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Explanation and Analysis of Spatio-Temporal Correlations—Towards a Conceptual Approach of a Semantic Comparison Visualization in a Use Case of Carparks in Mainz, Germany

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Abstract: Geospatial factors, because of their spatio-temporal correlations with demand-driven limited service, offer to improve urban planning decisions and expand the knowledge base in cities. Spatio-temporal analyses require an efficient and comprehensible visualization and explanation in order to analyze and understand geospatial relationships in urban areas. The aim of our research is to support domain experts in these analyses with user-oriented geovisualization. In this article, we propose concepts towards a semantic comparison visualization, which combines a visual analysis view and a visual explanation view. The visual analysis view is a knowledge-oriented view that focuses on analyzing resulting spatio-temporal correlations. The visual explanation view is an understanding-oriented view that focuses on explaining the underlying complex analysis process of geospatial factors and spatio-temporal correlations. We define general requirements for this aim and validate and evaluate our concepts related to these requirements. The results show the benefit of our concepts, but, at the same time, they also point to limitations and potential for optimization in further work.

Keywords: spatio-temporal visualization; spatio-temporal correlation; semantic comparison visualization; domain experts; urban planning; human–computer interaction

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1. Introduction

Explaining and analyzing spatio-temporal correlations in the context of urban planning and sustainability is a crucial aspect of understanding complex relationships between different urban factors. Urban areas are dynamic systems that are constantly changing over time. Understanding these changes is essential for making informed decisions about the future development of smart cities. We can use spatio-temporal data analysis to identify patterns or trends in the data and make predictions about future events. Furthermore, understanding geospatial key factors and spatio-temporal correlations plays a major role in demand-oriented planning or further development of limited service offers. For example, use cases include carparks or rental stations for bicycles. In more detail, the challenge is to understand which geospatial factors trigger high or low occupancy of carparks at different points in time. Here, different points in time can occur daily, weekly, or seasonally. Changes in the proximity of parking spaces can lead to a completely different occupancy situation. Consequently, this could significantly impact the availability of free parking spaces for long-term or short-term parking customers. In this context, planning decisions according to the location of carparks and their capacity depend to a large extent on these geospatial factors. Participants during these planning processes are domain experts such as urban planners or, in the context of mobility, companies for limited service offers, e.g., carpark operators. They all share an interest in the optimal use of the available parking spaces in cities and decisions on inner-city changes such as location optimization or site planning. However, domain experts often tend to impose their assessments on geospatial factors, even though they lack the objectivity required to evaluate them neutrally [1]. Hereafter, geospatial factors include geospatial information that directly or indirectly influences various use cases such as carparks. This information refers to data related to specific locations and points of interest (POI). Examples of geospatial information include healthcare facilities, recreational activities, or restaurants [2]. The calculation of geospatial factors includes, for example, the density or accessibility of shopping facilities, availability of health care, leisure activities, etc. In addition, non-geospatial parameters such as opening hours also play a central role [2,3], (see also Section 3). Both characterize the direct environment of carparks, to determine a measurable impact.

As mentioned before, a core aspect of urban data analysis during planning processes is the recognition of relevant urban patterns. However, pure numbers and tables often represent the results of geospatial data analysis in a complex, statistical way, but neglect geospatial aspects. This poses the challenge of efficiently interpreting the data obtained. A visual representation of the numbers can provide the ideal basis for more easily identifying meaningful patterns and making decisions based on them [4]. Effective visualizations offer the possibility to explore the data to derive correlations and to gain spatio-temporal knowledge in planning processes [5]. However, enormous amounts of data often lead to confusion or incompleteness of important relationships. In general, domain experts have limited expertise in implementing geospatial data analysis or creating geovisualizations, so they are not able to exploit the potential of analysis tools or present results in a comprehensible way [6]. In many meetings with carpark operators, we note a difficulty in interpreting and handling spatial contexts. At the same time, they cannot objectively justify or explain geospatial patterns that occur. Therefore, there is a strong need for novel visualization approaches that cover geospatial correlations and support domain experts during planning processes in order to understand the analyzed geospatial correlations. An effective visual explanation of the analysis process increases the comprehensibility and traceability for the experts. Visual explanatory approaches are needed, especially in the case of insights contrary to the prior knowledge of the domain experts. Existing methods and techniques for geovisualization offer a broad potential to support these challenges. Tailored approaches not only help to provide "fancy visualizations with cool interactions" ([7], p. 1), but also offer effective visual explanations which expand the spectrum of knowledge transfer in urban planning. With geovisual explanations, domain experts can test hypotheses, visualize individual parameters, and recognize possible effects of urban changes. Despite various existing approaches, there is still a lack of combined approaches that seamlessly integrate explanatory perspectives into analytical ones. In this article, we present a novel geovisual approach for explaining and analyzing multifactorial spatio-temporal correlations in urban areas based on existing geoanalytical results. Our goal is to explore the potential of combining an explanatory and an analytical feature in one visual view. For this purpose, we derived applicable requirements from meetings and discussions with domain experts and developed different visualization concepts. Specifically, our final visualization concept aims for a semantic comparison visualization that allows simultaneous analysis and explanation of spatio-temporal correlations for experts. In particular, we focus on the explanation demand, in order to support the user when needed and address the research gap.

The research question we address is, How can the understanding of spatio-temporal correlations be effectively supported by visualizing statistical analysis results and explaining geostatistical processes at the same time?

We present related research and derive challenges and findings that address this article in Section 2. In Section 3, we introduce the study area, explain the necessary background to the existing geoanalytical process of the data basis, and present the application context, including domain experts. The use case of this research addresses carparks in Mainz, Germany, and realizes real-world empirical data. Towards our proposed visualization design, we define general requirements for the explanation and analysis of spatio-temporal correlations in close cooperation with our domain experts in Section 4. We propose two implemented visual concepts—a visual explanation view (Section 4.1) and a visual analysis view (Section 4.3)—and relate them to the defined goals. In Section 4.5, we combine these two visual concepts and propose a concept of a semantic comparison visualization. We conclude and summarize our approach based on our study and show potential for future work in Section 5.

2. Related Work and Challenges

Spatio-temporal visualization is an active and rapidly evolving field, with recent advancements driven by the increasing availability of large-scale spatio-temporal data sets and the development of new technologies [4]. Current areas of application include the urban mobility sector, among others. Geovisual exploration and explanation systems are common tools to support data analysis processes in practice and applied research. Visualization systems for different issues in urban applications use and combine the broad portfolio of existing traditional or modern visualization techniques [8,9]. However, it is common for enormous amounts of data to lead to a lack of clarity or incompleteness in communicating essential correlations. In the following, we only present a selection of approaches that are directly related to the challenges in this research. This review aims to answer how traditional techniques have been applied and what kind of new modern techniques have been proposed.

2.1. Time Series Visualization

Time series visualization frequently uses traditional techniques such as line charts, bar charts, or timelines in combination with different kinds of visual variables [10,11]. In contrast, modern approaches and techniques increasingly try to emphasize human associations through advanced visualization. For example, radial visualization techniques such as Axes-based TimeWheel [12] or SpiralGraph [13] provoke temporal associations by imitating the structure of a clock. The techniques plot data for different points in time radially around the time axis, e.g., to allow a temporal comparison. In order to represent more extended periods, calendar-based visualizations are primarily used for temporal interactions (e.g., data filtering), or temporal color-coded pattern recognition in *Linked Views* or as part of dashboards [14]. In addition to the static representation of time-related data, these techniques often link animations with common time series visualizations to make the individual time steps or changes recognizable. For example, Cybulski [15] used animated visualizations to show changes in city unemployment. However, the visualization literature discusses animations as controversial because they can overtax cognitive overload and influence the effectiveness and perception of the visualizations [16]. Rensink noted that users can simultaneously perceive a maximum of four to five elements in an animated visualization. In contrast, animations are a powerful medium for telling data stories and a good alternative to static visualizations, especially if this visualization technique communicates dynamic changes or focuses the users' attention on specific areas [17].

The weakness of all purely time-based visualizations is the lack of geospatial information. Therefore, we consider a link with other techniques to be mandatory.

2.2. Statistical Multivariate Visualization

Statistical analyses and results often use pure statistical multivariate visualization techniques. The aim is to communicate the statistical key figures or insights in the models. Boxplots, coefficient plots, and correlation matrices are common techniques [18]. More comprehensive visualization systems such as VIS STAMP [19] support the identification of complex multivariate data patterns through parallel coordinate plots and self-organizing maps in combination with *Linked Views* and user interaction. Chan et al. [20] extended 2D scatterplots of a linear regression model to a 3D cube and represented correlations between variables by sensitivity lines. With this model-based approach, they can compare cube representations of different correlations with each other. Klemm et al. [21] developed a similar approach using a model-based 3D regression scatterplot heatmap to analyze correlations between variables.

Statistical visualizations are often limited to tables, matrices, and diagrams because they are used for statistical purposes. Such an approach neglects spatial relations, but, notably, the objective of these analyses does not require them.

2.3. Exploratory Spatio-Temporal Visualization

Exploratory spatio-temporal visualizations process the spatial component in addition to the temporal component. Here, a combination of various new and existing visualization techniques into powerful visualization systems is ubiquitous. Movement and trajectory data often require a space-time visualization in order to identify trends or patterns. In particular, 2D flow maps [22], 3D space-time cubes [23], or the 3D Great Wall of Space-Time [24] are some of the techniques which represent relationships between two or more spatial distributed locations. Other combined exploratory systems with trajectory data for exploring origin–destination patterns suggest TaxiViz with overlapping heatmaps [25], TripVista with a triple perspective view [26], or moveVis with animations [27]. If the temporal change occurs at the same spatial point, visualization techniques focusing on point- or station-based data are popular. Examples of 2D approaches are rose diagrams [28] or complex circos diagrams [29]. In addition, 3D point-based visualization techniques include data vases [30], helix, or pencil icons [31]. In this case, the approaches use 3D to display the temporal information in a stacked way. Similar to the use of animations, the visualization community is ambivalent about the benefit of 3D visualizations. On the one hand, 3D visualizations often suffer from occlusion and overplotting, which complicate the comparison of two data points in space due to distorted perception [32]. On the other hand, 3D visualizations can also counteract visual clutter and facilitate interaction by adding linked axes to the limited space of 2D visualization [33]. Queiroz Neto et al. [34] developed SHOC, a spatio-temporal system that supports domain tasks. It provides a simplified way to perform spatial comparisons and the identification of hotspots by using set-like operations with superimposed geometries. On a larger scale, Tang et al. [35] developed a station-based metro analysis system called VISOS, in which they implemented different, complex visualization techniques in a combined visual analytics approach. This system does not include POI data.

In general, we notice that a large number of systems for exploratory spatio-temporal analyses combine and link many established techniques, but, at the same time, also integrate new advanced approaches. However, when developing visual exploratory approaches, it is always crucial to consider the extent to which the complexity of the data leads to potential visual clutter [36].

2.4. Visualization of Spatio-Temporal Correlations

In urban contexts, the challenge of depicting spatio-temporal correlations increasingly arises. This challenge focuses on the investigation and visualization of correlations between one or more attributes. Frequently, the target group consists of users with statistical expertise. In general, a classification between area-based and point-based spatio-temporal correlations is functional. Area-based approaches use different choropleth maps with a divergent color scheme for positive or negative correlations [37], or in combination with interactive views with multivariate, geographically weighted boxplots and scalograms [38]. The use of additional visual variables (e.g., highlighted borders as a result of tests of statistical significance) [39], hotspot analyses [40], or Linked Views (e.g., topological network visualizations, triad configurations, correlation matrices) [41] extend choropleth maps in spatio-temporal correlation analyses. In contrast, point-based approaches examine spatio-temporal correlations on a micro-level. Sunburst charts [42], concentric rings [43], compass glyphs [44], or radial multi-layer donut charts [45] extend the approaches above in combination with geospatial maps. Here, too, various line types and arrow thicknesses visually indicate the different correlation strengths. Animation enhances these techniques. Point-based approaches often also use POI data, e.g., based on individual consumption locations or public transport smartcard data [45,46]. Miranda et al. designed a visual exploration framework that allows users to explore *Urban Pulses* within and across multiple cities under different conditions. Their data-driven approach was based on Flickr activity and a mathematical time-varying scalar function [47]. Pena-Araya et al. compared three visualization techniques (Dorling cartograms as small multiples, proportional symbols (circles) on maps as small multiples, and proportional symbols (bar charts) on a single map) for identifying correlation over space and time. Their results showed that a visualization's effectiveness depends strongly on the individual task. Based on these results, they derived design guidelines about geo-temporal visualization techniques for communicating correlations. For tasks with increased spatial complexity, they recommended using small multiples; for tasks with increased temporal complexity, they suggest a single map with bar charts [48].

Regarding spatio-temporal correlation visualizations, area-based approaches increasingly aim to represent statistical correlation and significance values. The implementation often results in choropleth maps. Point-based approaches use more innovative, usually radial approaches. Here, the user can explore the facts and correlations independently in a visual way, but without gaining insight into statistical values. The approaches visualize spatio-temporal correlations but neglect a deeper insight into statistical values. According to the design recommendations for identifying correlations over space and time by Pena-Araya et al., we note that a direct transfer to our use case and data basis would pose further challenges. First, they focused on larger areas (e.g., a map of the USA), and we experienced high cognitive load with juxtaposed small multiples when applying the approach to our data. Second, using bar charts on a single map shows the trends in our use case. However, this representation would significantly increase the cognitive load and visualization volume due to the amount of spatial information. Third, all approaches followed a generalized visualization that disregarded detailed information about correlations or precise geospatial information.

2.5. Explanatory Visualization

Explanatory visualizations are often used to communicate complex information in a clear and easy-to-understand format to a wide range of audiences, including those who do not have expertise in the subject matter. Stargatt et al. [49] provided an extensive review of genres, guidelines, techniques, concepts, and questions for developing explanatory visualizations. Focused on spatio-temporal analyses, GeoTime adds a narrative story system to identified patterns in spatio-temporal events to support analysts in identifying, extracting, arranging, and presenting them [50]. For example, it expands space-time-cubes with text editing fields, bookmarks, or snapshot functionality. Davis et al. [51] proposed a similar approach with stacked environmental context cubes to compare daily space-time movement patterns. Story synthesis [52] combines data analysis and the presentation of results by selecting, compiling, and arranging findings in useful layout views, e.g., a spatio-temporal movement analysis arranges events along a timeline and links them to a map. Roslingifier [53] is a semi-automated, data-driven storytelling method for visual explanation with techniques such as animated scatterplots. Other approaches include interactive step-by-step presentations for collaborative data analysis [54].

The presented approaches to explanatory visualization show that powerful combinations of analysis and explanation often exist in automated applications for data analysts. Established visualization techniques result in subsequent explanations. Spatio-temporal explanatory visualizations are rarely part of the applications.

2.6. Findings and Challenges

As a result of the current literature analysis, we defined the central challenge of this article. The key challenge was to visualize multifactorial spatio-temporal correlation results while simultaneously explaining the complex analysis process of underlying geospatial factors. Concerning existing work, our contribution is the development of an approach that considers demand-oriented stations of limited service offers, such as carparks and their spatio-temporal environment, in a semantic comparison visualization. We focus on geovisual techniques for the explanation and analysis. Current research mainly supports these challenges individually, claiming cartographic tools and techniques that support effective visual exploration and explanation. The research gaps relate mainly to temporal trends in spatial patterns [55] and the lack of appropriate tools for analyzing spatial relationships [56] in combined explanatory and analytical approaches. Statistical methods and results alone do not convey enough information for domain experts to make informed decisions [57]. Consequently, we focused on the requirements for analyses and explanation objectives, and aimed to combine both goals.

3. Study Area, Data Basis, and Domain Experts

3.1. Study Area and Data Basis

The research site of this study was Mainz, Germany. Our work used existing research about spatio-temporal correlation results between parking and geospatial factors, on the one hand, and the different steps of the geo-analysis process for calculating the geospatial factors on the other hand [2,3]. The existing process to measure the impact of geospatial factors in urban use cases examines a mathematical variable as a metric of geospatial impact [2]:

$$x_{ij} = \rho_{ij} = \sum_{p_k \epsilon P_j} r_{ki} \cdot o_j \cdot \omega_k \quad (1)$$

This metric (1) calculates the impact of different geospatial factors by combining three types of analysis—a reachability analysis (r_{ki}), an analysis of opening hours (o_j), and an analysis of the attractiveness of the POI (ω_k). The authors considered each POI (p_k) separately. Calculated together, the POI result in a common density ($x_{ij} = \rho_{ij}$) of each geospatial factor around every carpark. For more background information, refer to the work of Rolwes and Böhm [2]. The associated challenge was to explain the complex analytical process in a comprehensible way for domain experts. Geoanalytics identifies spatio-temporal correlations between parking occupancy and the density of geospatial factors following the metric of geospatial impact. Table 1 shows standardized regression results of slot-wise multiple linear regression analysis of an exemplary carpark 'Kronberger Hof' in Mainz, including its spatio-temporal correlation to 5 different geospatial factors and 12 time intervals.

Table 1. Standardized regression results of slot-wise multiple linear regression analysis of the carpark 'Kronberger Hof' in Mainz, Germany [2].

	Time of Day	Services and Specialty Retail	Grocery	Health	Food Services	Shopping	Adjusted R-Squared
Weekday	00:00–07:00	0.114 ***	0.000	0.000	0.000	−0.071	0.005
	07:00–12:00	0.255 ***	0.034	0.126	0.244 ***	0.171 *	0.639
	12:00–18:00	−0.008	0.063	0.240 ***	0.168 ***	−0.133 ***	0.058
	18:00–00:00	−0.009	0.020	0.049	0.405 ***	0.132	0.335
Saturday	00:00–07:00	0.000	0.000	0.000	−0.109	0.114	0.003
	07:00–12:00	0.000	−0.195 ***	0.004	0.747 ***	0.227 *	0.658
	12:00–18:00	0.000	−1.478	0.343	0.033	1.616 *	0.141
	18:00–00:00	0.008	0.237	0.000	0.155	−0.021	0.005
Sunday	00:00–07:00	0.000	0.000	0.028	−0.044 *	0.000	0.002
	07:00–12:00	−0.059	0.177	−0.038	0.217 ***	−0.051	0.036
	12:00–18:00	0.057	0.059	0.028	−0.145 ***	−0.241	0.015
	18:00–00:00	0.158	−0.040	0.049	0.207 ***	0.004	0.090

Significance level at 0.001 (***), 0.05 (*), n = 43,815 observations .

For this specific carpark located in the city center of Mainz, we consideedr about 44,000 occupancy records over a period of 4 years, 2015–2019, and approximately 1100 POI from 255 different OpenStreetMap (https://www.openstreetmap.de/ (accessed on 5 April 2022)) amenities in the spatial environment, with a maximum walking distance of 800 m (in consultation with the carpark operator). The vast data basis generally consisted of 13 carparks with continuous data about the parking occupancy in 60 min intervals. At this point, a table of numbers displayed the results in a complex, statistical way, but neglected spatial aspects. For example, during the working hours on weekday afternoons, health (b = 0.240; $p < 0.001$) and food services (b = 0.168; $p < 0.001$) showed a highly positive and significant effect (the parameter b indicates the standardized regression correlation coefficient; the parameter p indicates the statistical significance level). This example means that an increase in the density of surrounding healthcare facilities or restaurants positively impacts the carpark 'Kronberger Hof' occupancy on weekday afternoons. However, the spatial aspects of these findings are not part of this presentation. Users do not receive spatial background information or understand where and why spatial patterns occur. The associated challenge was to communicate these spatio-temporal correlation results in a user-oriented visualization with focus on geospatial patterns.

3.2. Group of Domain Experts

In our study, we worked in close cooperation with various domain experts in the field of mobility and urban planning. Our primary partner was the management level of the local parking company in Mainz, consisting of two persons. Both persons had decades of experience in controlling, managing, and optimizing carparks and their locations. Other partners during this study were a software company for parking management, consisting of one technical leader and two technical assistants, and three municipal partners, consisting of one innovation manager and two urban planners. In numerous meetings with our domain experts, we discussed various current systems, analyses, and prior knowledge based on concrete presentations, and derived their needs. This group of domain experts from different collaborative fields provided an ideal balance for our study because they represented interests from the perspective of management as well as urban planning. As a decision basis, domain experts need a tailored visualization with more geospatial details than a table of numbers. They need more detail about the influential surrounding urban area of the individual carpark, the background of the spatio-temporal correlations, and the analytical process leading to the spatio-temporal correlation results. They cannot fully interpret and comprehend geospatial correlations, especially when they occur contrary to their prior knowledge. On the one hand, domain experts can use the results of our work as a further basis for decision-making, e.g., in long-term planning processes, such as location planning and location optimization of carparks, or urban district changes, such as proactive traffic management. With the help of our study, it is easier for domain experts to visually identify and comprehend spatial relationships in order to justify their planning decisions. On the other hand, experts can use the results of our work in order to establish further cooperation between, for example, retailers or leisure facilities and parking garage operators. Voucher systems for swimming baths or shopping stores are a common way to direct visitors to a carpark. For this cooperation, domain experts need to understand the spatial environment of the car park and the influencing geospatial factors.

4. Visualization Concept for Spatio-Temporal Correlations

Earlier, we defined general requirements for the explanation and analysis of spatio-temporal correlations with the knowledge of domain experts (see Section 3) and the existing literature (see Section 2). Here, we did not gather the requirements in formal meetings using questionnaires for functional and non-functional requirements (as takes place, for example, for software products). This would have limited the requirements purely to the visualization background and the knowledge of the domain experts. Instead, the derived requirements and needs resulted from several meetings and discussions with our domain experts, describing what information they needed and what information they lacked, as well as what information they understood and what information they did not understand. During the sessions, we identified that experts had tacit prior knowledge of local conditions based on decades of professional experience. However, this knowledge was tied to individuals and was, thus, only temporary. We also aimed to include this knowledge in the requirements and concepts. These requirements challenged *WHAT* to communicate and visualize to the domain experts [58].

We classified the requirements into Understanding-oriented requirements and Knowledge-oriented requirements (see Table 2). In addition, we agreed to limit each to three main requirements.

Table 2. General requirements for the explanation and analysis of spatio-temporal correlations.

	Requirements
Understanding-oriented requirements	Geolocation and hotspots of geospatial factors Explanation of the analysis process of geospatial factors Explanation of spatio-temporal correlations
Knowledge-oriented requirements	Visualization and scaling of spatio-temporal correlations Exploratory and interactive functionality for geo-analysis Uncertainty and transparency of correlation results

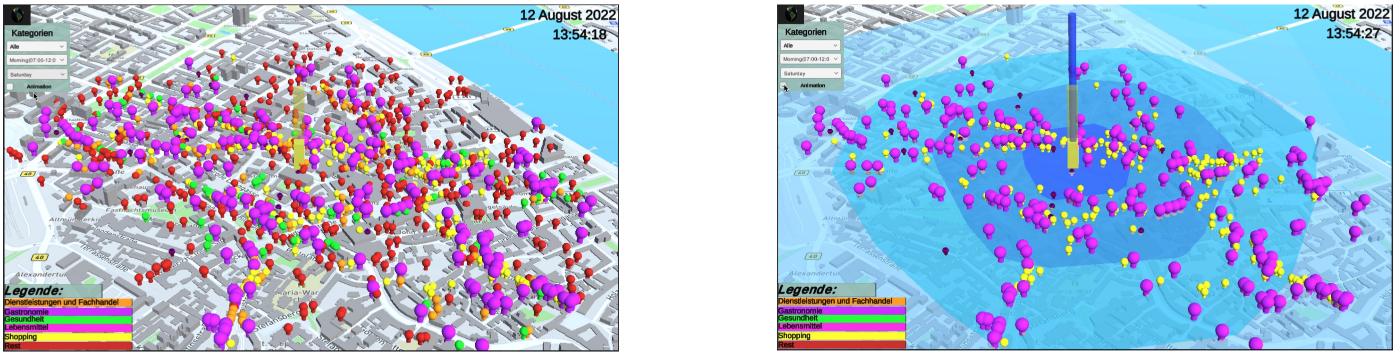
Understanding-oriented requirements are demand-driven, meaning they require the communication of the individual geolocations and hotspots of each geospatial factor with metadata. Thus, the user gains insights about the environment of a carpark and influencing areas. This requirement represents the starting point of many planning processes in order to gain an initial impression of geospatial phenomena and relevant areas. As Section 3 shows, the various geospatial factors consist of many individual possible destinations for customers. In order to reduce visual complexity, our concept needed a design that categorized these individual POI into geospatial factors and presented their density-related hotspots. By realizing this requirement, we can create fundamental knowledge for users and assist them in analyzing geospatial patterns. Identified geospatial patterns help to perform the analysis in a focused manner. In addition, users receive a first insight into the environment of a carpark and its influencing area and receive necessary metadata in order to create cross-references in the analysis. This requirement represents the starting point of many planning processes, as it is closely linked to the other understanding-oriented requirements. As a primary requirement, a comprehension-focused view needs to explain the analysis process of geospatial factors on the one hand and the resulting spatio-temporal correlations on the other hand. Domain experts specifically expressed the need to understand the background of spatio-temporal correlations and patterns in order to incorporate them into their decisions. Complex data analysis can be a hurdle, especially for users with little geospatial expertise. This data analysis process is more complex when it includes spatial analysis. As a result, domain experts often need a deeper understanding of these processes and cross-domain expertise. As mentioned above, the results of the geoanalytical process included three types of analysis—a reachability analysis, an analysis of opening hours, and an analysis of the attractiveness of the potential destination. In order to gain a detailed understanding of these individual analysis steps, the goal of the second requirement was to explain this geoanalytical process and the metric of geospatial impact (see (1) in Section 3) in more detail. Domain experts called for support and visual explanations in order to understand all calculation details of the analysis process of geospatial factors. If this requirement is fulfilled, domain experts will be able to understand the analysis steps involved in the underlying process, how geospatial factors and urban patterns change as a result of each analysis step such as the area of geospatial influence equal to the reachability area, and what effects these changes trigger. In order to obtain a holistic view of spatio-temporal phenomena, it is also necessary to explain the resulting spatio-temporal correlations. It is essential to clarify differences in the strength of these non-trivial correlations so that the users can perform their analyses effectively. Fulfilling this requirement with an effective explanation ensures that the user understands urban phenomena and helps to question personal assessments.

Knowledge-oriented requirements are the main requirements for analyzing spatio-temporal correlations in an exploratory way. Concepts need to visualize and scale correlations so that the users can identify geospatial key factors with their associated impact strength. This also involves creating a clear visual feature for positive or negative correlations so that users can recognize them directly. Domain experts were mainly interested in these key factors at different points in time, as they significantly affected the particular carpark. In order to identify differences in strength, the concept must support visual comparisons between geospatial factors. In concrete terms, this means that users should be able to clearly distinguish a strongly affecting geospatial factor from a weakly affecting one. In order to identify spatial patterns and hotspots, fulfilling this requirement is in close cooperation with the first requirement of the understanding-oriented requirements (see Table 2). At the same time, meeting this requirement also helps to challenge users' prior knowledge and to reveal unexpected spatio-temporal correlations. Furthermore, interactions are an appropriate approach for users to drill down their analysis further. In order to individualize geo-analyses for spatio-temporal correlations, knowledge-oriented requirements call for interactive, exploratory functions. Users can thus reduce visual complexity independently, dive deeper into the data, and focus their investigations on specific spatial areas. Existing techniques and concepts often link views together so that changes in one view affect a second view. Other common interactive, exploratory functionalities are details on demand, filtering, or brushing techniques such as a brushing focus lens for customized area-based analysis [59]. Fulfilling this requirement supports domain experts to tailor the analyses to their needs, testing hypotheses, analyzing specific urban areas, or challenging their prior knowledge. In addition, interactions often form a basis for comprehensive visual analytics systems. In order to increase trust and transparency in the results, the requirements call for visualization techniques for uncertainty. Users need to understand how reliable the results are and where the potential for optimization is. Especially in the case of unexpected spatio-temporal correlations, unusual events, or rejected hypotheses, the visualization concept needs to convince the user to trust the results despite prior knowledge to the contrary. Here, above all, close cooperation with the understanding-oriented requirements is necessary in order to promote trust with user-oriented explanations (see (1) in Section 3).

The following developed concepts address *HOW* to visualize and communicate the defined requirements for domain experts effectively. We present the individual concepts and evaluate them according to the established requirements. We also determine the limitations of the concepts.

4.1. Concept of a Visual Explanation View

In order to fulfill the *Understanding-oriented requirements*, our conceptual idea of a visual explanation view focuses on the explanation of the complex analysis process of geospatial factors with its metric of geospatial impact. We proposed an interactive 3D approach that visualizes stepwise the changes of each geospatial analysis step in the relevant environment of the carpark, e.g., the specific POI and the geospatial factors depending on the individual steps of the analysis process in a selected time interval. The analysis specifies the possible time points and can define seasonal intervals, week intervals, or day intervals [2,60]. With our concept, we aimed to visually explain the calculation details to the user step by step and generate an increased understanding. Animated visualization additionally assists the explanation. With the knowledge of the discussion in the literature about the benefit of animation and 3D, we used both techniques to call attention to the explanation. In our case, the map represents the core element of the application. In the initial state, we visualize all POI in the same size and shape due to equal weighting on the map. Only the color represents the corresponding geospatial factor. The user receives an overview of the urban area and recognizes geospatial clusters and hotspots. With interactions in the settings and options menu, the user can consciously trigger the explanatory animation for a carpark. For example, we focused on explaining the reachability analysis and the associated change in the geospatial factors on weekday afternoons. Figure 1a shows the initial state of the individual POI without considering the changes due to the reachability analysis. We used animated flowing isochrone heatmaps to explain the changes in the geospatial environment of the carpark. We modified the visualization of the individual POI so that nearby destinations for parking customers become larger and distant destinations become smaller. Due to this modification in size, the map's relevant POI remain after flooding (see Figure 1b). Irrelevant geospatial areas under consideration in the reachability analysis are flooded. Pop-ups provide additional explanations on the analysis process and metadata. With the help of these pop-ups, the domain expert receives in-depth information about the POI, such as its name or the walking distance to the carpark. Domain experts can use this understanding, for example, in order to establish cooperation between leisure facilities and carpark operators. Practical use cases from discussions with our domain experts include discounted admission fees for swimming baths in order to direct visitors specifically to a carpark. In a subsequent step, the explanation proceeds with another analysis of its geospatial effects, e.g., the effects of the analysis of opening hours. This explanation expands the understanding of the domain experts and allows, for example, limiting the discounted admission fee to time periods when the carpark shows a low occupancy rate. Here, we applied the changes of this analytical process step to the previously modified POI so that the geospatial factors would represent the combined effect.



(**a**) (**b**)

Figure 1. Prototypical visualization of the reachability analysis and the associated change in geospatial factors before (**a**) and after (**b**) the explanation of this analysis step (**a**) Start of visual explanation. Visualization in the initial state *before* considering the changes in the geospatial environment of a carpark due to the reachability analysis. (**b**) End of visual explanation. Visualization *after* considering the changes in the spatial environment of a carpark due to the reachability analysis using flooding animation.

We implemented this interactive 3D approach prototypically with Unity (see https://unity.com/ (accessed on 23 February 2023)) and Mapbox (see https://www.mapbox.com/ (accessed on 23 February 2023)), and evaluated it in an interim evaluation. The prototypical implementation in this phase primarily aimed at the feasibility and effectiveness of this visual explanation and did not reflect the final targeted technology. The long-term goal is an implementation where the user does not require knowledge of a game engine but can access the visual explanation view in a web browser. This has the advantage that users do not need a unique installation on their operating system before using the view. In this interim evaluation, we assessed this concept with domain experts and concluded that it offers potential for optimization. We noticed that a step-by-step explanation combined with animation improves the domain expert's understanding of the analysis process. At the same time, the flowing isochrones and the combined visualization of analytical process steps led to cognitive overload for users. In addition, we reconsidered our ideas on 3D techniques to generate more significant benefits for explaining the individual analysis steps. In a second iteration, we further elaborated on the concept. On the one hand, we used a 2D orthographic, animated view to provide general explanations (see Figure 2a). On the other hand, we transferred the general concept of a data cube, which enables multi-layered data layers through superimposition. We considered each complex, multifactorial step of the analysis on a separate detailed 3D explanation layer (see Figure 2b). Individual layers grow out of the map with animation so that the specific POI and the geospatial factors change. Specifically, the size of the displayed circle (equal to the POI) changes according to the respective analysis. As an example, the third layer from the top explains the effects of the attractiveness analysis of the metric of geospatial impact (see (1) in Section 3). A larger circle indicates a higher attractiveness for carpark customers as a potential destination. Users can thus see the progression of change through the personal analysis steps for each POI. This concept also enables the user to recognize the individual analysis and effects separately, and to relate the two layers to each other. For example, users can identify which geospatial analysis causes a more significant effect on relevant urban areas.

(**a**) (**b**)

Figure 2. Concept of a visual explanation view with a prototypical implementation of an orthographic and animated 2D explanation view (**a**) and a separate detailed 3D layer-based explanation view (**b**). (**a**) An orthographic, animated 2D view for general visual explanation. (**b**) A detailed 3D layer-based visual explanation of each POI change in the steps of the geospatial analysis process.

We can further recognize common analysis steps in a consciously initiated merge. As a final modification, due to the long-term implementation goal, a pure web-based application was desired, which we implemented with React (see https://react.dev/ (accessed on 23 February 2023)) and deck.gl (see https://deck.gl/ (accessed on 23 February 2023)). The use of Mapbox as a map-based component remained. Here, we used a dark background map to distinguish colors more clearly from each other.

4.2. Requirements Validation and Evaluation

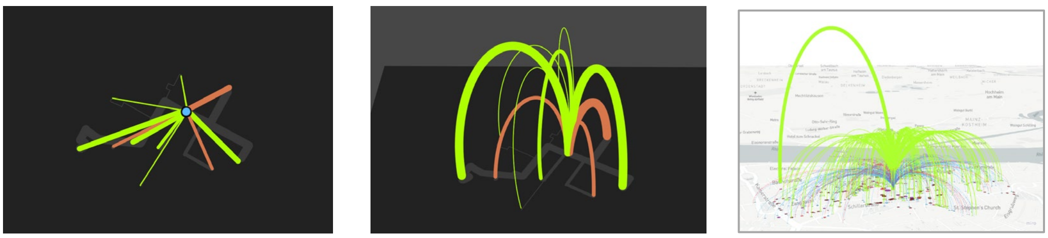
Table 3 presents the requirements validation for the proposed visual explanation view. This concept demonstrates its benefits, especially in the stepwise explanation of the analysis process of geospatial factors. The approach allows users to consider the different analyses separately and explain them one by one. At the same time, this view also provides the advantage of interactively linking geospatial analyses, as well as identifying spatio-temporal effects and changes in geolocation and hotspots together. Concerning the discussion about using 3D techniques, we have noticed an acceptance among users. They explore the explanatory layers by panning and tilting the view to identify underlying changes in individual POI. By visually adjusting the size of each POI resulting from the process, the user recognizes the different importance of each POI for the correlation calculation. Metadata help provide background information about each POI. In contrast, we assert that the view shows limitations in explaining resulting correlations. Our analyses indicate that the visualizations provided do not satisfy the users' need to explain spatio-temporal correlations. The designed approaches do not generate a sufficient and comprehensible benefit with the user group to explain resulting correlations efficiently. Here, we notice a need for further research. In addition, we recommend evaluating this step-by-step explanation concept when the analysis process involves a significantly larger number of individual steps. In general, this concept alone cannot fulfill all the defined requirements. This requires a view with more focus on visual analysis.

Table 3. Requirements validation for the concept of a visual explanation view (++ = strong fulfillment; + = fulfilment with limitations; o = limitations).

	Requirements	Requirements Validation
Understanding-oriented requirements	Geolocation and hotspots of geospatial factors	+
	Explanation of the analysis process of geospatial factors	++
	Explanation of spatio-temporal correlations	o

4.3. Concept of a Visual Analysis View

In order to fulfill the *Knowledge-oriented requirements*, our conceptual approach of a visual analysis view focused on an exploratory analysis of resulting spatio-temporal correlations. Here, we aimed to create a visual relationship between POI and carparks. Following the approach of flow maps [22], we extended it into the third dimension and used visual 3D arcs to link POI with associated carparks (see Figure 3). Both the height and the thickness of the arc represent the strength of the respective spatio-temporal correlation. Effective detection of geospatial key factors is one of the domain experts' most crucial analysis goals. Therefore, we wittingly proposed using these two techniques for the same information, to increase visual expressiveness. At the same time, we presented the arcs in the same color as the POI at the endpoint of the related arc. This enables the user to assign the POI. Additional metadata via pop-ups, such as detailed correlation coefficient or level of significance, support user understanding and consider the close connection to the explanatory approach. This allows the user to analyze the spatial environment of a carpark, detect associated POI, and identify the influence strength.



(**a**) (**b**) (**c**)

Figure 3. Conceptual 3D view to analyze spatio-temporal correlations between carparks and surrounding POI (**a**), (**b**), and prototypical implementation on a map (**c**). (**a**) Conceptual orthographic 2D view; (**b**) Conceptual 3D view with arcs; (**c**) Prototypical implementation on a map.

In addition to the pure map-based visualization, further linked spatio-temporal diagrams, views, and filtering options are indispensable. These also promote the use of comprehensive visual analytics systems to address the requirement of exploratory and interactive functionality for geo-analysis. Linking timelines, radial diagrams, or other animations counteract visual clutter and enable dynamic queries or individual adjustments. Additional views (exemplary in a sidebar in the analysis system) or 3D visualization on the map in connection with the respective carpark are possible. We recommend ensuring that this additional visualization only complements existing primary visualization and that users can add to them on demand. For example, users deliberately select a carpark in order to examine it in more detail. As an example, the radial diagram in Figure 4 also shows the strength of the correlation of every geospatial factor and the coefficient of determination in the charts' background. Thus, the visualization offers deeper insights into the geospatial analysis to generate trust and transparency in the correlation results. Here, too, users can compare geospatial factors with each other in order to consciously direct their attention to certain spatial areas.

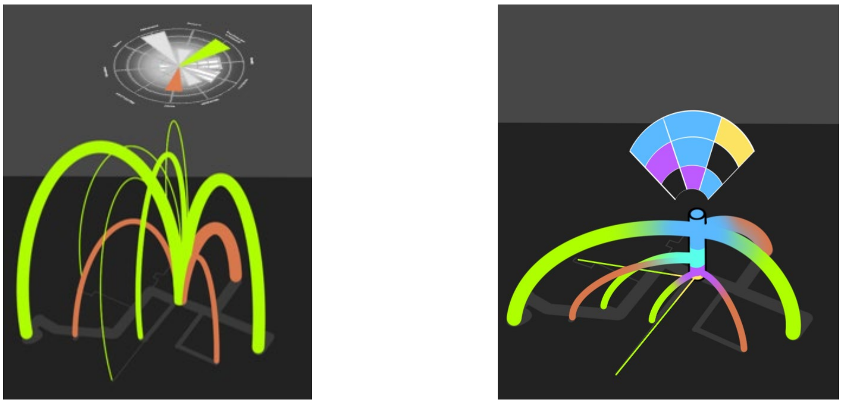


Figure 4. Conceptual visualization of linked arcs with different types of radial diagrams. The color represents the individual geospatial factor.

In general, visual overlaps can occur in this conceptual idea. A high number of POI surrounding a carpark result in a large amount of information on the screen. Therefore, in addition to the twofold implementation above (the height of the arc and the thickness of the arc), finding a solution that counteracts visual clutter is essential. We proposed two different options for this. First, we increasingly directed the user's attention to areas of the map that show high spatio-temporal correlation. To archive this goal, we used pulsating and highlighting POI of the main geospatial key factor on the map so that the user can identify spatial areas and urban hotspots with high correlation. Second, we proposed using an additional minimap. Minimaps offer the possibility to outsource further information and to reduce the main view's content. In this case, e.g., a linked 2D minimap shows an overview of the study area's positive or negative geospatial factors (see Figure 5).

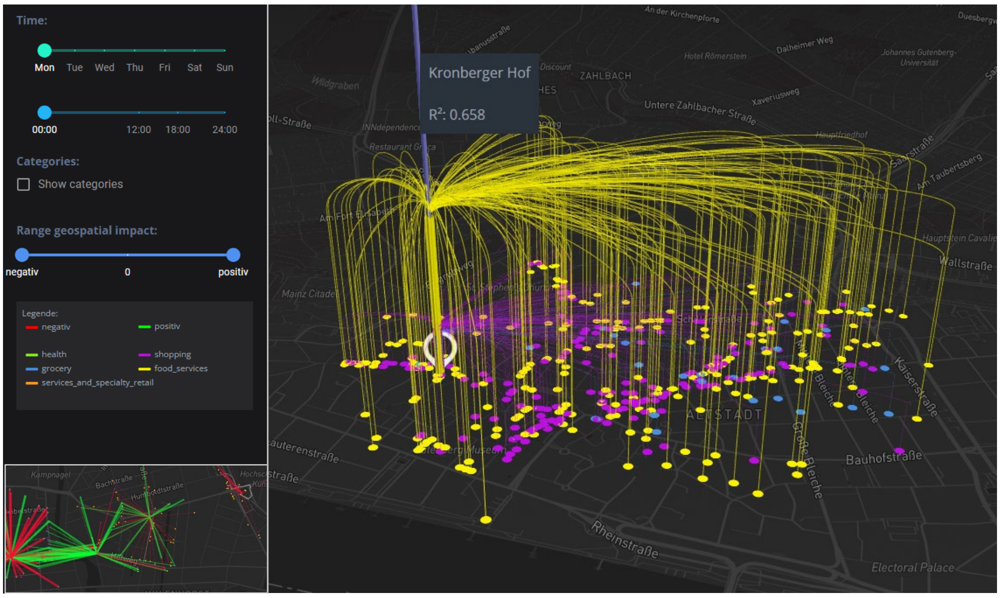


Figure 5. Prototypical implementation for analyzing spatio-temporal correlations with additional sidebar and linked 2D minimap.

4.4. Requirements Validation and Evaluation

Table 4 presents the requirements validation for the proposed visual analysis view. This view shows its main strengths in the visual implementation and scaling spatio-temporal correlation in combination with interactive analysis functionality. The use of 3D arcs offers a comparison between geospatial factors via the height of their arcs. Here, 3D techniques show their advantages. With the connection between the carpark and the POI, users can recognize correlations. With pulsating and highlighting POI, users identify the main geospatial key factors and essential areas on the map. In combination with the 3D arcs, this allows the user to track and understand the impact of highlighted POI. Further, the interactive functionality indicates positive evaluation results. Data filtering reduces visual overload. Users thereby increase their explorative analysis options and support user-defined analyses. At the same time, users evaluate the thickness of the 3D arcs as challenging to detect when the correlations are low. In addition, the accurate assessment of the correlations is challenging. The user's understanding increases after repeated use. Experts evaluated the designed link to radial diagrams to reduce the uncertainty in results as positive. We identified a lack of explanations for spatio-temporal correlations. In some cases, users could not explain correlations themselves, especially for negative spatio-temporal correlations. These identified lacks point out the need for an extended explanatory component. In general, this concept alone cannot fulfill all the defined requirements.

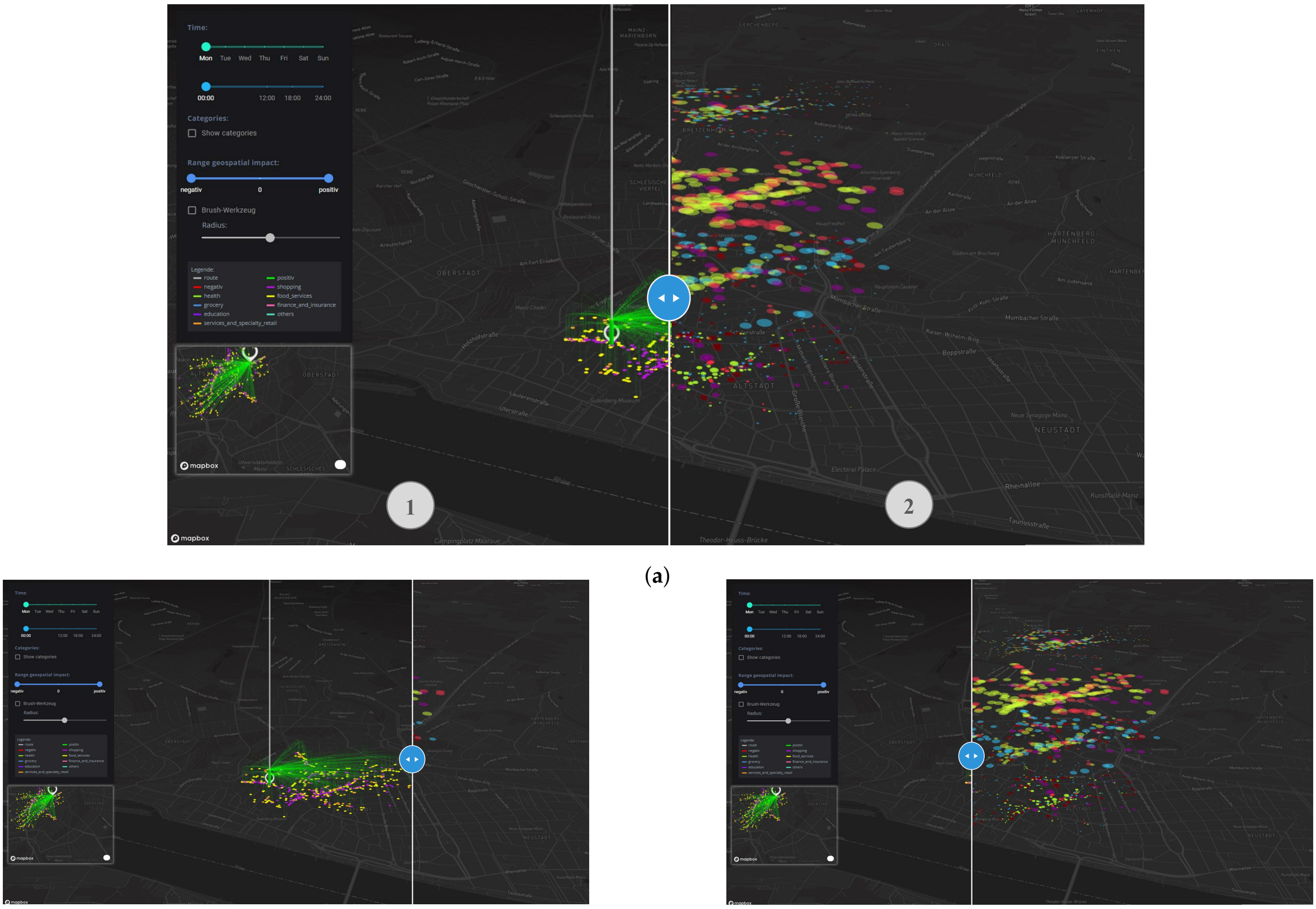
Table 4. Requirements validation for the concept of a visual analysis view (++ = strong fulfillment; + = fulfilment with limitations; o = limitations).

	Requirements	Requirements Validation
Knowledge-oriented requirements	Visualization and scaling of spatio-temporal correlations	++
	Exploratory and interactive functionality for geo-analysis	+
	Uncertainty and transparency of correlation results	+

4.5. Concept of a Semantic Comparison Visualization

Our concept for the semantic comparison visualization combined the two concepts we examined above and proposed a side-by-side view (see Figure 6). We used the strengths of each view to design a common, effective view for the explanation and the analysis of spatio-temporal correlations. A multi-monitor display or juxtaposition of small multiples [48] is often proposed in order to show the same spatial context with different information in two or more views side by side. We deliberately chose not to use this option, as capturing the range of multiple views requires a high cognitive effort. We drew similar conclusions for lens-based approaches, which make a second layer visible on a single view through a magnifying glass [61]. Again, the approach requires the user to exert a high cognitive load in order to examine the results. In contrast, our concept allows the user to vary between a visual analysis view 1 and a visual explanation view 2, individually.

With the visual analysis view (Figure 6b), the user can analyze urban areas in a targeted exploratory way and, if necessary, add semantically linked explanations and comparisons by using the vertical slider on demand. Our approach focused on the interactive play-in and play-out of the view, which stimulates the user's curiosity for exploratory investigations. Following the concept of a semantic comparison visualization, the user may start with the visual analysis view. This result-oriented view focuses on analyzing spatio-temporal correlations using 3D arcs and additional diagrams. Filtering options might help to customize the view according to the analysis questions of the domain experts. As described before, this view does not sufficiently support the necessary understanding of the analysis process. With the visual explanation view (Figure 6c), the user receives stepwise explanations of the complex analysis process of geospatial factors and related geospatial effects. This view supports user understanding by enriching analysis questions with the corresponding explanatory information about the metric of geospatial impact and its analyses. This conceptual idea offers the benefit that the explanation and the analysis are semantically linked in one view considering brushing techniques. Interactive filtering or selection changes in one view are automatically reflected in the other view. The user also needs a minimal distance between click targets to visualize both aspects coherently. The concept does not require additional integration of unique features for explainability, as these are provided by default and available to the user as soon as they need them. Following our idea, we needed an overarching element to connect the two views and give the impression that both views present information in the same overall spatial context. Consequently, we used a geographical map as the overarching element. Basic geographical information, such as roads or borders, connects both views so that the user does not notice any separation on the map. Despite the advantages of this approach, the amount of information on the screen also increases. Even though the slider represents a clear visual cut between the two views, the high amount of visualization input can lead to cognitive overload. This potential deficit is relatively small, as we seamlessly integrate the additional information and the user can add or reduce it as needed. The concept does not display both views at full width, so the user may feel that information is hidden or even missing. Again, we considered this as a minor issue due to our visualization approach's interactive and on-demand nature. Nevertheless, the advantages of the semantic comparison view outweigh the limitations, so we deliberately choose this combined approach. Moreover, the user can control the amount of visual information by filtering it and only adding explanatory information when needed. We also implemented our prototypical semantic comparison visualization as a pure web-based application with React, deck.gl, and Mapbox. As mentioned above, this offers the advantage that the users do not need to execute any additional installation on their operating system and can access the prototype directly. Thus, we can provide our various domain experts with easy access to the prototype.



(**a**)

(**b**) (**c**)

Figure 6. Prototypical implementation of a semantic comparison view (**a**), exemplary with focus on the analysis (**b**), and the explanation of spatio-temporal correlations (**c**). (**a**) Prototypical implementation of a semantic comparison view with a visual analysis view 1 and a visual explanation view 2. (**b**) Semantic comparison view with focus on the visual analysis view. (**c**) Semantic comparison view with focus on the visual explanation view.

4.6. Requirements Validation and Evaluation

Table 5 presents the requirements validation for the proposed semantic comparison visualization. This visualization approach combines the two views and, thus, benefits from the strengths of both individual concepts. Users focus on the analysis view and extend this view with semantic explanations on demand. The concept fulfills the requirements for visualizing and scaling spatio-temporal correlations and explaining the underlying analysis process of geospatial factors. Domain experts evaluated the conceptual idea of the semantic comparison view as "an interesting new idea in order to combine analysis and explanation". They assessed the vertical slider as an interactive idea that effectively presented explanations spatially coherently. From the domain experts' point of view, it was crucial to have the same map as the overarching element so that they could focus on the presented information. Compared to multi-monitor displays or small multiples, they rated semantic comparison visualization as more accurate and effective in order to add additional explanations during analysis. They considered geospatial references more difficult with multi-monitor displays or small multiples than with a vertical split screen. They positively emphasized that they could use the vertical slider to decide when to insert additional explanations in the analysis of spatio-temporal correlations, e.g., to examine specific areas in detail. Furthermore, they rated this combined visualization approach "clear and unambiguous" to use, but, at the same time, cognitively challenging because the "amount of information increases". Especially, the exact localization of each POI became more difficult with each explanation layer. In order to ensure the precise location of the POI in the respective explanation layer, the experts recommended a reference to the map, e.g., by vertical lines between the ground and the 3D layer and highlighting the selected areas or POI in both views. Dynamic queries, brushing and linking, and filtering support users in testing their hypotheses. Experts evaluated these adjustment options as essential to counteract information overload, especially with increasing numbers of explanation layers in the visual explanation view. From their point of view, it is essential to transfer changes from one view to the second view. As a concrete example, they named the filtering of the visual explanation view to an explicit analysis step (e.g., the explanation layer of the reachability analysis). This would allow them to adjust their needs to individual analyses. Despite the developed possibilities for explorative analysis, we identified the potential for optimization following the evaluation. We recommend further options and tools to analyze selected urban areas and counteract visual cognitive overload. Similar to the literature review, 3D visualization techniques on the map are also discussed in the evaluation. On the one hand, experts saw the advantages of using 3D techniques due to the complex spatio-temporal data, although they were generally critical of 3D techniques. On the other hand, they needed a few moments in the combined view to deal with it. The experts rated the use of 3D techniques here as judiciously applied and perceived a gain in information through 3D arcs in combination with various explanation layers, despite the challenge of the complexity of the data and the underlying geoanalysis. However, we noticed the need to expand the concept. As mentioned above, the concept needs further explanation to increase the comprehensibility and traceability of spatio-temporal correlations, especially what exactly the influence consists of. For example, the experts mentioned a persistent lack of understanding of the meaning of negative correlations. Concrete examples can support users, e.g., with additional textual spatio-temporal correlation explanations, using storytelling techniques [62].

Table 5. Requirements validation for the concept of a semantic comparison visualization (++ = strong fulfillment; + = fulfilment with limitations; o = limitations).

	Requirements	Requirements Validation
Understanding-oriented requirements	Geolocation and hotspots of geospatial factors	+
	Explanation of the analysis process of geospatial factors	++
	Explanation of spatio-temporal correlations	o
Knowledge-oriented requirements	Visualization and scaling of spatio-temporal correlations	++
	Exploratory and interactive functionality for geo-analysis	+
	Uncertainty and transparency of correlation results	+

5. Conclusions and Future Work

Understanding spatio-temporal correlations can support planning decisions in cities. For this purpose, statistical tables alone are not sufficient. In this article, we proposed a concept towards a semantic comparison visualization that focuses on the simultaneous explanation and analysis of spatio-temporal correlations. We derived general requirements with the knowledge of domain experts and comprehensive literature research. Subsequently, we developed different concepts for a visual explanation and a visual analysis view. The individual results reinforced their combination into a common semantic comparison approach. An evaluation and requirements validation with domain experts confirmed the fulfillment of the defined general requirements. At the same time, it showed the limitations and needs for optimizing our approach. Therefore, we recommend developing this approach in two ways in future works. First, the evaluation shows potential for improvement in the explanation of spatio-temporal correlations. Here, we aim to conduct further research on visual explanations, e.g., with advanced storytelling or user-guiding techniques. Secondly, we recommend integrating our approach into a visual analytics system. We also recommend an investigation regarding a generalization of our approach. We aim to extend our approach to other use cases in order to show general usability. For this purpose, the first results were obtained in another context with similar urban challenges [60]. Here, too, the results show urban spatio-temporal correlations, which are also used for predicting carpark occupancy. This, therefore, suggests striving for an explanation and analysis by visualization. The developed concept shows general benefits, so we will aim for further implementation in combination with extended analysis options, e.g., station-based or area-based analysis options.

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Abbreviations

The following abbreviations are used in this manuscript:

POI Point(s) of interest

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