This article has been accepted for publication in IEEE Transactions on Visualization and Computer Graphics. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2021.3109387

Multiscale Visualization: A Structured Literature Analysis

Eren Cakmak, Dominik Jäckle, Tobias Schreck, Daniel Keim, Johannes Fuchs.

Abstract—Multiscale visualizations are typically used to analyze multiscale processes and data in various application domains, such as the visual exploration of hierarchical genome structures in molecular biology. However, creating such multiscale visualizations remains challenging due to the plethora of existing work and the expression ambiguity in visualization research. Up to today, there has been little work to compare and categorize multiscale visualizations to understand their design practices. In this work, we present a structured literature analysis to provide an overview of common design practices in multiscale visualization research. We systematically reviewed and categorized 122 published journal or conference papers between 1995 and 2020. We organized the reviewed papers in a taxonomy that reveals common design factors. Researchers and practitioners can use our taxonomy to explore existing work to create new multiscale navigation and visualization techniques. Based on the reviewed papers, we examine research trends and highlight open research challenges.

Index Terms—Multiscale Visualization, Multiscale Navigation, Multiscale Exploration, Literature Analysis, Taxonomy, Survey.

1 Introduction

Many multiscale visualizations have been proposed in visualization research. These multiscale visualization approaches are essential in various application domains to analyze large and high-dimensional datasets, such as in geography [1], physics [2], or biology [3]. For instance, in molecular biology, multiscale visualizations are used to analyze genomes' multiscale hierarchical structure, such as the nucleus with a division into chromosomes, fibers, and, at the lowest scale, atoms [4]. Typically, in contrast to single-scale visualizations, multiscale visualizations scale to larger datasets, produce less clutter, and reveal the emergence of patterns at different levels of scale. For example, aggregation methods can be recursively utilized to promote a top-down or bottom-up hierarchical visual exploration of large datasets [5]. However, designing multiscale visualizations is challenging due to the plethora of existing approaches and different design considerations.

In previous visualization research, authors regularly use the expression multiscale (multi-scale) visualization in different contexts with often varying meanings. Examples of different contexts include interaction-based multiscale zooming methods [6] or multiscale statistical summary visualizations [7]. Visualization experts know about the expression's ambiguity and typically specify the accurate meaning in their respective papers. However, the different definitions of what is meant by a multiscale visualization may be confusing for novice readers. For example, selecting a multiscale visualization approach can be challenging for data analysts due to the expression's ambiguity. Currently, there has been little work to categorize and compare multiscale visualizations to understand their design practices. To address this challenge, we provide a systematic literature analysis of multiscale visualizations to gain insights into common design factors and improve communication between researchers.

Manuscript received April 19, 2005; revised August 26, 2015.

In this work, we provide a comprehensive overview of multiscale visualization approaches. We systematically analyzed 122 papers from multiple journals and conferences to understand general design practices for multiscale visualizations. The result is a categorization of multiscale visualization approaches into a taxonomy. We discuss how different multiscale visualizations enable us to analyze and relate information at various scales to gain insight into complex systems, such as in molecular biology [3]. Further, we summarize design considerations and highlight open research challenges for multiscale visualizations. Overall, we provide a basis for the systematic reasoning about multiscale visualizations, and the key contributions are: (1) a unified definition of the terminology, (2) a taxonomy of design practices for multiscale visualizations, (3) a summary of design considerations, and (4) a collection of crucial open research challenges. An extensive list of the reviewed papers, the resulting paper codings, and the taxonomy are accessible online at multiscale-vis.dbvis.de.

2 Background

In this section, we first examine some definitions and derive a unified consensus on the multiscale visualization terminology. We also search for similar concepts and synonyms in visualization research. The second part discusses commonalities and differences of our literature analysis to related work, such as relevant theoretical work and surveys.

2.1 Terminology

Some expressions are often so widely used that people use them without specifying their exact meaning. The term multiscale visualization belongs to these expressions. The potential characteristics and interpretations of multiscale visualizations are quite broad in visualization research. Therefore, we reviewed existing definitions to derive a consensus of what is meant by multiscale visualization.

This article has been accepted for publication in IEEE Transactions on Visualization and Computer Graphics. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2021.3109387

In a broader context, multiscale visualizations are a form of multiscale analysis. In many fields, multiscale analysis is widely in use to understand the emergent properties of systems in the real world, such as in physics [2] or biology [8]. The essential term ”multiscale” has the following dictionary definition: “operating or occurring over different levels“ [9]. The dictionary definition highlights the main characteristics of multiscale analysis, analyzing data at various levels of detail. Such a multiscale analysis's primary goal is to investigate complex systems by examining small-scale patterns and their effects on emerging large-scale patterns [8]. For instance, multiscale analysis is useful to analyze local interactions between animals in collective animal behavior to understand individual animals' influence on large-scale swarm behavior [10].

In the following, we examine definitions of multiscale visualizations to derive a more precise definition. First, Furnas and Bederson [11] specify multiscale visualization (multiscale interfaces) as an approach to display data at different magnifications or scales. Next, Stolte et al. [12] provide another perspective. The authors emphasize that multiscale visualizations utilize data and visual abstraction methods to present the data at different abstraction levels. Data abstractions transform and reduce the underlying dataset (e.g., aggregation or filtering), and visual abstractions change the data point representations (e.g., semantic zooming or distortions). Further, Elmqvist and Fekete [5] propose a multiscale structure and navigation strategies to turn existing approaches into multiscale visualizations and present data at multiple aggregation levels. Ebert et al. [13] describe the need for multiscale interactions to understand scientific data and system-of-systems at multiple problem scales. More recently, Viola and Isenberg [14] characterize multiscale visualizations as representations that display and relate abstracted data across various levels of scale.

We want to highlight that the previous definitions include different concepts such as navigating and relating abstracted data (e.g., aggregated data) across scales. These concepts are essential in multiscale analysis in various domains. For example, in the visualization of DNA nanostructures [3], domain experts have to navigate and relate information across different scales to understand complex system-of-systems. Overall, concepts such as the presentation and navigation of different abstraction scales expose patterns and relationships in datasets at varying scales. Therefore, we derive the following definition from the listed previous research: “*Multiscale visualizations allow users to present, navigate and relate data across multiple abstraction scales*.“ Our definition integrates various interpretations to specify the ideal characteristics of multiscale visualizations.

We reviewed the visualization literature to identify similar concepts and notions to the expression *multiscale visualization*. We utilize these similar expressions in our literature analysis as search terms to identify related papers. We used the IEEE VIS paper keyword search by Isenberg et al. [15] and the derived keyword topics [16] to search for synonyms. Additionally, we scanned the keywords and abstracts of the updated metadata collection about IEEE VIS publications [17]. We equally reviewed the CHI conference proceedings accessible on the ACM digital library for related expressions. We searched for the author keywords

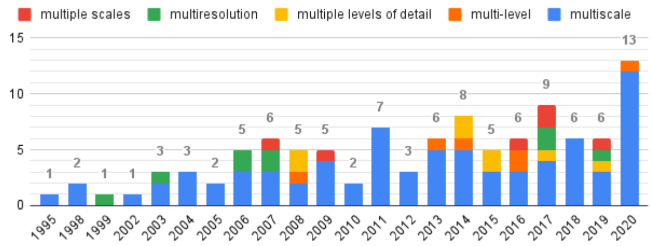


Fig. 1. The five most frequently used expressions among the surveyed 122 papers. The most common expression is multiscale visualization.

(tags) for “multiscale“ and scanned the resulting 29 papers for related expressions. We identified multiple reoccurring similar expressions such as *multi-scale*, *multiple scales*, *multi-level*, *cross-scale*, *multi-resolution*, and *multiple resolutions* in combination with terms such as *visualization*, *interface*, *representation*, *viewing*, *interaction*, *navigation*, *model*, *design*, and *analysis* are used to describe similar concepts in visualization research. To determine which of the related expressions is most often used in the literature, we investigated the term usage of our literature analysis search results (see Fig. 1). The term multiscale (multi-scale) is the most commonly used term of the previously listed expressions.

2.2 Related Work

Multiscale visualization has been a part of visualization research for quite some time. Next, we discuss related theory and survey papers that describe multiscale visualizations.

Theoretical Work: Many related theory papers discuss multiscale visualization approaches. Furnas and Bederson [11] provide an analytical framework and space-scale diagrams to understand multiscale interfaces. Stolte et al. [12] formalize multiscale visualizations using abstraction methods for data cubes. Kehrer and Hauser [18] discuss multifaceted visualization approaches, including a multi-model scenario. Goodwin et al. [1] discuss the modifiable areal unit problem (MAUP) [19] and propose a framework for multivariate visual comparison across multiple geographical scales. Viola and Isenberg [14] examine and formalize the concept of abstraction in visualization research. The authors discuss multiscale visual abstractions for spatial and temporal data. In comparison, our work focuses less on providing another theoretical framework and concentrates more on presenting an overview of multiscale visualization design practices in visualization research.

Surveys: In visualization research, three surveys investigate multiscale visualizations in specific application domains. Vaquero et al. [20] review the visualization and interaction techniques for multiscale biomedical data, such as anatomy or genomics. Ezzati-Jivan and Dagenais [21] survey multiscale navigation of execution trace data, focussing on multilevel trace abstraction and visualization methods. Miao et al. [22] discuss multiscale visualization techniques for the analysis and manipulation of 3D DNA structures in molecular biology. These surveys investigate multiscale visualizations for particular application domains. Furthermore, Ebert et al. [13] describe challenges and opportunities for multiscale scientific visualizations. In contrast, our work systematically reviews design practices for multiscale visualizations in a broader context of visualization research, exceeding the traditional scope of a survey.

This article has been accepted for publication in IEEE Transactions on Visualization and Computer Graphics. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2021.3109387

Hierarchical Visualizations: Further related work focus on hierarchical and tree-based visualizations. Yang et al. [23] propose a framework called Interactive Hierarchical Displays (IHD) for the multi-resolution view and navigation (e.g., drill-down) of hierarchies. Elmqvist and Fekete [5] propose a more general framework that presents a multiscale structure and navigation methods to turn existing visualization techniques into multiscale approaches. Schulz et al. [24] elaborate on the design space of implicit tree visualizations. In contrast to these works, we provide a broader review of visualization research by analyzing design factors in existing multiscale visualizations.

In summary, all these previous approaches present significant contributions by introducing frameworks, techniques, or domain-specific surveys. However, none of the previous work explored the broader visualization literature for existing multiscale visualization. Such a literature analysis is essential to understand common practices (e.g., interaction methods and targets) for multiscale visualizations. Our literature analysis is the first analysis of design practices for multiscale visualizations to the best of our knowledge.

3 Methodology

Our literature analysis's primary goal is to give a comprehensive overview of multiscale visualizations. The guidelines for qualitative literature analysis [25] inspired our methodological approach. We focus on papers that use the expression *multiscale visualizations* or the identified related expressions (see Sec. 2.1). Moreover, our literature analysis cannot include all possible multiscale data models in visualization research, as this would go far beyond the scope of our work. We did not explore visualization approaches that only employ hierarchical or tree-based models. Specifically, we omitted all papers that only utilize multiscale models (e.g., hierarchical clustering) without any multiscale visualization. In the following, we describe our literature search and analysis procedure.

3.1 Selection of Literature

First, we used multiple search engines to identify relevant papers from various conferences and journals. We used the search term *visualization* and the identified related expressions (see Sec. 2.1) for online keyword search. We used the following search engines, which lead to the results: IEEE Xplore digital library (327 results), ACM digital library (651 results), EG digital library (129 results), and DBLP computer science bibliography (781 results).

The automatically identified papers were refined in three steps. In the first step, we only included peer-reviewed full papers published in journals or conferences. The step reduced the number of papers from 1888 to 1312. In the second step, we manually excluded papers that were not related to multiscale visualizations. In this step, we excluded papers that only use multiscale models (e.g., hierarchical clustering) without any multiscale visualization. As a result, the papers were further filtered from 1312 to 75. As for the last step, we recursively scanned the paper references and followed the citations in both directions on Google Scholar. Hence, the number of papers increased again from 75 to 122.

3.2 Coding Scheme

We developed a coding scheme and tagged the 122 papers with labels. The coding scheme is designed to capture multiscale visualization characteristics and is based on existing taxonomies. To keep our coding scheme focused and manageable, we combined some labels in more abstract categories. Therefore, some details might get lost, like the distinction between line charts and scatterplots, which have been summarized as statistical graphics. A paper can have multiple labels of a specific coding category, for instance, multiple target labels. The authors coded the papers. We randomly selected and encoded 20 papers redundantly to validate our coding process. For the redundantly encoded papers, Cohen's kappa coefficient for inter-rater reliability reached a substantial agreement with $\kappa = 0.61$ (83% overall agreement). We tagged the 122 papers with the following coding scheme (see Tab. 1). A detailed description of each tag is described in the supplementary material.

Journal: We labeled the papers with the year and journal or conference to identify trends and the leading paper outlets.

Visualization Idioms: Munzner [26, Chapter 7-9] describes various categories of visualization techniques for different dataset types, such as spatial or network data. We selected ten prominent visualization idioms from the described visualization techniques to label the respective multiscale visualizations. We also added an extra category "other" describing unique visualizations that do not fall into any defined visualization idioms category. The following list summarizes the labels.

- *statistical graphics*: traditional charts, such as line charts, bar charts, or scatterplots.
- *parallel coordinates*: display multivariate datasets as lines between parallel axes.
- *dense layouts*: pixel-oriented visualization techniques display data records' values as colored pixels.
- *glyph*: multivariate data records are mapped to glyph, icon, and symbol representations.
- *3D*: three-dimensional geometric visualizations.
- *geographic*: geographic visualizations for spatial data, such as choropleth maps.
- *spatial fields*: visualizations of scalar-, vector-, and tensor fields.
- *graph*: graph (network) and tree visualizations.
- *stacked charts*: present data in multiple stacked layers, such as streamgraph visualizations.
- *other*: visualization techniques not fitting into any of the categories above.

Target: We labeled the target of the visualization using the suggested detailed targets by Munzner [26, Chapter 3].

Interaction: We used the manipulation methods for visualizations of Brehmer and Munzner [27] to tag the supported interaction methods. The listed manipulation methods [27] unify interaction and visual encodings as both are closely related to each other.

Composite Visualization: We used the design space of composite visualizations [28] to capture and label the combination of different visual representations in the same view.

Dataset Type: We facilitated four basic dataset types (*tables*, *networks & trees*, *fields*, *geometry*) described by Munzner [26, Chapter 2] to tag each paper.

This article has been accepted for publication in IEEE Transactions on Visualization and Computer Graphics. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2021.3109387

Category	Labels	Multi-Label	Source
Journal	name of the journal or conference and year		Source of Publication
Visualization Idiom	statistical graphics, parallel coordinates, dense layouts, glyph, 3D, geographic, spatial fields, graph, stacked charts, other	✓	Munzner [26, Chapter 7-9]
Target	trends, outliers, features, distributions, extremes, dependency, correlation, similarity, topology, paths, shape	✓	Munzner [26, Chapter 3]
Interaction	select, navigate, arrange, change, filter, aggregate	✓	Brehmer and Munzner [27]
Composite Visualization	juxtaposed, superimposed, overloaded, nested, and integrated views	✓	Javed and Elmqvist [28]
Dataset Type	tables, networks & trees, fields, geometry	✓	Munzner [26, Chapter 2]
Attribute Type	categorical, ordinal, quantitative, hierarchical	✓	Munzner [26, Chapter 2]
Navigation Strategy	top-down and bottom-up exploration strategies		Battle and Heer [29]
Level of Analysis	microscale, mesoscale, macroscale	✓	Shi et al. [30] and Xu et al. [31]
Application Area	CompSystems (computing systems), LifeBio (life sciences, biology), ML-StatsModel (machine learning, statistics), ScienceEngr (physical science, engineering), SocHum (social science, humanities), OtherApp (other application areas), NAApp (domain agnostic)		IEEE VIS Paper Submission Keywords [32]
Paper Type	technique (technique & algorithm), system, design study (application & design study), evaluation (empirical study), or model (theory & model)		IEEE VIS Paper Types [33]
Evaluation	computational benchmark, qualitative evaluation, quantitative evaluation, usage scenario, and no evaluation	✓	visualization evaluation strategies [34], [35], [36]

TABLE 1
The applied coding scheme with tags. A detailed description of each tag is given in the supplementary material. In case a category is multi-label, then several labels can be assigned to one paper.

Attribute Type: Munzner [26, Chapter 2] described the four attribute types *categorical*, *ordinal*, *quantitative*, and *hierarchical*. We labeled the papers using these attribute types.
Navigation Strategy: We consider two navigation strategies top-down and bottom-up exploration strategies [29]. The strategies can be described by drill-down (top-down) and roll-up (bottom-up) operations.
Level of Analysis: We consider the three levels of analysis scale: micro-, meso-, and macroscale. These analysis levels are often used to describe the analysis scale (e.g., in Shi et al. [30] and Xu et al. [31]). Microscale analysis is the smallest level of scale that displays individual data points, such as examining nodes and edges in a graph. The mesoscale analysis is in-between and investigates structural properties, for instance, analyzing motifs and communities in a graph. Macroscale analysis focuses on the dataset's global properties, such as the number of nodes and edges in a graph. Ideally, a multiscale visualization visualizes all three analysis scales to enable users to relate abstracted data across scales.
Application Area: We utilized the IEEE VIS application areas keywords (see Tab. 1) to tag the application domain [32].
Paper Type: We categorized the papers according to the five IEEE VIS paper types (see Tab. 1) to point out popular paper types in the research field [33].
Evaluation: We investigated common evaluation strategies in visualization research [34], [36] and on quantitative evaluation studies [35]. We used five tags to label the evaluation strategies: *computational benchmark*, *qualitative evaluation*, *quantitative evaluation*, *usage scenario*, and *no evaluation*.

4 RESULTS

The following section outlines prevalent coding labels and a taxonomy of similar multiscale visualization contributions. Furthermore, we derived design considerations based on our structured literature analysis. Researchers can explore the complete paper codings and the taxonomy online at multiscale-vis.dbvis.de.

4.1 Coding Results

First, we provide a high-level overview of the coding labels based on the coding scheme categories (see Tab. 1). In the supplementary material, we included charts to expose temporal trends for each coding category. The following percentages always refer to the 122 papers and do not necessarily add up to 100%, as a paper can have multiple category labels at the same time.
Publication Venues & Paper Types In recent years, an increasing number of multiscale visualization papers have been published (see Fig. 2). The top three publication venues are IEEE TVCG (44/122), Computer Graphics Forum (15/122), and ACM CHI (14/122). The remaining 49 papers were published in related journals or conferences. The most common paper types are technique (46%), design study (25%), and model (16%) papers. The two other paper types, system (7%) and model (6%), rarely appear over the years. From 2015 to 2020, the proportion of paper types has remained constant, except for a fluctuating number of design study papers. Recently, the IEEE TVCG publications reached an all-time high with nine papers in 2020 as the topic is gaining popularity for visualizing large-scale datasets.
Visualization Idioms The following labels, statistical graphics, geographic, 3D, and graph, occur separately in 25-28% of all papers. The previous four labels, considered altogether, appear in about 80% of all papers. The number of 3D, geographic, and graph idioms has steadily increased since 2008 due to a growing number of multiscale visualizations in social sciences and biology (e.g., 3D DNA visualization [22]). Each of the remaining idioms occurs as follows: 10% dense layouts, 10% glyph, 7% parallel coordinates, and 5% spatial fields, as well as stacked charts. Interestingly, our label "other", representing unique visualization techniques and tailored design studies, appears in 40% of all papers.
Target The commonly assigned target labels for visualizations are with 80% features, 57% shape, 41% similarity, 39% distribution, and 30% for topology as well as trends. The remaining target labels appear in 28% paths, 27% correlation, 27% outliers, and 18% dependency of all papers. The

This article has been accepted for publication in IEEE Transactions on Visualization and Computer Graphics. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2021.3109387

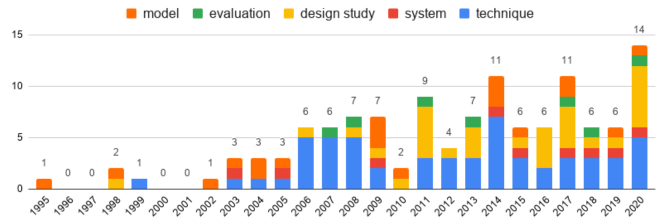


Fig. 2. The chart presents the paper types for the years 1995-2020.

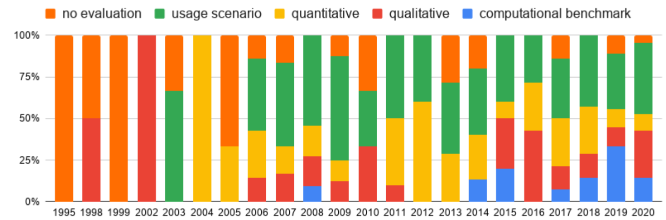


Fig. 3. The proportion of paper evaluations for the years 1995-2020, showing a positive trend towards more extensive paper evaluations.

target label "extremes" occurred only ten times, which is rare considering the number of analyzed tabular datasets (46%).

Interaction In almost all papers, essential interaction methods are the navigation (85%) and selection (83%) of abstraction scales. Papers without those two labels discuss more theoretical contributions, such as frameworks or workflows. The proportion of the labels aggregation (47%) and change (34%) has remained constant since 2006. The interaction methods filter (30%) and arrange (17%) have slightly increased after 2014. Notably, the interaction methods select and navigate likewise aggregate and change tend to appear together as navigation across scales often includes selecting an appropriate scale, and aggregation involves changing data abstraction scale.

Composite Visualization An overall 45% of all papers received the label juxtaposed. Each remaining label nested, superimposed, integrated views, and overloaded appeared overall in 13-15% of all papers. In terms of temporal shifts, we observed 13 superimposed views from 2013 to 2017, contrasting to the only four previously superimposed views from 2003 to 2013. Furthermore, 40 papers did not describe any composite views, as the approaches proposed only visualization techniques or discussed theoretical work.

Dataset Type The utilized types are 50% geometry, 46% table, 25% network & tree, and 7% field datasets. We want to highlight that tabular datasets appear nearly 13% in conjunction with geographic or network & tree datasets, i.e., in the form of geographic attributes. Multiscale analyses of field datasets first appeared in 2014 and are overall underrepresented with only eight papers.

Attribute Type The analyzed attribute types are in 81% of the cases categorical, 46% quantitative, and only 2% ordinal. Furthermore, 18% of papers analyze hierarchical data attributes. We want to highlight that there are no dedicated multiscale visualizations for only ordinal data attributes.

Navigation Strategy Overall 74% of papers utilize top-down approaches, with only eight papers applying bottom-up approaches. Seven of the eight bottom-up approaches were proposed after 2013. There are only three approaches that describe only the bottom-up navigation strategies.

Level of Analysis For the next category, the label occurrences are as follows: 89% microscale, 75% mesoscale, and 12% macroscale. For 65% of all papers, the labels microscale and mesoscale occur together. We noticed that most multiscale visualizations are not displaying macroscopic information, which is essential for relating the abstracted structures to the overall global dataset properties.

Application Area The labels appear with the following frequencies: 28% LifeBio, 11% SocHum, 8% CompSystems, 5% ScienceEngr, and 2% MLStatsModel. Further, 34% of all papers are domain agnostic, and 15% are in other application areas. The following trends have emerged. The number of papers in life science and biology has steadily increased from one in 2013 to six papers in 2020. Multiscale visualizations for machine learning applications appeared after 2017 and will inevitably increase in the future, as multiscale visualizations are suited to display deep learning architectures at varying scales, such as network layers and their underlying neurons.

Paper Evaluation The number of utilized evaluation approaches are 51% usage scenario, 29% quantitative as well as 20% qualitative user studies, 20% no evaluation, and 11% computational benchmark. We also examined the proportion of evaluation methods over the years (see Fig. 3). The analysis indicates an increase in quantitative and qualitative user studies, including a slight decrease in usage scenarios. Additionally, since 2014, there has been an increase in computational benchmarks in paper evaluations. Overall, there is a positive trend towards more detailed evaluations with benchmarks and user studies.

4.2 Multiscale Visualization Taxonomy

In the following section, we introduce prevalent classes of contributions in multiscale visualization research. Our taxonomy consists of six main classes of paper contributions with multiple sub-classes (see Fig. 4). We outline how we derived the taxonomy based on several clustering iterations and the refinement of the clusters. First, we encoded the labels using one-hot encoding and applied k-means clustering using the cosine similarity to identify similar multiscale visualization papers. Considering the input parameters, we used the silhouette coefficient and the elbow method to identify a decent number of k-clusters. We decided to select $k = 6$ after we examined k between two and twenty. In the second step, we manually analyzed the clusters and chose appropriate class names for each cluster. We also refined and reassigned 22 borderline papers to more suitable classes. Finally, we recursively applied the previously described steps to the resulting six classes to identify similar sub-classes of papers. We assigned each of the 122 reviewed papers to exactly one sub-class. In the supplementary material, we included a detailed summary of the label occurrences for each sub-class. Next, we describe the common design factors of each sub-class.

4.2.1 *Multiscale Visual Representations*

Multiscale visual representations are listed as a primary contribution across the reviewed papers. The class contains multiscale visualization technique papers, including two

This article has been accepted for publication in IEEE Transactions on Visualization and Computer Graphics. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2021.3109387

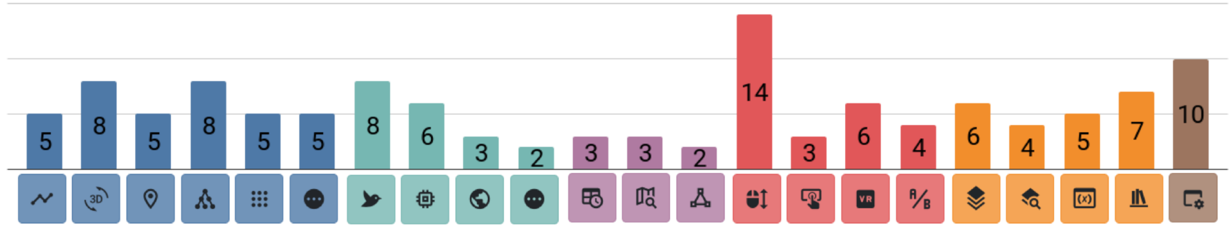


Fig. 4. The chart shows the resulting taxonomy, including the number of papers. The six classes are *Multiscale Visual Representations*, *Multiscale Visualization Applications*, *Multiscale Visual Analytics*, *Multiscale Interaction & Navigation*, *Theoretical Work*, and *Multiscale Visualization Systems*.

design studies that list visualization techniques as part of their contribution. The class is further divided based on visualization idioms (see Fig. 5) into the six sub-classes: statistical graphic, 3D, geographic, graph & tree, dense, and miscellaneous representations. The remaining visualization idioms did not occur often enough to form sub-classes.

Statistical Graphics *(5/36)*: All sub-class papers utilize juxtaposed statistical graphics to analyze temporal patterns at multiple scales. The primary targets are exploring temporal data (e.g., time series) to discover similar features (5), including identifying trends (4). The sub-class papers provide the following interaction methods to change (5), navigate (4), and aggregate (4) data. The datasets are tabular (5), examining mainly quantitative data attributes (4). For example, a unique paper is the work of Mao et al. [37], which depicts multiscale statistical trends in text documents, including low-level semantics (e.g., topic shifts) and high-level characteristics (e.g., general trends), as a smooth curve.

3D *(8/36)*: The second sub-class employs 3D multiscale visual representations tailored for biological applications (8) to explore 3D hierarchical datasets (3). The sub-class consists of visualizations for geometric (7) and field datasets (4). The central targets are to identify distributions of geometric shapes (8) and similar features (7). The proposed interaction methods are to select (7) and navigate (6) 3D spaces in a top-down manner. The analysis level is mainly mesoscale (7), including interactive aggregations methods to locate and compare geometric shapes (3). An example paper is ClearView [38], an interactive focus+context visualization method for complex volumetric data.

Geographic *(5/36)*: The next sub-class summarizes geographic visual representations that provide insight into spatial phenomena. The targets are to discover in all papers spatial distributions, trends, outliers, and features, such as shapes. The interaction methods are to select, navigate, filter, aggregate, and change spatial scales (4). The navigation strategy is top-down from coarse to fine granular (5) and depicts micro-, and mesoscale (3). For example, the TopoGroups [39] technique provides an overview and navigation means to explore geographical distributions across different aggregation scales.

Graph & Tree *(8/36)*: The following sub-class is about abstracting and visually exploring graph data such as networks and trees. The sub-class papers summarize graph structures into a hierarchy of strongly connected subgraphs, for example, recursively into a multiscale visualization of small world networks [40]. The regular targets are to explore similar aggregated graph topologies (8), paths (7), and features (5). Nearly all approaches enable users to select, navigate and aggregate the graphs in a top-down fashion to examine nodes (microscale) and meta-nodes (mesoscale). Interestingly, paper evaluations only report usage scenarios (7), except for some computational benchmarks (2). Lately, for instance, Pezzotti et al. [41] proposed a technique to explore large bipartite graphs (social networks) to reveal a hierarchy of clusters.

Dense Layout *(5/36)*: The next sub-class papers present temporal events with dense layouts, also known as pixel-based visualizations. The primary targets are to compare similar features (5), including identifying temporal trends (3) in large datasets. All sub-class papers combine navigation and aggregation interaction methods for tabular datasets at micro-, and mesoscale. All evaluations are primarily usage scenarios. For instance, dg2pix [42] provides an overview of large dynamic graphs using a dense pixel-based visualization to explore graph embeddings at multiple temporal scales. A notable paper is Pálenik et al. [43] that proposes a pixelmap to analyze spatio-temporal particle simulations at multiple temporal and spatial scales.

Miscellaneous *(5/36)*: The last sub-class contains rarely occurring visualizations idioms. Like the two parallel coordinate approaches that combine aggregations with navigation methods to summarize features, trends, and outliers [44], [45]. The remaining three papers propose distinct techniques. For example, Veras and Collins [46] propose a display-optimized tree cut algorithm to reduce clutter for multiscale visualizations, such as treemap or sunburst diagrams. Since the sub-class contains different approaches, describing common design factors is pointless.

***Summary*:** The central element of the class papers is to visually explore and compare similar features (32), distributions (23), shapes (16), network topologies as well as paths (16) of data across multiple scales. However, relating data across scales is challenging and often overwhelming for users due to the cognitive and interaction overload [39].

4.2.2 *Multiscale Visualization Applications*

The second class encompasses design study papers that describe and solve application-focused challenges using multiscale visualizations. Fig. 6 provides a general overview of the surveyed 122 papers' application areas.

Biological Applications *(8/19)*: The sub-class papers appeared in biology and life sciences. The papers commonly utilize juxtaposed visualizations (4), such as 3D and graph representations. Typical targets are to explore and summarize similar network (5) and geometric (4) datasets features (8) and distributions (4), such as 3D shapes (5), network topologies (5), and paths (5). The interaction methods are selecting (8) and navigating (6) in a top-down fashion to filter and change categorical data (8) attributes across micro- and mesoscale. The paper evaluations are usage scenarios

This article has been accepted for publication in IEEE Transactions on Visualization and Computer Graphics. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2021.3109387

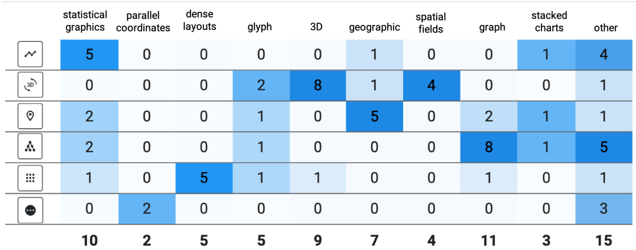


Fig. 5. The Figure presents how often visualization idioms appear in the six multiscale visual representation sub-classes. Papers usually utilize multiple visualization idioms in their approaches, for instance, ZAME [48] depicts a matrix visualization with glyphs.

(6), including some qualitative user studies (4). For instance, Abstractocyte [47] enables exploring 3D mesh and node-link representation of astrocytes and neurons.

Computing Applications *(6/19)*: The second sub-class contains design study papers in computing, including machine learning applications (2). The used visualization idioms are graph (4) and other juxtaposed (5) domain-specific visual representations for categorical and quantitative data attributes. The targets are to investigate features (6), network topology (5), and outliers (4) in tabular (5) and network datasets (3). The utilized interaction methods are selecting (6), navigating (5), filtering (5), and changing (5) the data granularity using aggregation methods. All papers are presenting usage scenarios as a central part of their evaluation. A recent sub-class paper is, for instance, Cao et al. [49] river-based visualization to explore adversarial examples in deep neural networks at multiple levels.

Spatio-Temporal Applications *(3/19)*: The third application sub-class is about multiscale spatio-temporal analysis. The sub-class consists of papers focusing on visually analyzing spatio-temporal data across multiple spatial scales. For example, Biswas et al. [50] propose a workflow to examine the uncertainty of multiple weather ensemble models across varying spatial resolutions. Given that the sub-class consists of only three papers, the description of common design factors is excessive.

Miscellaneous Applications *(2/19)*: The last sub-class contains papers that did not fit into the previously listed sub-classes. One paper describes the multi-level visualization design for poetry [51], and the other paper the interactive analysis of social tag networks and hierarchies [52]. The discussion of common design factors for this sub-class is again challenging, considering the number of papers.

***Summary*:** Visualization researchers proposed biological (8), computing (6), and spatio-temporal (3) design study papers. However, the proposed application-specific solutions are often challenging to transfer and generalize to similar issues of other application areas.

4.2.3 Multiscale Visual Analytics

The third class contains multiscale Visual Analytics (VA) approaches for temporal, geospatial, and graph datasets. Since the class contains only eight papers, we will briefly discuss some design factors for the whole class. The targets are exploring quantitative (7) and categorical (5) data attributes to identify overall distinct features (7), outliers (7), and trends (6). The papers implement a rich set of interaction methods, including selecting (8), navigating (8), filtering (7), and changing (6), as well as aggregating (6) data.

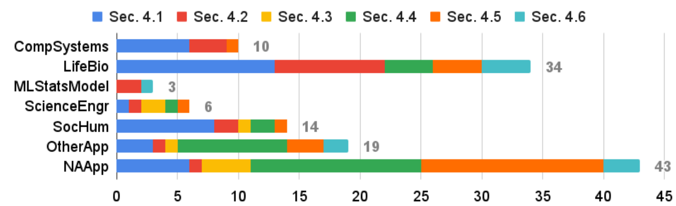


Fig. 6. The chart presents the application areas distribution for the corresponding taxonomy classes Sec. 4.2.

Temporal VA Approaches *(3/8)*: The first sub-class encompasses three papers to explore time-series data, utilizing the Visual Analytics mantra [53]. The papers allow exploring features, extremes, trends, and outliers in time-series data. For instance, Sips et al. [54] proposed a rare bottom-up navigation approach that utilizes a matrix-like visualization for the multiscale exploration time-series patterns.

Geospatial VA Approaches *(3/8)*: The second sub-class consists of approaches for geospatial datasets that provide extensive systems for the multiscale analysis of geospatial features, such as shapes. For example, Wang et al. [55] presented a multi-resolution VA approach for weather simulation ensembles, comprising nested parallel coordinate plots. The paper has unique characteristics, combining juxtaposed, superimposed, and nested composite visualizations with set operations and range queries to highlight parameter correlations for the weather simulations.

Graph-Based VA Approaches *(2/8)*: The last sub-class contains VA approaches for graph datasets. The approaches enable users to analyze relationships and clusters across scales to identify similar network topologies. For example, Multiscale Snapshots [56] utilizes graph embeddings with multiple visual metaphors to semi-automatically analyze temporal states and trends in dynamic graphs. The two approaches display various temporal scales using different visual representations at all analysis levels.

***Summary*:** Visual Analytics aims to overcome the information overload of large-scale datasets by interactive semi-automated means which involve the user in the visual exploration process [53].

4.2.4 Multiscale Interaction & Navigation

Multiscale interaction techniques are often reported contributions across the reviewed papers. We divided the papers into four sub-class that encompass similar multiscale interaction techniques for visualizations, display devices, virtual environments, and some empirical user studies. A unique characteristic is that most papers (23) in this class contribute quantitative user study (see Fig. 7).

Interaction Techniques *(14/27)*: The first sub-class comprises interaction and navigation techniques for multiscale interfaces. The sub-class interaction methods are useful for locating and identifying features (12), such as shapes (9), in multiscale spaces. The papers utilize a wide range of composite visualizations, with integrated (7) and juxtaposed (5) views. Typically, authors present interaction methods on geometric (8) and tabular (5) datasets, using categorical data attributes (12). Many sub-class papers utilize top-down navigation strategies (13). For instance, Javed et al. [57] present the PolyZoom technique to progressively build a

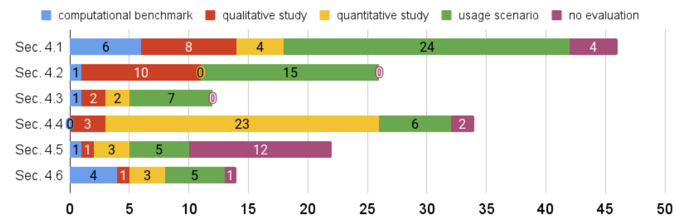


Fig. 7. The chart displays for the corresponding taxonomy classes the presented evaluations. Papers regularly contain multiple evaluation methods, for instance, a usage scenario and a benchmark.

hierarchy of focus regions that enables users to backtrack and relate multiple magnification scales.

Interaction Techniques for Display Devices *(3/27)*: The sub-class contains multiscale interaction techniques for different display devices. The targets are to lookup geometric datasets using top-down navigation strategies. A unique paper is FingerGlass [58] which allows navigating between locations at multiple scales using multitouch screens.

Interaction in Visualization Environments *(6/27)*: The next sub-class contains papers that describe interaction techniques for multiscale virtual environments. The sub-class targets are the identification of categorical data attributes (microscale) in geometric datasets. For example, HyperLabels [59] proposed navigational aids (labels) for the simultaneous top-down and bottom-up exploration of hierarchical molecular 3D models.

Empirical Studies *(4/27)*: The last sub-class includes evaluation papers that assess multiscale navigation techniques. For example, Pietriga et al. [60] compare four multiscale interaction techniques (e.g., pan-zoom and constrained distortion lenses) for searching tasks. The main target is to identify and locate geometric shapes in a top-down manner. Two sub-class papers [61], [62] investigate the effect of display size in multiscale navigation. The results indicate no apparent benefit for larger display sizes [62].

***Summary*:** The class encompasses multiscale interaction techniques, which pose new challenges as users are often lost in the multiscale information space, also known as the desert fog problem [63].

4.2.5 Theoretical Work

Theoretical visualization research (e.g., framework and workflows) is a central part of the contribution (22). The following class primarily contains such theory and model papers. We divided the papers into four sub-classes: multiscale visualization theory, multiscale navigation theory, frameworks, and related surveys. We only outline some outstanding papers for these theory sub-classes as there is no substantial overlap between the respective coding labels.

Multiscale Visualization Theory *(6/22)*: The first sub-class includes theoretical papers describing multiscale information visualization's characteristics and challenges. For instance, Viola and Isenberg [14] analyze the concept of abstraction used in visualization research and emphasize the importance of multiscale visual abstractions for presenting multiscale processes in particular application domains. We included the work of Cui et al. [64] in the sub-class as the authors propose quality measurements for data abstractions. Such abstraction quality metrics are useful to assess how much the abstracted data differs from the initial data.

Multiscale Navigation Theory *(4/22)*: The second class involves model papers about multiscale navigation theory. For example, Jul and Furnas [63] introduce the desert fog problem and further extend view navigation theory. The authors propose the critical zones concept using navigational aids to reduce and overcome the desert fog problem. Further, Guiard et al. [65] discuss the concept of multiscale pointing and introduce a framework for Fitt's law in multiscale navigation.

Frameworks for Multiscale Visualizations *(5/22)*: The sub-class contains frameworks for multiscale information visualization. For example, Elmqvist and Fekete [5] presented a hierarchical aggregation model to turn existing visualization techniques into multiscale visualizations that scale to large datasets. The authors also describe interaction methods to analyze the aggregated hierarchy, such as drill-down and roll-up operations. In another work, Goodwin et al. [1] propose a theoretical framework for visual comparison across scale and geography. The framework allows users to explore local and global variations, including sensitivities and correlation across multiple spatial scales.

Surveys *(7/22)*: The last sub-class includes related surveys and reviews. For instance, Cockburn et al. [66] survey interfaces for both focused and contextual viewing (e.g., overview+detail or focus+context). Such interfaces are exceptional cases of multiscale visualizations as the views display two varying magnification scales. Another recent example is the preliminary study of multiscale maps by Dumont et al. [67] that investigates how the map scale influences the displayed map content. For example, the authors discuss how the visual complexity varies across scales, such as abstracting buildings and roads.

***Summary*:** The class contains frameworks and workflows that propose solutions for particular multiscale visualization challenges, such as the desert fog problem [63].

4.2.6 Multiscale Visualization Systems

The last class contains technical multiscale visualization systems, which we did not further subdivide into sub-classes as there was no further plausible distinction.

Systems *(10/10)*: The following papers describe scalable systems, toolkits, and architectures to enable multiscale visual analysis of large datasets. Stolte et al. [12] presents a system for multiscale visualizations using zoom graphs and data cubes operations. The targets are to identify (8) explicit target features (8), such as geometric shapes (6). The approaches utilize the statistical graphics visualization idiom (5). The systems allow selecting (8), navigating (8), and aggregating (5) tabular (7) and hierarchical (4) geometric (6) datasets. The application areas are either biological (3) or domain agnostic applications that focus on micro-, and mesoscale analysis. The system papers report a broad set of evaluation methods among usage scenarios (5). Representative papers are, for example, the recently proposed Kyrix [68] and Kyrix-S [69] toolkits that provide a declarative model and grammar to create and manage pan/zoom visualization scales for large-scale datasets.

***Summary*:** The class contains research introducing novel architectures and software solutions for multiscale visualizations, such as the Splash [70] framework or Kyrix-S [69] declarative grammar.

4.3 Design Considerations

Based on our systematic literature analysis, we extracted seven essential design considerations.

Multiscale structures enhance visual scalability. Researchers utilized multiscale structures, with easily distinguishable and interpretable visual summaries, to reduce clutter and increase the visual scalability [5]. Moreover, Visual Analytics approaches can increase visual scalability [71], such as dynamic analysis pipelines [72].

Understand relations across different scales. Users can relate data across multiple scales by using either various juxtaposed views [73] or interactive lenses [74]. Using different scales, users can progressively build multiscale hierarchies of focus regions [57] or employ space-distortion techniques to highlight multiple focus regions [75]. Noteworthy in the context are space-scale diagrams [11], which support the understanding of multiscale interfaces.

Guide users during multiscale navigation. Researchers display context information across multiple scales to alleviate interaction overload in multiscale visualizations [39]. For example, residual landmarks across scales can be used to guide and navigate users towards interesting patterns [63]. We identified the following approaches for guiding users in multiscale environments through visual cues [63], topology-aware interaction methods [76], overview visualization [41], animations [77], and navigation viewport optimization [20].

Visualize abstraction measurements across scales. Displaying data abstraction measurements helps to assess the effects of abstraction methods and uncertainty across scales [64], [78]. For instance, the comparison of scale-independent aggregation measurements enables to quantify the abstraction quality across geographic scales [79].

Combining data and visual abstraction methods. The exploration of both data and visual abstraction methods reveals trade-offs and insight about sensitive abstraction parameters [12]. For example, exploring the trade-off between reducing precision (e.g., compression) and resolution (e.g., sampling) reveals useful analysis scales [80].

Recursively abstract data features. Typically, abstraction methods are recursively utilized to condense information (e.g., hierarchical clustering [81]) and gradually explore data features (e.g., drill-down and roll-up operations [82]). A representative technique is ZAME [48], which uses a hierarchy to abstract and explore graph data utilizing multiple alternative visual representations.

Design tailored multiscale domain visualizations. Domain experts benefit from distinct visual encodings and adaptive interaction methods for domain-specific scales [22]. Therefore, domain experts themselves need to select the most appropriate design from a set of abstraction and visualization methods for their analysis tasks [47].

5 Discussion

In the previous section, we described our taxonomy and the derived design considerations for multiscale visualization approaches. Based on these results, we discuss the following research challenges and limitations of our literature analysis.

5.1 Research Challenges

The visual analysis of data at multiple scales poses several challenges. Understanding the emergence of data patterns across scales represents a challenge for users due to the amount of data and displayed data scales [39]. Therefore, developing more semi-automated analysis methods is essential to help users identify, compare, and relate useful analysis scales and visual representations. In this context, particularly multiscale visualizations based on dense layouts, glyphs, spatial field visualization idioms are underrepresented. Further, new data abstraction measurements and dimensionality reduction methods can also reveal similarities and differences across abstraction scales in one view. We believe that such methods are well suited for the multiscale exploration of the underrepresented field, network, and tree datasets. The development of such methods can likewise enhance the analysis of uncertainty across scales. In addition, multiscale visualizations can be distinguished into approaches for real-world multiscale environments (e.g., biological data) and large non-spatial spaces (e.g., networks), both requiring dedicated frameworks, visualization techniques, and interaction methods. Another considerable challenge is to evaluate how different composite visualizations for multiscale visualizations affect data exploration. For instance, evaluating how simultaneously displayed juxtaposed, superimposed, or integrated views of different scales influence multiscale analysis.

The interaction and navigation across scales are fundamental in multiscale visualizations, often leading to interaction overload. A unique research gap for multiscale interaction and navigation techniques are novel methods to arrange, filter, and change the data appropriately to multiple displayed scales. Such methods are notably needed if users navigate horizontally (e.g., filtering) and vertically (e.g., aggregation) simultaneously. Moreover, only a few multiscale visualizations also visualize the data on a macroscale, which is potentially useful for novel user guidance methods and interactive overview visualizations. In addition, the improvement of multiscale transition and navigation models (e.g., 3D camera management systems) are also of enormous importance for preserving the users' mental map during navigation. Researchers proposed largely top-down navigation in this context, and bottom-up navigation approaches and frameworks are still rarely utilized. Further, seamlessly switching between different visual abstractions and technical devices, such as displays, tablets, and smartphones, can further advance the collaborative exploration of large multiscale information spaces.

Multiscale visualizations repeatedly claim to enhance visual scalability. For instance, the visualization of multiple abstraction scales (e.g., aggregation) allows analyzing and extracting knowledge from large datasets [5]. However, multiscale visualization scalability is typically not quantified, and existing approaches generally are not compared against each other. Hence, the comparison of computational and visual scalability of multiscale visualizations is still outstanding. In this regard, a detailed trade-off analysis between data and visual abstraction methods for multiscale visualization may reveal useful information. For instance, comparing the multiscale data and visual abstraction methods in statistics and engineering will provide new insight into the scalability of the recently proposed approaches. Overall, we believe that more empirical studies are required to assess the scalability of existing multiscale visualizations, especially interaction methods for particular user tasks. Such empirical studies will considerably improve the reusability of multiscale visualizations.

A further examination of paper codings also reveals research gaps that have not been sufficiently studied. For example, multiscale machine learning applications are noticeably underrepresented in the reviewed papers. A potential solution can be to design unique bottom-up interaction methods for machine learning models that combine overview visualizations with navigational aids and annotation methods to analyze and understand the functionality of different layers and neurons in deep learning models. Overall, researchers can utilize the resulting paper codings in our online interface to identify further research gaps. For instance, an analysis of the dataset type labels unveils that ”field” data is rarely used, implying that the multiscale visualization approaches for continuous fields (e.g., human magnetic resonance imaging scan) are still largely unexplored.

5.2 Limitations

In our systematic literature review, we used the results of our initial exploration of similar expressions (see Sec. 2.1) as keywords to query the search engines. However, multiscale visualization approaches might not necessarily use one of the listed keywords explicitly. We tried to resolve the issue by recursively scanning paper references and citations in both directions. Consequently, some reviewed papers do not necessarily list the expression, although the authors describe similar concepts. Further, we did not include all multiscale modeling approaches (e.g., hierarchical clustering) in visualization research since such a survey requires several additional categories (e.g., type of model construction) that reflect multiscale data models' characteristics, which is far beyond one paper's scope. Moreover, the derived taxonomy highlights only the most important design practices and research challenges. For instance, there are more research challenges for multiscale visualizations reported than previously discussed.

Despite all those limitations, we hope our resulting taxonomy will stimulate new multiscale visualization approaches, including new multiscale visualization theory, interaction methods, and evaluations.

6 Conclusion

In this work, we contribute a structured literature analysis of design practices in multiscale visualization research. We selected and reviewed 122 papers with an extensive coding scheme to reveal general multiscale visualization designs, such as typical visualization idioms, targets, and interaction methods. Based on this systematic review, we derived a taxonomy for multiscale visualizations, which describes distinct design factors and design considerations to help identify trends and gaps in research. We believe that our results help researchers and practitioners design, present, and analyze datasets at multiple abstraction scales.

Acknowledgments

This work was funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy - EXC 2117 - 422037984. MaterialDesign icons are licensed under the Apache License 2.0.

References

[1] S. Goodwin, J. Dykes, A. Slingsby, and C. Turkay, "Visualizing multiple variables across scale and geography," *IEEE Transactions on Visualization and Computer Graphics*, vol. 22, no. 1, pp. 599–608, 2015.

[2] G. C. Peng, M. Alber, A. B. Tepole, W. R. Cannon, S. De, S. Dura-Bernal, K. Garikipati, G. Karniadakis, W. W. Lytton, P. Perdikaris *et al.*, "Multiscale modeling meets machine learning: What can we learn?" *Archives of Computational Methods in Engineering*, pp. 1–21, 2020.

[3] H. Miao, T. Klein, D. Kouřil, P. Mindek, K. Schatz, M. E. Gröller, B. Kozlíková, T. Isenberg, and I. Viola, "Multiscale molecular visualization," *Journal of Molecular Biology*, vol. 431, no. 6, pp. 1049–1070, 2019.

[4] S. Halladjian, H. Miao, D. Kouřil, M. E. Gröller, I. Viola, and T. Isenberg, "Scale trotter: Illustrative visual travels across negative scales," *IEEE Transactions on Visualization and Computer Graphics*, vol. 26, no. 1, pp. 654–664, 2019.

[5] N. Elmqvist and J.-D. Fekete, "Hierarchical aggregation for information visualization: Overview, techniques, and design guidelines," *IEEE Transactions on Visualization and Computer Graphics*, vol. 16, no. 3, pp. 439–454, 2009.

[6] W. Javed and N. Elmqvist, "Stack zooming for multifocus interaction in skewed-aspect visual spaces," *IEEE Transactions on Visualization and Computer Graphics*, vol. 19, no. 8, pp. 1362–1374, 2012.

[7] C. Turkay, A. Slingsby, H. Hauser, J. Wood, and J. Dykes, "Attribute signatures: Dynamic visual summaries for analyzing multivariate geographical data," *IEEE Transactions on Visualization and Computer Graphics*, vol. 20, no. 12, pp. 2033–2042, 2014.

[8] M. Alber, A. B. Tepole, W. R. Cannon, S. De, S. Dura-Bernal, K. Garikipati, G. Karniadakis, W. W. Lytton, P. Perdikaris, L. Petzold *et al.*, "Integrating machine learning and multiscale modeling—perspectives, challenges, and opportunities in the biological, biomedical, and behavioral sciences," *NPJ Digital Medicine*, vol. 2, no. 1, pp. 1–11, 2019.

[9] Dictionary.com and O. U. Press. (2020) Lexico. [Online]. Available: https://www.lexico.com/definition/multiscale

[10] U. Lopez, J. Gautrais, I. D. Couzin, and G. Theraulaz, "From behavioural analyses to models of collective motion in fish schools," *Interface focus*, vol. 2, no. 6, pp. 693–707, 2012.

[11] G. W. Furnas and B. B. Bederson, "Space-scale diagrams: Understanding multiscale interfaces," in *Proceedings of the SIGCHI Conference on Human factors in Computing Systems*, 1995, pp. 234–241.

[12] C. Stolte, D. Tang, and P. Hanrahan, "Multiscale visualization using data cubes," *IEEE Transactions on Visualization and Computer Graphics*, vol. 9, no. 2, pp. 176–187, 2003.

[13] D. Ebert, K. Gaither, Y. Jang, and S. Lasher-Trapp, "Cross-scale, multi-scale, and multi-source data visualization and analysis issues and opportunities," in *Scientific Visualization*. Springer, 2014, pp. 353–360.

[14] I. Viola and T. Isenberg, "Pondering the concept of abstraction in (illustrative) visualization," *IEEE Transactions on Visualization and Computer Graphics*, vol. 24, no. 9, pp. 2573–2588, 2017.

[15] P. Isenberg, T. Isenberg, M. Sedlmair, J. Chen, and T. Möller, "Toward a deeper understanding of visualization through keyword analysis," INRIA, France, Tech. Rep. RR-8580, Aug. 2014.

[16] P. Isenberg, T. Isenberg, M. Sedlmair, J. Chen, and T. Möller, "Visualization as seen through its research paper keywords," *IEEE Transactions on Visualization and Computer Graphics*, vol. 23, no. 1, pp. 771–780, 2017.

[17] P. Isenberg, F. Heimerl, S. Koch, T. Isenberg, P. Xu, C. D. Stolper, M. Sedlmair, J. Chen, T. Möller, and J. Stasko, "vispubdata. org: A metadata collection about ieee visualization (vis) publications," *IEEE Transactions on Visualization and Computer Graphics*, vol. 23, no. 9, pp. 2199–2206, 2016.

[18] J. Kehrer and H. Hauser, "Visualization and visual analysis of multifaceted scientific data: A survey," *IEEE Transactions on Visualization and Computer Graphics*, vol. 19, no. 3, pp. 495–513, 2012.

[19] S. Openshaw, *The Modifiable Areal Unit Problem*, ser. Concepts and Techniques in Modern Geography. Geo Books, 1983.

[20] R. M. M. Vaquero, J. Rzepecki, K.-I. Friese, and F.-E. Wolter, "Visualization and user interaction methods for multiscale biomedical data," in *3D Multiscale Physiological Human*. Springer, 2014, pp. 107–133.

[21] N. Ezzati-Jivan and M. R. Dagenais, "Multi-scale navigation of large trace data: A survey," *Concurrency and Computation: Practice and Experience*, vol. 29, no. 10, p. e4068, 2017.

[22] H. Miao, E. De Llano, J. Sorger, Y. Ahmadi, T. Kekic, T. Isenberg, M. E. Gröller, I. Barišić, and I. Viola, "Multiscale visualization and scale-adaptive modification of dna nanostructures," *IEEE Transactions on Visualization and Computer Graphics*, vol. 24, no. 1, pp. 1014–1024, 2017.

[23] J. Yang, M. O. Ward, and E. A. Rundensteiner, "Interactive hierarchical displays: a general framework for visualization and exploration of large multivariate data sets," *Computers & Graphics*, vol. 27, no. 2, pp. 265–283, 2003.

[24] H.-J. Schulz, S. Hadlak, and H. Schumann, "The design space of implicit hierarchy visualization: A survey," *IEEE Transactions on Visualization and Computer Graphics*, vol. 17, no. 4, pp. 393–411, 2010.

[25] B. N. Green, C. D. Johnson, and A. Adams, "Writing narrative literature reviews for peer-reviewed journals: secrets of the trade," *Journal of Chiropractic Medicine*, vol. 5, no. 3, pp. 101–117, 2006.

[26] T. Munzner, *Visualization analysis and design*. CRC Press, 2014.

[27] M. Brehmer and T. Munzner, "A multi-level typology of abstract visualization tasks," *IEEE Transactions on Visualization and Computer Graphics*, vol. 19, no. 12, pp. 2376–2385, 2013.

[28] W. Javed and N. Elmqvist, "Exploring the design space of composite visualization," in *2012 IEEE Pacific Visualization Symposium*. IEEE, 2012, pp. 1–8.

[29] L. Battle and J. Heer, "Characterizing exploratory visual analysis: A literature review and evaluation of analytic provenance in tableau," in *Computer Graphics Forum*, vol. 38, no. 3. Wiley Online Library, 2019, pp. 145–159.

[30] W. Shi, J. Dorsey, and H. Rushmeier, "Learning-based inverse bi-scale material fitting from tabular brdfs," *IEEE Transactions on Visualization and Computer Graphics*, 2020.

[31] K. Xu, M. Xia, X. Mu, Y. Wang, and N. Cao, "Ensemblelens: Ensemble-based visual exploration of anomaly detection algorithms with multidimensional data," *IEEE Transactions on Visualization and Computer Graphics*, vol. 25, no. 1, pp. 109–119, 2018.

[32] "Vis paper submission keywords." [Online]. Available: http://ieeevis.org/year/2020/info/call-participation/paper-keywords

[33] "Infovis paper types." [Online]. Available: http://ieeevis.org/year/2020/info/call-participation/infovis-paper-types

[34] K. Andrews, "Evaluation comes in many guises," 2008.

[35] S. Carpendale, "Evaluating information visualizations," in *Information Visualization*. Springer, 2008, pp. 19–45.

[36] H. Lam, E. Bertini, P. Isenberg, C. Plaisant, and S. Carpendale, "Empirical studies in information visualization: Seven scenarios," *IEEE Transactions on Visualization and Computer Graphics*, vol. 18, no. 9, pp. 1520–1536, 2011.

[37] Y. Mao, J. Dillon, and G. Lebanon, "Sequential document visualization," *IEEE Transactions on Visualization and Computer Graphics*, vol. 13, no. 6, pp. 1208–1215, 2007.

[38] J. Kruger, J. Schneider, and R. Westermann, "Clearview: An interactive context preserving hotspot visualization technique," *IEEE Transactions on Visualization and Computer Graphics*, vol. 12, no. 5, pp. 941–948, 2006.

[39] J. Zhang, A. Malik, B. Ahlbrand, N. Elmqvist, R. Maciejewski, and D. S. Ebert, "Topogroups: Context-preserving visual illustration of multi-scale spatial aggregates," in *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, 2017, pp. 2940–2951.

[40] D. Auber, Y. Chiricota, F. Jourdan, and G. Melançon, "Multiscale visualization of small world networks," in *IEEE Symposium on Information Visualization 2003 (IEEE Cat. No. 03TH8714)*. IEEE, 2003, pp. 75–81.

[41] N. Pezzotti, J.-D. Fekete, T. Höllt, B. P. Lelieveldt, E. Eisemann, and A. Vilanova, "Multiscale visualization and exploration of large bipartite graphs," in *Computer Graphics Forum*, vol. 37, no. 3. Wiley Online Library, 2018, pp. 549–560.

[42] E. Cakmak, D. Jäckle, T. Schreck, and D. A. Keim, "dg2pix: Pixel-based visual analysis of dynamic graphs," in *Proc. IEEE VIS Symposium on Visualization in Data Science*, 2020.

[43] J. Pálenik, J. Byška, S. Bruckner, and H. Hauser, "Scale-space splatting: Reforming spacetime for cross-scale exploration of integral measures in molecular dynamics," *IEEE Transactions on Visualization and Computer Graphics*, vol. 26, no. 1, pp. 643–653, 2019.

[44] Y.-H. Fua, M. O. Ward, and E. A. Rundensteiner, *Hierarchical parallel coordinates for exploration of large datasets*. IEEE, 1999.

[45] G. Richer, J. Sansen, F. Lalanne, D. Auber, and R. Bourqui, "Enabling hierarchical exploration for large-scale multidimensional data with abstract parallel coordinates," in *International Workshop on Big Data Visual Exploration and Analytics 2018*, vol. 2083, 2018, pp. 76–83.

[46] R. Veras and C. Collins, "Optimizing hierarchical visualizations with the minimum description length principle," *IEEE Transactions on Visualization and Computer Graphics*, vol. 23, no. 1, pp. 631–640, 2016.

[47] H. Mohammed, A. K. Al-Awami, J. Beyer, C. Cali, P. Magistretti, H. Pfister, and M. Hadwiger, "Abstractocyte: A visual tool for exploring nanoscale astroglial cells," *IEEE Transactions on Visualization and Computer Graphics*, vol. 24, no. 1, pp. 853–861, 2017.

[48] N. Elmqvist, T.-N. Do, H. Goodell, N. Henry, and J.-D. Fekete, "Zame: Interactive large-scale graph visualization," in *2008 IEEE Pacific Visualization Symposium*. IEEE, 2008, pp. 215–222.

[49] K. Cao, M. Liu, H. Su, J. Wu, J. Zhu, and S. Liu, "Analyzing the noise robustness of deep neural networks," *IEEE Transactions on Visualization and Computer Graphics*, 2020.

[50] A. Biswas, G. Lin, X. Liu, and H.-W. Shen, "Visualization of time-varying weather ensembles across multiple resolutions," *IEEE Transactions on Visualization and Computer Graphics*, vol. 23, no. 1, pp. 841–850, 2016.

[51] A. Mittmann, A. von Wangenheim, and A. L. dos Santos, "A multi-level visualization scheme for poetry," in *2016 20th International Conference Information Visualisation (IV)*. IEEE, 2016, pp. 312–317.

[52] L. Gou, S. Zhang, J. Wang, and X. Zhang, "Tagnetlens: multiscale visualization of knowledge structures in social tags," in *Proceedings of the 3rd International Symposium on Visual Information Communication*, 2010, pp. 1–9.

[53] D. A. Keim, F. Mansmann, J. Schneidewind, and H. Ziegler, "Challenges in visual data analysis," in *Tenth International Conference on Information Visualisation (IV'06)*. IEEE, 2006, pp. 9–16.

[54] M. Sips, P. Köthur, A. Unger, H.-C. Hege, and D. Dransch, "A visual analytics approach to multiscale exploration of environmental time series," *IEEE Transactions on Visualization and Computer Graphics*, vol. 18, no. 12, pp. 2899–2907, 2012.

[55] J. Wang, X. Liu, H.-W. Shen, and G. Lin, "Multi-resolution climate ensemble parameter analysis with nested parallel coordinates plots," *IEEE Transactions on Visualization and Computer Graphics*, vol. 23, no. 1, pp. 81–90, 2016.

[56] E. Cakmak, U. Schlegel, D. Jackle, D. Keim, and T. Schreck, "Multiscale snapshots: Visual analysis of temporal summaries in dynamic graphs," *IEEE Transactions on Visualization and Computer Graphics*, 2020.

[57] W. Javed, S. Ghani, and N. Elmqvist, "Polyzoom: multiscale and multifocus exploration in 2d visual spaces," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2012, pp. 287–296.

[58] D. P. Käser, M. Agrawala, and M. Pauly, "Fingerglass: efficient multiscale interaction on multitouch screens," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2011, pp. 1601–1610.

[59] D. Kouřil, T. Isenberg, B. Kozlíková, M. Meyer, M. E. Gröller, and I. Viola, "Hyperlabels—browsing of dense and hierarchical molecular 3d models," *IEEE Transactions on Visualization and Computer Graphics*, 2020.

[60] E. Pietriga, C. Appert, and M. Beaudouin-Lafon, "Pointing and beyond: an operationalization and preliminary evaluation of multi-scale searching," in *Proceedings of the SIGCHI Conference on Human factors in Computing Systems*, 2007, pp. 1215–1224.

[61] M. Rønne Jakobsen and K. Hornbæk, "Sizing up visualizations: effects of display size in focus+ context, overview+ detail, and zooming interfaces," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2011, pp. 1451–1460.

[62] M. R. Jakobsen and K. Hornbæk, "Interactive visualizations on large and small displays: The interrelation of display size, infor-

mation space, and scale," *IEEE Transactions on Visualization and Computer Graphics*, vol. 19, no. 12, pp. 2336–2345, 2013.

[63] S. Jul and G. W. Furnas, "Critical zones in desert fog: aids to multiscale navigation," in *Proceedings of the 11th Annual ACM Symposium on User Interface Software and Technology*, 1998, pp. 97–106.

[64] Q. Cui, M. Ward, E. Rundensteiner, and J. Yang, "Measuring data abstraction quality in multiresolution visualizations," *IEEE Transactions on Visualization and Computer Graphics*, vol. 12, no. 5, pp. 709–716, 2006.

[65] Y. Guiard, M. Beaudouin-Lafon, J. Bastin, D. Pasveer, and S. Zhai, "View size and pointing difficulty in multi-scale navigation," in *Proceedings of the Working Conference on Advanced Visual Interfaces*, 2004, pp. 117–124.

[66] A. Cockburn, A. Karlson, and B. B. Bederson, "A review of overview+ detail, zooming, and focus+ context interfaces," *ACM Computing Surveys (CSUR)*, vol. 41, no. 1, pp. 1–31, 2009.

[67] M. Dumont, G. Touya, and C. Duchêne, "Designing multi-scale maps: Lessons learned from existing practices," *International Journal of Cartography*, vol. 6, no. 1, pp. 121–151, 2020.

[68] W. Tao, X. Liu, Y. Wang, L. Battle, Ç. Demiralp, R. Chang, and M. Stonebraker, "Kyrix: Interactive pan/zoom visualizations at scale," in *Computer Graphics Forum*, vol. 38, no. 3. Wiley Online Library, 2019, pp. 529–540.

[69] W. Tao, X. Hou, A. Sah, L. Battle, R. Chang, and M. Stonebraker, "Kyrix-s: Authoring scalable scatterplot visualizations of big data," *IEEE Transactions on Visualization and Computer Graphics*, 2020.

[70] M. Glueck, A. Khan, and D. J. Wigdor, "Dive in! enabling progressive loading for real-time navigation of data visualizations," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2014, pp. 561–570.

[71] G. Robertson, D. Ebert, S. Eick, D. Keim, and K. Joy, "Scale and complexity in visual analytics," *Information Visualization*, vol. 8, no. 4, pp. 247–253, 2009.

[72] J. Zhao, F. Chevalier, E. Pietriga, and R. Balakrishnan, "Exploratory analysis of time-series with chronolenses," *IEEE Transactions on Visualization and Computer Graphics*, vol. 17, no. 12, pp. 2422–2431, 2011.

[73] M. Meyer, T. Munzner, and H. Pfister, "Mizbee: a multiscale synteny browser," *IEEE Transactions on Visualization and Computer Graphics*, vol. 15, no. 6, pp. 897–904, 2009.

[74] C. Tominski, S. Gladisch, U. Kister, R. Dachselt, and H. Schumann, "Interactive lenses for visualization: An extended survey," in *Computer Graphics Forum*, vol. 36, no. 6. Wiley Online Library, 2017, pp. 173–200.

[75] N. Elmqvist, N. Henry, Y. Riche, and J.-D. Fekete, "Melange: space folding for multi-focus interaction," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2008, pp. 1333–1342.

[76] W. Javed, S. Ghani, and N. Elmqvist, "Gravnav: Using a gravity model for multi-scale navigation," in *Proceedings of the International Working Conference on Advanced Visual Interfaces*, 2012, pp. 217–224.

[77] J. J. Van Wijk and W. A. Nuij, "A model for smooth viewing and navigation of large 2d information spaces," *IEEE Transactions on Visualization and Computer Graphics*, vol. 10, no. 4, pp. 447–458, 2004.

[78] M. Cho, B. Kim, H.-J. Bae, and J. Seo, "Stroscope: Multi-scale visualization of irregularly measured time-series data," *IEEE Transactions on Visualization and Computer Graphics*, vol. 20, no. 5, pp. 808–821, 2014.

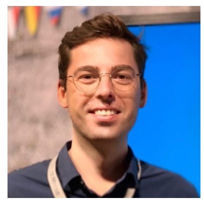
[79] W. Zeng, C. Lin, J. Lin, J. Jiang, J. Xia, C. Turkay, and W. Chen, "Revisiting the modifiable areal unit problem in deep traffic prediction with visual analytics," *IEEE Transactions on Visualization and Computer Graphics*, 2020.

[80] D. Hoang, P. Klacansky, H. Bhatia, P.-T. Bremer, P. Lindstrom, and V. Pascucci, "A study of the trade-off between reducing precision and reducing resolution for data analysis and visualization," *IEEE Transactions on Visualization and Computer Graphics*, vol. 25, no. 1, pp. 1193–1203, 2018.

[81] J. Woodring and H.-W. Shen, "Multiscale time activity data exploration via temporal clustering visualization spreadsheet," *IEEE Transactions on Visualization and Computer Graphics*, vol. 15, no. 1, pp. 123–137, 2008.

[82] D. Archambault, T. Munzner, and D. Auber, "Grouseflocks: Steerable exploration of graph hierarchy space," *IEEE Transactions on Visualization and Computer Graphics*, vol. 14, no. 4, pp. 900–913, 2008.

Eren Cakmak is a research associate in the Data Analysis and Visualization Research Group and the Centre for the Advanced Study of Collective Behaviour at the University of Konstanz. He received his M.Sc. in Computer and Information Science from the University of Konstanz in 2018. His main research interests are the interactive visual analysis of dynamic graphs and spatio-temporal data.



Dominik Jäckle is an independent researcher located in Munich, Germany. He received his Ph.D. degree in computer science from the University of Konstanz in 2018. His main research interest centers around high-dimensional data analysis. Currently, he works as a Data Scientist at the BMW Group.

Tobias Schreck is a Professor and head of the Institute of Computer Graphics and Knowledge Visualization, Graz University of Technology. He received the Ph.D. degree in computer science from the University of Konstanz in 2006. He was an Assistant Professor with the University of Konstanz and a Post-Doctoral Fellow with TU Darmstadt. His research interests include visual analytics and applied 3D object retrieval.

Daniel A. Keim is a Professor and the head to the Information Visualization and Data Analysis Research Group at the University of Konstanz. He received a habilitation in computer science from the University of Munich and has been program cochair of the IEEE InfoVis, the IEEE VAST, and the ACM SIGKDD Conference.

Johannes Fuchs is a research scientist and lecturer at the University of Konstanz. His main research interests are in the area of visual analytics and information visualization with a special focus on data glyph design, visualization for education, and quantitative evaluation. Johannes has a PhD in computer science from the University of Konstanz.