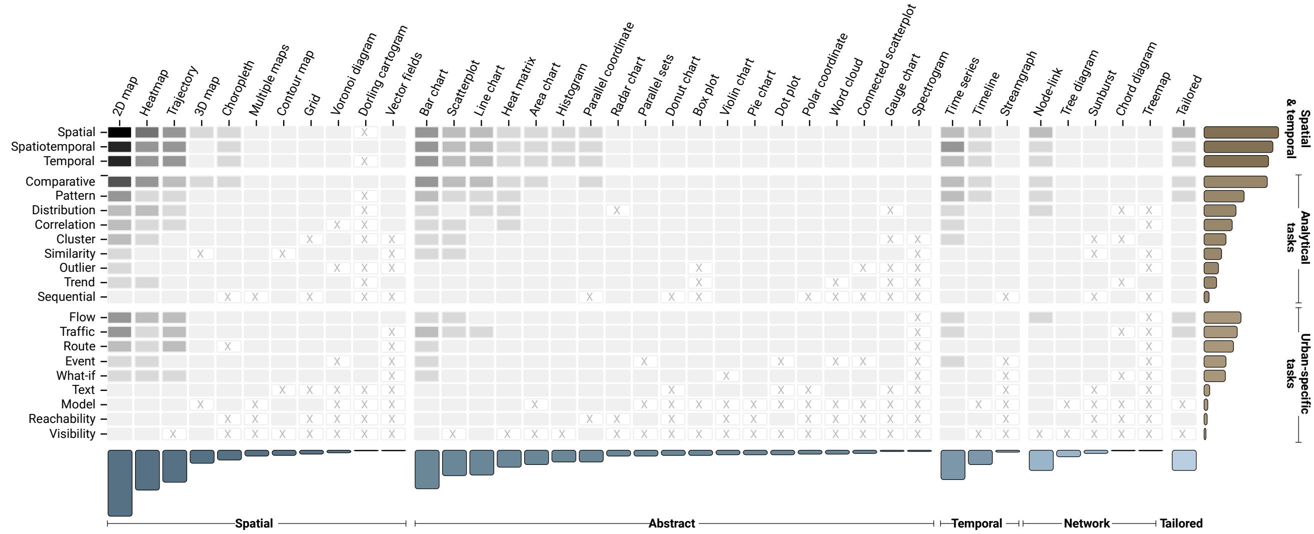
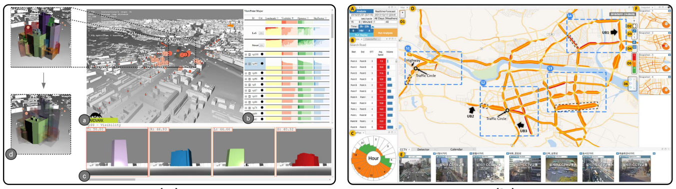


Fig. 4. Distribution of `visualization` tags with respect to `analytics` tags. Each cell shows the percentage of surveyed systems that were tagged with the respective visualization and analytics tags. If no systems matched a specific set of tags, the cell is represented by X, while the cell with the maximum value of 112 matches is represented by . Bar charts show the number of systems with that respective tag.

The spatial & temporal category describes whether the system supports analyses based on location or time. The analytical task category describes which tasks are supported by the system. The urban-specific task category covers analytical tasks that are more specific to the urban domain. We also describe the tags that arose from this review. It is important to highlight that a mix of tags can characterize a system's capabilities. For example, Rulff et al.'s [36] supported analyses of acoustic data based on spatiotemporal similarities. Here, *spatiotemporal* falls under the spatial & temporal category, and *similarity* belongs to the category of analytical tasks. Figure 4 presents an overview of the distribution of visualization and analytics tags.

`Spatial & temporal`. In this category, we include tags connected to the analysis of spatial and temporal components of the urban data. This category includes tags that cover the need to analyze how urban phenomena evolve and interact over various locations and periods. We surfaced three tags for this category: *spatial*, *temporal*, and *spatiotemporal*. Since a system can support each of these analyses individually (i.e., enable spatiotemporal and temporal analysis through its components but not be capable of purely spatial analysis), these tags are not mutually exclusive. The vast majority of systems (95%) supported spatial analysis (e.g., [95, 21, 96, 97, 31, 98, 99]). For example, Ferreira et al. [21] supported spatial analysis of view impact. 82% of systems supported temporal analysis (e.g., [42, 33, 50, 100]). Shi et al. [50] supported temporal analysis for event detection. 87% of systems supported spatiotemporal analysis (e.g., [37, 101, 27, 102, 103]). Li et al. [27]., for example, presented a framework to support analysis of interdependencies in spatiotemporal data, such as air quality data. Among all the works reviewed, only one was not covered by any of these tags. Gou et al.'s [104] system was solely used for detecting traffic lights in non-georeferenced static images.

`Analytical tasks`. This category encompasses the analytical tasks supported by the systems. Nine tags have been considered in this category, covering a range of analyses prevalent across many studies. The most frequent examples include *comparative* (80%) (e.g., [37, 83, 105]), *pattern* (50%) (e.g., [90, 80, 31]), *distribution* (40%) (e.g., [106, 94, 107, 108, 73]), and *correlation* (36%) (e.g., [109, 75]) analyses. For instance, Lyu et al.'s [105] system enables comparative analysis to examine multiple key indicators including accessibility to amenities, benefits for diverse resident types, and measures of inequality to assess and mitigate urban inequality. Garcia et al.'s CrimAnalyzer [31] supported pattern analysis for crime data, and Sun et al.'s system [107] supported distribution analysis for traffic data. In addition to these, other analytical tasks include *clustering* (28%) (e.g., [110, 111, 112, 77]), *similarity* (22%) (e.g., [65, 60, 113]), *outlier* (18%) (e.g., [114, 115]), *trend* (16%) (e.g., [109]), and *sequential* (6%) (e.g., [111, 116]) analyses. While clustering techniques group samples based on their similarity, not all systems support both clustering and similarity analysis. For instance, Maciejeski et al.'s [110] system focuses on predictive modeling of spatiotemporal hotspots through cluster analysis without using similarity analysis between individual events. QuteVis [113] supports similarity analysis without clustering by utilizing a weighted similarity computation among multiple user-drawn sketches, which are visualized as cues for comparing retrieved traffic situations and identifying influential factors. Among the systems that support both functionalities, MobilityGraphs [80] facilitates cluster analysis to aggregate, visualize, and analyze spatial locations and flows into regions and temporal clusters while also employing similarity analysis to measure and compare the relatedness of different spatial situations or clusters. TelcoFlow [115] offered outlier analysis to detect anomalies in mobile phone data. Malik et al.'s [109] system employed trend analysis to identify patterns such as daily and weekly cycles, significant incident correlations, and spatial co-occurrence of incidents (e.g., crime hotspots). Steptoe et al.'s [111] system facilitated the detec-



(a) (b)

Fig. 5. Examples of urban-specific tasks: (a) visibility [35] and (b) traffic [84] analyses.

tion of patterns in sequential data (i.e., sequence of activities or events).

`Urban-specific tasks.` Contrasting with the last category, in this class, we cover higher-level and domain-specific tasks common in the surveyed systems. 47% of the systems supported *flow* analysis focusing on the origin-destination movement within urban spaces [117, 91, 52, 60]; 42% supported *traffic* analysis addressing vehicular dynamics [101, 118, 119, 100, 120]; *Route* analysis for navigation and pathfinding was supported by 37% [121, 70, 39, 88]. We differentiated this analysis from *reachability* analysis (supported by 4%), which focused on the analysis of access, connectivity, and accessibility within urban environments [122, 123, 40]. For example, Zeng et al. [123] proposed a system to find locations that satisfy certain criteria, such as distance to schools.

The analysis of the impact or repercussion of historical *events* was supported by 28% of the systems (e.g., [110, 124, 54, 55]). In contrast, *what-if* analysis distinguishes itself by requiring user interaction with the system to create and assess hypothetical scenarios. Such type of analysis was supported by 27% of the systems (e.g., [79, 30, 102, 98]). For example, Andrienko et al. [102] used scenarios to analyze how removing metro lines impacts travel times.

Text analysis was supported by 7% of the systems (e.g., [125, 126, 106]), a similar percentage to *model* analysis, which pertains to the construction, use, or evaluation of machine learning models (e.g., [104, 127, 128]). *Visibility* analysis was supported by 2% of the systems [21, 34, 35]. These systems provide interaction and visualization mechanisms to evaluate the visibility of buildings to landmarks or open spaces. Figure 5 highlights examples of urban-specific tasks.

5.3. Data

For this dimension, we have reviewed data aspects of the surveyed urban visual analytics systems. Six categories are included. The physical category considers whether the system leveraged data regarding the natural and built environment of cities. The environmental monitoring & simulation category covers aspects related to the observation of environmental conditions and the modeling of natural events, including weather patterns and flood scenarios. Transport & mobility covers aspects related to private and public transportation. The social & economic category contains tags related to societal behaviors and economic variables. The public safety & health category covers aspects related to crime, emergencies, and public health. We have also reviewed works on whether they utilized data from the Visual Analytics Science and Technology (VAST) Challenge, a visualization competition that provides data to visualization researchers and programmers. Using the tags from the aforementioned categories, we have reviewed the systems' data characteristics, themes, and sources. Figure 6 presents the distribution of visualization and data tags.

`Physical aspects.` One of the widely used data in urban visual analytics is physical data, which describes the physical particularities of the environment, such as polygons for neighborhood areas, city boundaries, and bodies of water, or graphs for street networks. Such data directly supports spatial analyses, providing a basis layer upon which various urban elements can be examined and understood. By examining the surveyed urban visual analytics systems, we identified six tags within this category. 18% of works made reference to using *OpenStreetMap* data (e.g., [29, 129, 130, 56]). 10% of works used *points of interest*, such as hospitals and metro stations (e.g., [131, 47]). 5% of works used *building* data (e.g., [68]). For example, Santos et al. [132] used an open dataset with detailed information regarding New York City's building lots to enable land-use change analysis. Also 5% of works leveraged *street network* data for their analysis (e.g., [116, 133]). For example, He et al. [133] used network data to support bike lane planning.

`Environmental monitoring & simulation.` In this category, we included tags related to data with information regarding the monitoring of the environment or simulation and modeling of natural events. Over 25 systems leveraged. These include systems that used *air quality* data (6%) (e.g., [27, 85, 103]), *weather* data (7%) (e.g., [134, 113]), and *flood* data (5%) (e.g., [117, 135]). Ribičić et al. [117], for example, presented a multi-view system to analyze flooding simulations. 3% of the analyzed works employed data that included detailed monitoring of *noise* within urban environments (e.g. [18, 36, 32]). We have also surveyed work with information regarding *water quality* [129], sunlight access and *shadow* [16, 2], and *sky exposure* [21]. Figure 7 presents examples of visual analytics systems using flooding simulations and sunlight access data.

`Transport & mobility.` This type of data represents a focal point within urban studies, addressing a broad spectrum of challenges related to traffic congestion, routing, public transportation, walkability, reachability, and accessibility. This is underscored in our review, with 79 of the surveyed papers incorporating transport and mobility data in their works. In this case, six tags stood out, with the highest occurrence recorded for *taxi* (24%) (e.g., [70, 58, 77, 120]), *mobile* phone data (18%) (e.g., [121, 71, 73]), *traffic jam* (14%) (e.g., [61, 84, 136]), and *public transportation* (11%) (e.g., [95, 137, 119]). Palomo et al. [46], for instance, proposed a system to inspect metro schedules with a visualization inspired by EJ Marey's train schedule.

`Social & economic.` Another common type of urban data is related to socioeconomic factors. In this category, we include tags that describe phenomena that are primarily driven by human activity. Such data can assist in the analysis of economic patterns, demographic shifts, property market trends, etc. In our review, 13% of the works leveraged social media data [126, 80, 41]. For instance, Miranda et al. [138] utilized Twitter data to analyze the behavioral patterns of cultural communities by classifying geo-located tweets based on language. 6% of systems

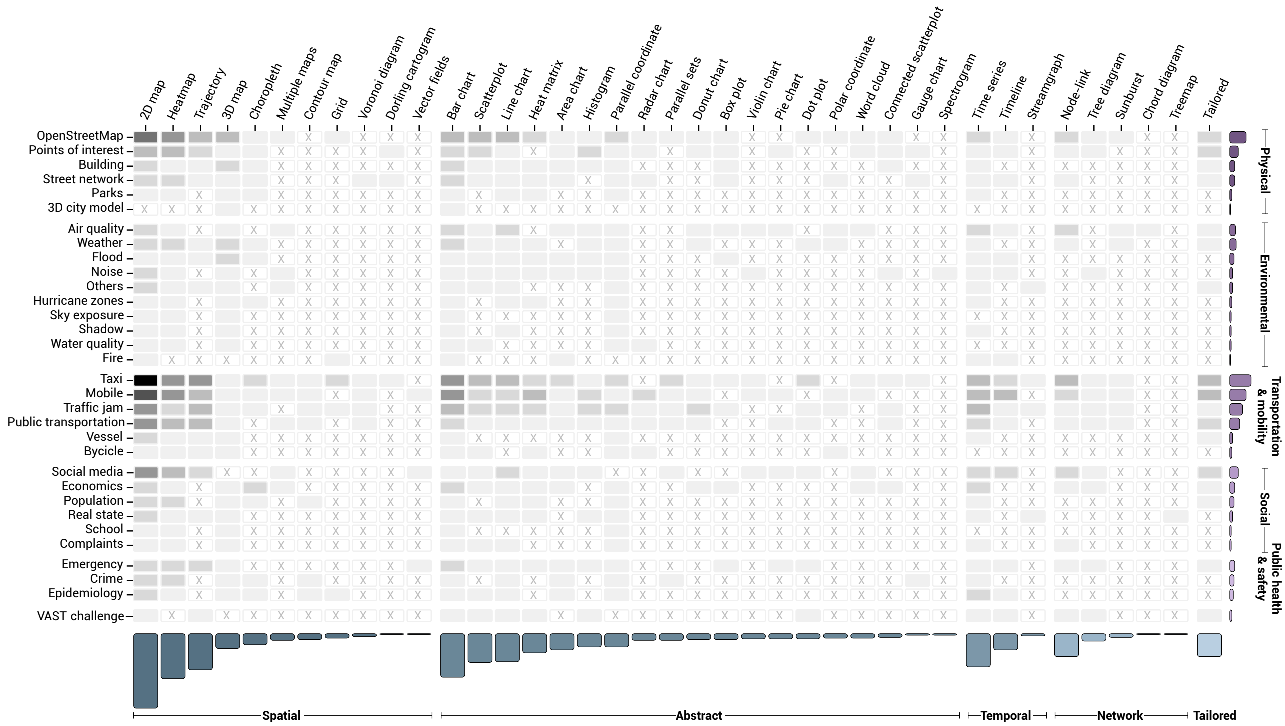


Fig. 6. Distribution of `visualization` tags with respect to `data` tags. Each cell represents the percentage of surveyed systems that were tagged with the respective visualization and data tags. If no systems matched a specific set of tags, the cell is represented by X, while the cell with the maximum value of 31 matches is represented by ■. Bar charts show the number of systems with that respective tag.

employed *economic* data (e.g., [139, 27]). Aliaga et al. [139], for example, used data regarding jobs to support the analysis of the interplay between urban land use and meteorological factors. 5% of the works used *population* data (e.g., [74]). 3% of the works leveraged *real estate* data (e.g., [86, 132].

Public safety & health. This data category contains tags covering data related to crime, emergencies, and public health.

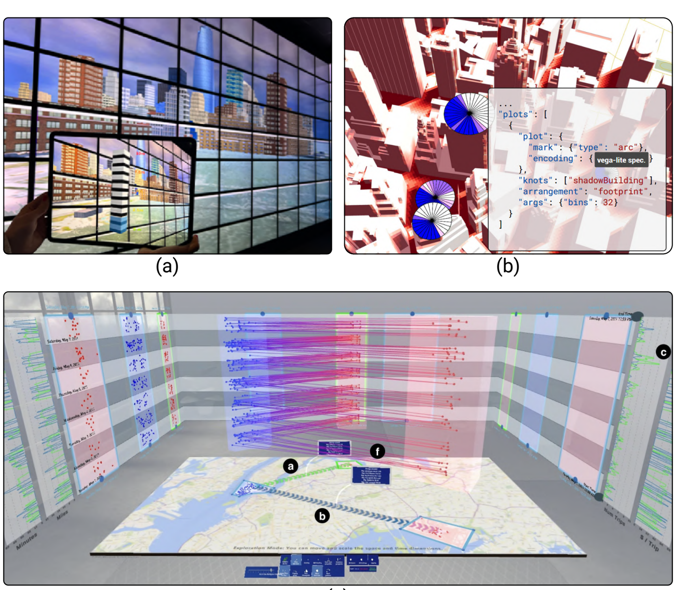


Fig. 7. Examples of systems using different data: (a) flood simulation [55], (b) sunlight access simulation [2], and (c) taxi trips [120].

Among all data categories, public safety & health was the one with the lowest number of papers, 18, which represents 14% of the total. The three tags in this category include *emergency* (5%) (e.g., [124, 111, 40, 140, 141]), *crime* (5%) (e.g., [37, 48, 31]), and *epidemiological* data (4%) [110, 142, 143]). In our work, we distinguished between emergency and epidemiological data. The first refers to data focused on crisis response (such as the data used by Li et al. [40] to analyze evacuation strategies), and the second is focused on disease data (such as COVID-19 data used by Frank et al. [143] to understand the virus' spreading behavior).

VAST Challenge. This data category encompasses works that implemented systems to solve real-world urban problems using VAST Challenge datasets. Approximately 2% of the surveyed works leveraged these datasets. For example, Chen et al. [82] used the VAST Challenge 2014 Mini Challenge 2 dataset to analyze human behaviors by identifying general movement patterns and detecting abnormal events. Steptoe et al. [111] leveraged the VAST Challenge 2015 DinoFun World dataset to create a system capable of exploring visitor behaviors in a theme park by analyzing trajectories and communication patterns of park visitors. In SensorAware [73], the VAST Challenge 2019 Mini Challenge 2 dataset was used to help emergency management teams understand situations related to radiation measurements in the city and identify areas needing sensor deployment, cleansing, or evacuation.

5.4. System

An additional critical dimension of our evaluation encompassed the systems' attributes, covering: the organization of

Fig. 8. Distribution of `visualization` tags with respect to `system` tags. Each cell represents the percentage of surveyed systems that were tagged with the respective visualization and system tags. If no systems matched a specific set of tags, the cell is represented by [X], while the cell with the maximum value of 126 matches is represented by ■. Bar charts represent the number of systems with that respective tag.

their interfaces and features supported by the system, construction tools utilized, data and system availability, requirement gathering, evaluation methodologies, and the domain application of the system. Figure 8 shows the distribution of visualization and system tags.

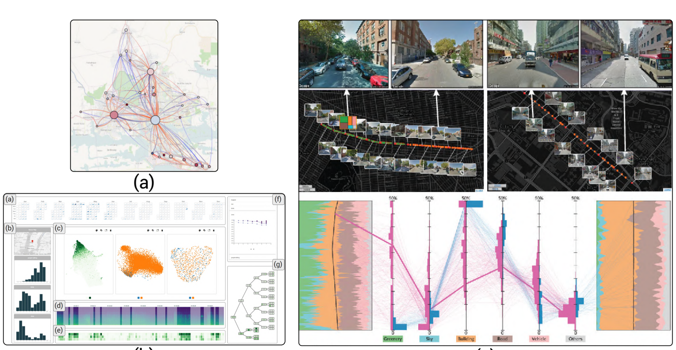


Fig. 9. Examples of the different compositions employed by the surveyed systems: (a) overlay [80], (b) juxtaposition [36], and (c) nesting [94].

`Composition of views.` In our examination of urban visual analytics, we categorized them based on their methodologies for integrating multiple visualizations. Considering the multi-faceted nature of urban data, our review highlighted the varied strategies employed to extract insights from distinct dimensions of the data. For this category, we tagged urban visual analytics systems following Deng et al.'s recent taxonomy [144] with design patterns for composite visualizations. As such, each system was tagged as using one or more of the following composition patterns: overlay, juxtaposition, or nesting. Figure 9 exemplifies these patterns. In our review, we found that the vast majority of systems used *overlay* composition (96%), in which views are composed by visually overlaying visualizations on others (e.g., [139, 41, 48]). Von Landesberger [80], for example, overlaid graphs onto maps. *Juxtaposition* appears in 81% of the systems. In this pattern, visualizations are positioned side by side, with no overlap (e.g., [70, 46, 138, 35, 18, 27, 145, 36]). Miranda et al. [145] juxtaposed an image gallery with a map view to enable the exploration of street-level image data. *Nesting* appears in 51% of the surveyed systems. In it, visualization components are embedded into the internal area of other components (e.g., [92, 94, 97]). Shen et al.'s system [94], for example, enhanced parallel coordinates with the use of theme river-style visualization. Since these tags are not mutually exclusive, there were systems that combined these visualization composition patterns, and some works even incorporated all the patterns [64, 94].

`System features.` This category covers various functionalities and capabilities of the surveyed urban visual analytics systems, reflecting how users can interact with and benefit from the system. In total, over 15 distinct tags were defined to represent the broad spectrum of features implemented in the urban visual analytics systems. These tags can be broadly grouped into two groups: (1) Tags related to querying capabilities: *Interactive queries* were supported in 46% of the systems (e.g., [107, 112]); *Custom queries* were supported by 44% of the systems; these queries allow the users to create personalized queries through the selection or definition of various data attributes (e.g., [90, 113]); *Natural language queries* (1%) in systems that supported the use of natural language as a query mechanism (e.g., [146]). Finally, 2% of the systems enabled users to query the data through *user-defined visualizations* ([2]). (2) Tags related to the technical data infrastructure. The *simulation* (13%) tag was used to cover systems that performed or leveraged simulation data (e.g., [117, 135, 147, 55]); The *Streaming* (13%) tag characterizes systems that supported continuous ingestion of data (e.g., [18]); *Model interaction* (10%) was used to characterize systems that enabled human-in-the-loop model investigation (e.g., [114, 148]). *Data integration* (14%) defines systems that integrated data from different domains (e.g., [149]). *Provenance* (2%) was used to distinguish systems that provided a detailed record of the data and processes used [150]. For instance, in TPFlow [151], provenance is incorporated to track and document the data partitioning and analysis steps, providing a mechanisms for analysts to revisit and refine them.

`Construction tools.` In this category, we reviewed the construction tools used to implement the urban visual analytics systems. Only 29% of the papers formally described the use of at least one construction tool in the development of the system. Despite their overall lower number, some tools stood out, such as *D3*, being used by 12% of the surveyed works (e.g., [46, 35, 76, 41, 152]), and *OpenGL* with 7% (e.g., [153, 34, 154, 16]), often associated with its capability to efficiently render 3D city models. Next, *Leaflet* was used in 7% of the systems (e.g., [129, 50], followed by *Qt* (4%) [78, 153] and *WebGL* (4%) [97, 2]. Other tools appeared in less than 1% of the surveyed works, including *QGIS* [82], *Vega-Lite* [2] and *ArcGIS* [105].

`Data availability.` In this category, we assessed whether the urban visual analytics tools used open datasets, closed datasets, or a combination of both. Accordingly, three tags have been designated for this category: open, closed, and partially open. It is important to note that, in this case, a single work cannot be associated with more than one of the tags, as they represent mutually exclusive options regarding data availability. In our review, the percentage of works that utilized *closed datasets* (47%) (e.g., [155, 156, 133]) was relatively balanced with those that exclusively employed *open datasets* (39%) (e.g., [125, 41]). Meanwhile, the proportion of works where the data was *partially open* was 13% (e.g., [157, 74]).

`System availability.` To assess the availability of a system's source code, we examined whether the projects were publicly available (e.g., GitHub). Consequently, we classified the systems in a binary manner as either *open* or *closed* based on the availability of their source code. In our analysis of the systems, a notable imbalance was observed between open and closed systems. Specifically, 90% of the reviewed systems were *closed* source and did not make their code publicly available. Conversely, only 10% of the works were *open* source, with source code publicly accessible in some form (e.g., [158, 51, 2]).

`Requirements methodology.` To elucidate the design methodologies behind the urban visual analytics systems surveyed, we reviewed the papers regarding the strategies employed to surface system requirements. Such review resulted in 5 tags that described how authors identified system requirements. Such a process is fundamental for understanding how the system's components and functionalities came to be to address particular domain problems. In the reviewed works, 50% mentioned collaboration with experts (e.g., [81, 113, 87]), and 13% involved experts from different domains (e.g., [137, 89]). Within these works, 2% had collaborations lasting less than 6 months (e.g. [100]), 5% between 6 months to 1 year (e.g., [58, 152]), and 2% reported long-standing collaborations lasting more than 1 year (e.g., [48]).

`Evaluation.` We have also reviewed works regarding their evaluation methodology. We classified the works following the taxonomy recently proposed by Khayat et al. [159]. The taxonomy provides a comprehensive guide for evaluation methods in visual analytics. The vast majority of the works employed *qualitative case studies* (86%) (e.g., [44, 30, 160, 55, 69]), followed by *expert feedback* (63%) (e.g., [29, 135, 33, 35, 161]). *Quantitative automation testing* was employed by 13% of the works (e.g., [121]). *Quantitative user testing* (e.g., [162]) and *quantitative user opinion* (e.g., [153]) were employed by 8% of the works. For example, Lorenzo et al. [121] used automatic approaches to quantitatively compare estimated origin-destination flows. Meghdadi et al. [162] measured their system's effectiveness by timing task completion with 18 users. Lu et al. [153] assessed their system through user questionnaires and quantifying their feedback.

`Domains.` Lastly, we tagged each work based on the application domain of the system. At the end of this process, we identified 12 distinct tags to categorize each urban visual analytics system, aimed at addressing and managing specific urban issues. To achieve this, we conducted a thorough review to identify the domain of contributing experts and analyzed study cases, ensuring a comprehensive understanding of each system's application domain. *Urban mobility* was the tag that appeared the most, with 52% occurrences [63, 64, 131, 137, 69, 136]. The systems' applicability to urban mobility can be seen in multiple case studies. For instance, in MobiSeg [64], the system was used to integrate and analyze heterogeneous mobility data (e.g., taxi trajectories, metro passenger RFID card data, and telco data) to identify segments in urban regions based on people's movement activities. MetroBUX [69] was used to identify periods and regions of high uncertainty in bus arrival times, highlighting peak hours and regions. In another instance, TCEVis [136] authors showed how the system identified and quantified the impact of various factors (e.g., holidays and weather conditions) on traffic congestion. Another frequent tag was *urban planning*, being present in 31% of our sample [16, 145, 105]. For instance, in IF-City [105], a synthetic case study showcased how the system can reallocate residents and modify urban designs to improve fairness and benefits across diverse resident types by simulating various planning scenarios. Urban Mosaic [145] authors, on the other hand, highlighted its applicability by showing how the system was able to help practitioners identify and address accessibility challenges, such as the installation of tactile pavings for older adults. The *social behavior* tag arose in 25% of the studies [42, 82, 141]. In CLEVis [141], the authors demonstrated their system's ability to aid in understanding social behaviors through case studies on Hurricane Katrina's impact, drug overdose patterns, and town-wide crime analysis. Following, the *public safety* tag was found in 13% of the works [48, 140, 31]. A notable example of a system's applicability to public safety is demonstrated by the Mirante system [140], which revealed how urban infrastructure impacts vehicle robbery patterns and how urban revitalization efforts reduced passerby robbery. The other domain tags were used in less than 10% of the systems: *pollution* [85, 72], *architecture* [21, 35], *politics* [76], *flood management* [55], *meteorology* [139], *public health* [59], *logistics* [53], *radio propagation* [154].

6. Visualization toolkits, frameworks & authoring tools

Urban visual analytics systems rely on several toolkits, frameworks & authoring tools to implement their visualization requirements. As more implementation tools are created and made available for reuse by the community, the effort to create intricate systems reduces. The expressiveness of the visualization tools chosen to support the implementation of an urban visual analytics tool is key to building powerful and engaging user interfaces, which allow stakeholders to validate hypotheses, generate insights, and build knowledge from the exploration of the datasets of interest. In the second part of this work, we surveyed visualization tools that may support the urban visual analytics requirements described in Section 5.

We identified over 30 visualization tools with distinct characteristics that fit a diverse set of development requirements. These tools range from low-level libraries (D3 [163]) to complex visualization applications (e.g., Tableau [164] and ArcGIS [165]). It also includes tools designed for the creation of predefined visualizations (e.g., Chart.js [166], and Google Maps [167]) and tools based on the grammar of graphics that allow the creation of custom designs (e.g., Vega [168], and ggplot2 [169]). Figure 10 presents an overview of the reviewed construction tools and their capabilities to implement different visualizations.

As previously described in Section 5.1, the visualization requirements of the surveyed systems were classified into spatial, abstract, temporal, hierarchical, and tailored. In what follows, we discuss the most adequate tools currently available to implement these requirements.

`Spatial`. The visualization of spatial data plays a central role in urban visual analytics systems since data produced by cities are usually associated with geographical locations. This data is oftentimes visualized over a single or *multiple maps*, which conveys the spatial context of the city. Depending on the urban data characteristics (e.g., spatial dimension) and the tasks performed using the system, both *2D and 3D maps* may be used. Almost all identified implementation tools facilitate the generation of 2D maps. If little spatial context is required, it is possible to implement 2D maps using libraries such as D3, Vega, and Vega-Lite [170]. However, when more sophisticated maps are required, it is necessary to adopt specific map visualization tools (e.g., Google Maps [167], Mapbox [171], Geemap [172], and Bing Maps [173]). When 3D maps are required, the number of implementation tools available is considerably smaller. Robust tools, such as ArcGIS [165] and QGIS [174], provide 3D mapping capabilities, but they are harder to integrate into a customized system. On the other hand, a few libraries (e.g., Mapbox [171], kepler.gl [3], deck.gl [175], pydeck [176], CesiumJS [177], and Maptalks [178]) are available to create 3D maps but usually focus on terrain visualization, have limitations in rendering buildings or do not provide access to the underlying data. If the system requires rendering large areas and accessing the geometry of buildings, streets, and other urban structures, the only available option would be developing a map render using e.g., WebGL [179] or OpenGL [180]. Several other visualizations can be overlayed on a map context. *Grids*, *heatmaps*, and *choropleth* maps are used to show aggregated scalar data over different regions and may be implemented using Leaflet [181] and react-map-gl [182]. *Contour maps* are popular for visualizing level sets of scalar functions such as temperature or rain volumes and may implemented in urban visual analytics systems using Bertin [183] and geoplot [184]. Movement data, such as wind data and human mobility, can be represented using *trajectory* or *vector fields* visualizations, and implemented using ipyleaflet [185] and MapTiler [186]. The last approach to visualizing geographical data is to discard the use of the map context. One of the most used techniques in this class is the *dorling cartogram*, which may be developed using Vega, Vega-Lite, or the Urban Toolkit [2].

`Abstract`. Other primary visualization types in urban data analysis are abstract charts. This type of visual representation covers a wide variety of visualizations that range from classic statistic charts to graphical representations of non-visual complex data such as text and sound. Abstract visualizations also include designs to represent multivariate data, such as radar and parallel coordinate charts. Statistics charts are some of the most well-known types of visualization. *Bar charts*, *histograms*, *scatterplots*, *line charts*, and *box plots*, among others, are mandatory for building effective urban visual analytics applications. There are several tool choices for implementing statistical charts. Common approaches include charts libraries such as Chart.js [166], FusionCharts [187], or Highcharts [188]. In situations where custom charts are required, an effective approach is to adopt visualization tools built over the concept of Grammar of Graphics [189], such as ggplot2, and Vega-Lite, which provide high flexibility without requiring low-level coding. When low-level coding control is desired, the most established approach is using D3. Abstract visualizations are not

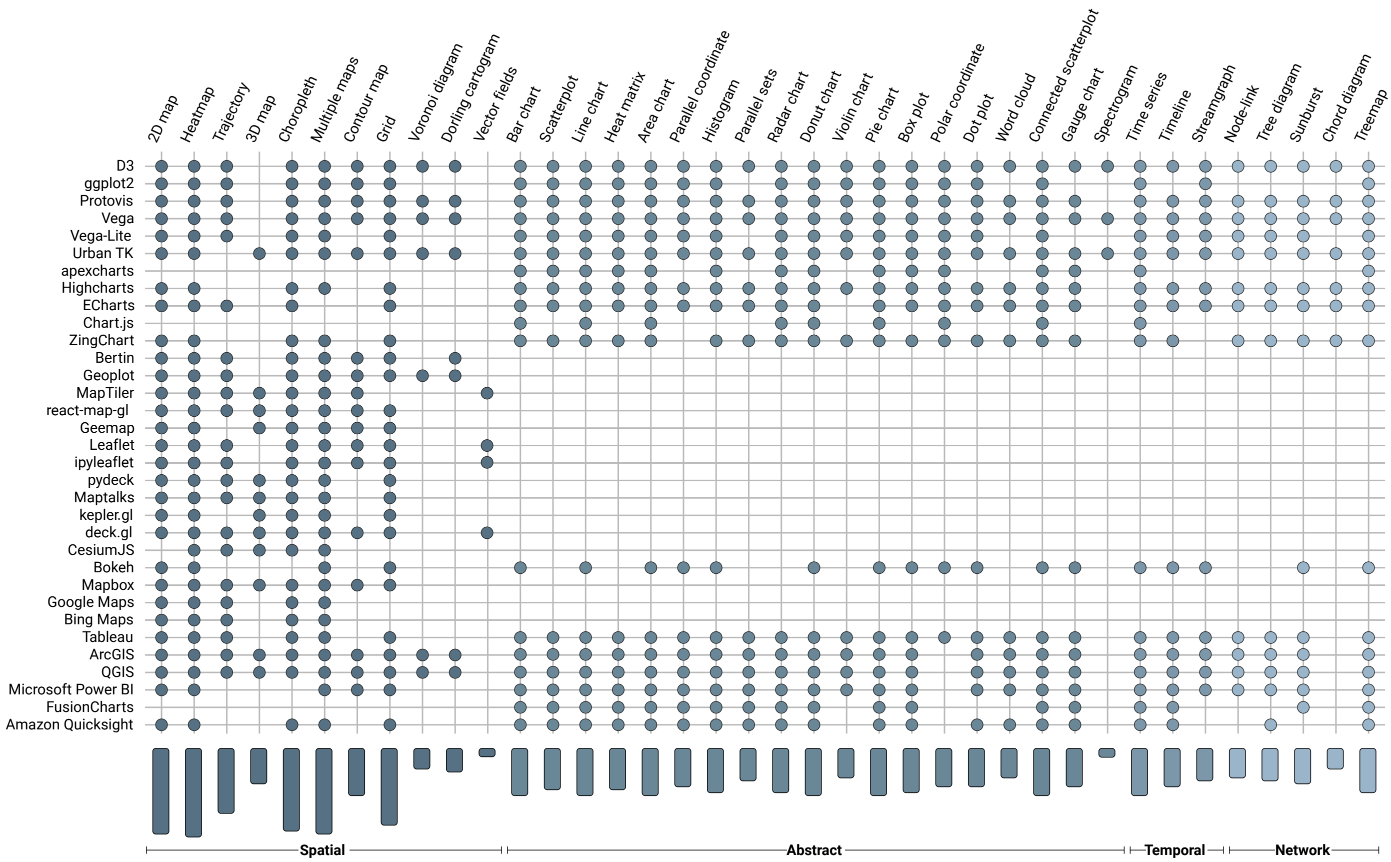


Fig. 10. Reviewed construction tools and their support for different visualizations. The tools are sorted from low-level libraries (e.g., D3) to higher-level template-based tools (e.g., Power BI).

only restricted to statistic charts. Some complex data, such as text and sound, are also visualized using this approach. In fact, texts are commonly represented using word clouds, while sounds are usually shown using *spectrograms*. These visualizations can also be constructed using predefined visualizations from libraries such as ZingChart [190] and ECharts [191], visualization grammars from toolkits such as Vega-Lite, and low-level D3 coding. Finally, in the context of urban visual analytics, datasets are complex and usually composed of multiple attributes. The visualization of multivariate data can be approached using several strategies such as *parallel coordinates* and *polar coordinates*. The implementation of these visualizations can be performed using the same tools as the previously cited abstract charts.

`Temporal.` Most urban data describe events or phenomena that occur over time. For this reason, it is important to build visual representations such as *time series*, *timelines*, and *streamgraphs*. The same scenario observed in abstract visualizations is also valid for temporal visualizations. More precisely, these visualizations can be developed using low-level tools (WebGL and D3), visualization toolkits based on the grammar of graphics (ggplot2 and Vega), specific purpose libraries (FusionCharts [187] and Bokeh [192]), and standalone visual analytics applications (Tableau [164] and Amazon Quicksight [193]).

`Network.` Urban data visualization heavily explores the relational and hierarchical nature of geographic regions, time resolutions, and other data. In fact, multi-resolution analysis is a powerful visual exploration strategy associated with the famous Shneiderman's visualization mantra *overview first zoom and filter, then details-on-demand* [194]. Among the most popular network data visualization strategies, we can cite *node-link*, *chord* and *tree* (dendogram) diagrams, as well as, *treemaps*, and *sunburst* charts. Network visualization can be implemented using tools from all abstraction levels: low-level libraries (WebGL and D3), grammar-based toolkits (Protovis [195] and Vega-Lite), chart-specific libraries (ECharts and apexcharts [196]) and visualization systems (Microsoft Power BI [197] and Amazon Quicksight [193]).

`Tailored.` Finally, some data has specific aspects that may require using particular visual designs. In this case, low-level and grammar-based approaches are the only available options and should be chosen from case to case. In fact, WebGL, D3 and Vega-Lite are currently the most popular options available.

7. Discussion

In this section, we discuss future research opportunities from the surveyed urban visual analytics and construction tools discussed in Sections 5 and 6. Our discussion is framed along the same previously mentioned discussions: visualization, analytics, data, and system.

7.1. Visualization

Visualization metaphors. An interesting observation from our survey is that there appears to be a set of "standard" visualizations: most systems use combinations of thematic maps (e.g., choropleth maps and heatmaps) and widely used non-spatial visualizations, such as bar charts, scatterplots, and line charts (as seen in Figures. 4, 6, and 8). One possible explanation for this pattern is the fact that urban visual analytics systems are, in general, intended to be used by domain experts with varying degrees of visualization and data analysis literacy. Therefore, one important design decision is to employ known visual metaphors to assemble a visualization system. Also related to this is the fact that these visual metaphors are implemented in the vast majority (if not all) of the construction tools and, therefore, are easily included in visualization systems. On the other hand, more complex visualizations, such as parallel coordinated charts, violin charts and spectrograms are less common and typically found in advanced technical applications designed for users with a robust background in visualization and data analytics. These visual metaphors are not universally present in construction tools like the previous ones. Finally, tailored visualizations, although often necessary for more domain-specific scenarios, are present in a smaller fraction of the surveyed works. By their own nature, these visual metaphors require tools that provide more freedom (e.g., low-level tools) or allow for customization and integration of multiple visualization techniques for their implementation. Consequently, creating tailored visualizations to meet specific domain needs involves navigating the trade-offs between using preexisting libraries, which offer speed and simplicity, and writing custom code, which, while more time-consuming, provides the necessary flexibility for integrating multiple visualization techniques and crafting novel visual metaphors.

Use of 2D and 3D maps. The majority of surveyed urban visualization systems predominantly use 2D maps as a visual metaphor to convey the spatial aspect of urban data. Most of the construction tools support the generation of 2D maps. It is important to note that the degree of customization available varies significantly with the choice of construction tool: high-level tools tend to support standard thematic maps, while low-level tools enable the creation of tailored map designs, often necessitating programming. Yet, given that urban environments are intrinsically three-dimensional, more sophisticated application scenarios necessitate the analysis of both physical and thematic urban data in 3D [23]. Unlike their 2D counterparts, 3D maps are rarely supported by construction tools. Furthermore, most of the tools that do support 3D maps often focus on the rendering of the city's physical aspects (buildings, streets, trees, etc.) and provide limited capabilities related to the transformation and visual analysis of 3D thematic data. Many aspects of visual analytics system design are much more complex in 3D environments. In fact, elements such as navigation, occlusion, and the interactions of these with the visual metaphors for thematic data related to different physical aspects (buildings, streets, etc.) are still open problems [198]. For these reasons, most of the surveyed systems that use 3D maps rely on low-level construction tools such as WebGL or OpenGL. All of this underscores a pressing need for better construction tools that facilitate the implementation and customization of data visualizations within 3D urban environments.

7.2. Analytics

Analytical tasks. Since most urban datasets describe phenomena and events observed in cities and throughout a period of time, it is natural to expect that most surveyed systems support spatial & temporal analytic tasks. In our review, we have categorized the tasks into two groups: lower-level tasks and urban-specific tasks. Tasks from the first group, which are common across various contexts, include essential functions such as extracting patterns, distributions, clusters, outliers, and correlations. These tasks are important for summarizing and describing datasets of interest. As shown in Figure 4, urban visual analytics systems rely on several visualizations to support these tasks. Since these tasks are fundamental, they can be facilitated by several construction tools. For example, although D3, Vega-Lite, and Tableau have very distinct characteristics, all of them have capabilities for visualizations to support these tasks. Finally, it is also worth mentioning that, although out of the scope of this paper, several popular non-visualization tools are commonly used to support analytical tasks, such as statistical and machine learning libraries (e.g., scipy [199] and scikit-learn [200]).

The second group of tasks in urban visual analytics systems are the urban-specific tasks. As shown in the domain category in Section 5.4, these tasks are very specific and vary based on the use cases. For instance, urban mobility systems like MobiSeg [64] focus on analyzing movement patterns and integrating mobility data, while systems like MetroBUX [69] and TCE-Vis [136] illustrate the need for tools that can manage specific, high-variability datasets, such as traffic flows and bus arrival times. In other realms, like urban planning, for example, systems such as IF-City [105] and Urban Mosaic [145] demonstrate the importance of versatile tools that facilitate the simulation of planning scenarios. Also, as shown in Figure 4, urban visual analytics systems rely on a few visualization types to support urban-specific tasks. Given the complexity and specificity of these tasks, just a few construction tools are available to support their implementation. For example, OSMnx [1] is a tool created to retrieve, analyze, and visualize street networks.

7.3. Data

Availability. Although several relevant urban challenges can benefit from urban visual analytics systems (Figure 6), most of the surveyed works are related to transportation and mobility. These applications are also the ones that rely on a wider range of visualizations. While it is hard to fully justify this pattern, one possible reason is the availability of public datasets. In fact, many cities provide data related to taxi [15, 201] or bus [202] trips, which have motivated the visualization community to explore the topic. Other topics, such as sunlight access, flooding and landslide, and noise, may suffer from the lack of city-wide public datasets, since they depend on custom sensors or computationally intense simulations that are difficult to perform at scale. We note that such data may also require advanced visualization designs, such as volume rendering or vector field visualization. The main source of data for cities' physical layers is OpenStreetMap [203]. However, since the data is collaboratively produced by a community of users, the quality and completeness of the data might pose a problem [204]. The usage of this data also depends on tools to download, store, manage, and render the physical layers, which may be challenging. Recent work advancing the idea of *urgent computing* [205], where urban data also plays a key role, could offer pathways for new visualization research. Such integration between urgent computing and urban visual analytics can markedly improve crisis response capabilities by enabling real-time simulations that enhance disaster management strategies (e.g., severe weather events [206]).

7.4. System

System performance. A critical factor taken into account during the design of a visual analytics system is its computational performance. Previous work has shown that latency in interactive visualization systems can affect the data exploration process [207]. Several factors contribute to latency in interactive urban visual analytics systems: data processing, data transformation and rendering. In the urban scenario, this issue is even more important given the common spatial operators to join and summarize thematic information with respect to the physical elements of the city [208]. Most construction tools focus on the visual elements and thus are either oblivious or abstract away the latency and performance issues from the users. In this case, either the user must accept latency when exploring reasonably large datasets or has to use separate data management solutions, which require expertise in programming and/or databases. A recent study [209] has proposed the use of machine learning models to automatically optimize query plans for applications using Vega and a database management system. However, this work has not been validated with urban or spatial data in general. Developing generalizations of such approach to other grammar-based approaches that can effectively support urban data (such as the Urban Toolkit) is an interesting direction for research.

Collaboration. As reported in Section 5.4, our analysis reveals that 50% of the surveyed works explicitly mention active collaboration with domain experts to build the system requirements. When these collaborations are documented, experts are often restricted to roles of data providers or evaluators rather than core contributors throughout the design and development process. This limited involvement could result in tools that are misaligned with the real-world operational demands of urban experts. We note, however, that experts' contributions in the construction of urban visual analytics systems might be more prevalent than reported, indicating an oversight in reporting rather than a definitive lack of expert involvement. This uncertainty underscores the need for better clarity in the documentation of collaborative efforts across studies. More detailed reporting on the nature and extent of the participation of domain experts during the system construction phase is essential to better understand these cross-domain collaborations. Their deep involvement ensures that the tools developed are technically proficient and practically useful in real-world emergencies. While collaborative visualization [210] offers opportunities to bring together domain experts to understand and investigate data, a potential avenue for future research is the creation of tools that facilitate the tracking of the collaborative system design process itself. Given the complexity of building urban visual analytics systems, early design commitments might lead to challenges in adapting to unforeseen requirements or changes in the collaborative landscape. Therefore, tools to track preliminary visualization designs, workflows, and experiments could significantly facilitate the tool-building process.

Availability. Construction tools like Tableau, Microsoft Power BI, and ArcGIS provide robust sharing capabilities and inherently support the findability and accessibility aspects of FAIR principles, thereby facilitating the reproducibility of results [211]. However, on the other end of the spectrum, low-level construction tools (often used to build more customized and complex systems), in general, do not have built-in capabilities to support FAIR principles. This scenario often leaves the burden of ensuring FAIR compliance on the developers. This situation exacerbates the challenge of experimental reproducibility, which frequently lags due to the complexities involved in documenting processes and code [212]. This not only renders comparative analysis challenging but also frequently undermines the practical applicability of the data in alternate urban contexts. Systems based on visualization grammars present a good balance in this aspect; however, the support for general urban data is still limited. This scenario underscores the need for approaches that can facilitate reproducibility and replicability [213]. Developing strategies to enhance the FAIRness of urban works while allowing for shareable and reproducing results represents a critical research avenue for the future and underscores the importance of integrating these principles across computational requirements, analysts' needs, and developers' constraints to achieve practical and effective results [214].

Integration. As shown in Figure 10, all visualizations used in the surveyed works are supported by at least one construction tool. However, other tools may be required to fully implement all data, analytics, and system requirements discussed in Section 5.2. For example, complex datasets (e.g., OpenStreetMap buildings or weather simulations) may require the use of specific tools or libraries to load, clean, and parse them into visualization-ready formats; complex analytical methodologies may require the use of open-source solutions [215, 216]. While a comprehensive list of non-visualization tools are out of the scope of this paper, it is important to note that combining visualization and non-visualization tools is not straightforward. Exploring new construction tools that facilitate the interoperability and interaction between these may lead to a more comprehensive understanding and coverage of the design space pertinent to urban visual analytics. This exploration presents an interesting research pathway.

As part of our survey, we have noticed a shift away from client-only applications (built leveraging languages such as C++ and libraries such as OpenGL), towards web-based ones.

While facilitating deployment to users, the client-server nature of these systems raises new challenges on how to best integrate data, analytics, visualization, and system components. However, recent works and technologies (e.g., Web Assembly, WebGPU) have facilitated the integration of these components, alleviating the need for Python or C++-based servers to handle data-intensive workloads. In turn, these have enabled the design of a new class of construction tools, such as Mosaic [217]. There are growing opportunities to leverage these new technologies in urban visual analytics systems, especially for managing large datasets and enhancing rendering capabilities.

8. Conclusions & takeaways

In this paper, we have reviewed over 130 relevant systems to create a fine-grained taxonomy of over 160 tags in 22 categories covering visualization, analytics, data, and system dimensions. Such characterization allowed us to assess the most popular visualizations, analytical tasks, data, and system features. These were then used to evaluate construction tools based on their capabilities to implement different visualizations. From this work, there are a few key takeaways.

First and foremost, few works in urban visual analytics are publicly available. This scarcity of availability is a contentious topic given potential privacy issues surrounding the datasets and the unrealistic expectations placed upon prototype developments [218]. Despite these challenges, there is a compelling case for dedicating increased efforts towards the cultivation of communities centered on the development of urban frameworks. This is especially important given the potential societal implications that urban visual analytics systems can harbor. Ensuring transparency is key to fostering trust in data-driven decision-making processes. While the immediate benefits from the public dissemination of code may appear modest, there are certainly potential advantages. Reflecting on our experience in the development of urban visual analytics systems, making some of our contributions publicly available led to new collaborations [219] and gained attention from various media outlets [220, 221].

Second, echoing recent calls from the visual analytics community [222], more effort should be dedicated to making interoperable components and building sustainable infrastructures for urban visual analytics. As highlighted, an urban visual analytics system is the result of the integration of multiple components. Currently, time and effort are expended on redundant tasks and *reinventing the wheel*. Thoughtful design of components with reusability in mind can yield benefits both downstream and upstream. Successful examples in urban computing, such as OSMnx [223], serve as guides that underscore the potential utility of components when designed with reusability as a core principle. Together with publicly available codes and interoperable components, visualization research outcomes might be more easily transferable to other geographical contexts, multiplying the utility of a singular system. In doing so, urban experts would be able to leverage existing urban visual analytics systems to address localized challenges without the necessity of developing an entirely new system from the ground up.

Lastly, we found that the delineation of collaborations with urban experts frequently lacks depth. Usually, these collaborations are portrayed within the narrow confines of roles as data providers and evaluators, rather than recognizing these experts as essential contributors to the design process. This undervalues the potential depth that urban experts can bring to the development of visualization tools. In a domain where proficiency in programming has become increasingly standard, we believe that a more careful consideration of urban experts' unique needs and insights can be fruitful. Their already-in-place workflows and perspectives can enrich the development process. Though this is a topic that involves time commitment and expectations from both sides (experts and visualization researchers) [224], more meaningfully involving them in the design and implementation can enhance the utility and relevance of visualization research, leading to greater acceptance and application of research findings in urban contexts.

As part of future work, we see value in a more careful evaluation of the sustainability of urban visual analytics tools. This might require directly enquiring visualization researchers and domain experts, assessing pain points and shortcomings of these collaborations, and whether urban visual analytics systems and contributions were actually embedded into their domain practices.

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