Towards Understanding Time-Varying Spatial 3D Data Analysis with Animation and Small Multiples in Virtual Reality and Desktop

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Abstract

The growing availability of time-varying spatial 3D (S4D) data, such as ocean and atmospheric datasets, has created opportunities for studying dynamic phenomena across time and 3D space. However, designing effective visualizations for S4D data remains challenging due to the high cognitive demands and complexity of these datasets. While techniques like animation and small multiples have been applied in Virtual Reality (VR) and desktop environments, the lack of understanding of analysts' tasks and challenges limits the development of better visualization techniques. To fill this gap, we conducted an empirical study with domain experts across various fields, comparing four visualization techniques: VR animation, VR small multiples, desktop animation, and desktop small multiples. We identified the strengths and weaknesses of the four techniques, as well as key analytical tasks, current practices, and challenges in S4D data analysis. Finally, we outlined future research opportunities for advancing S4D visualization techniques.

Index Terms: Time-varying spatial 3D data, 3D Spatio-temporal data, virtual reality, immersive visual analytics.

1 Introduction

Spatial 3D (S3D) data is information captured across width, height, and depth, with spatial relationships playing a crucial role in its analysis and interpretation [20]. Time-varying spatial 3D (S4D) data extends this concept by incorporating temporal dynamics, representing a sequence of S3D data over time [20]. Many domains involve analyzing S4D data that is collected from real-world phenomena that are continuous across both time and 3D space [10]. For example, ocean science uses S4D data to analyze changes in temperature, salinity, and oxygen levels [29]. In atmospheric science, it supports understanding air quality and pollutant dispersion [30].

Visualization has been proven to be an effective approach in supporting spatiotemporal analysis [3], such as identifying spatial and temporal trends [10, 35] and distributions [6, 33], since it can transform abstract data into perceivable and interactive visual representations. However, these visualizations are primarily designed for data distributed across 2D spaces. Designing effective visualizations for S4D data that spans 3D spaces across time is challenging [20]. One major challenge stems from human cognitive limits [20]. Tracking the evolution of complex 3D spatial patterns over time requires users to process and synthesize large amounts of spatial and temporal information, which can exceed human cognitive and comprehension abilities. Another challenge arises from the fact that S4D datasets are often massive, capturing fine-grained spatial and temporal details. Visualizing such high-resolution data requires balancing clarity with the need to retain critical details while avoiding visual clutter and occlusion [10].

Some attempts have been made in designing effective visualizations for S4D data. Currently, animations [1, 9] and small multiples [18, 13, 19] are two existing visualization techniques for presenting S4D data. Both techniques visualize each S3D data instance as a volumetric cube. Animations play these cubes sequentially over time, enabling users to observe temporal changes dynamically. In contrast, small multiples display these cubes for discrete time periods as static representations arranged in a linear or grid format, allowing users to view multiple time steps simultaneously. These visualizations have been tested not only in desktop environments, but also in Virtual Reality (VR), which provides the benefits of spatial reasoning and unlimited display places.

Despite these initial attempts, a recent survey [20] highlights that current visualizations are insufficient for supporting S4D analysis and calls for more effective visualizations. Two critical gaps hinder progress toward fulfilling this call. An immediate gap lies in the lack of explicit studies on the strengths and weaknesses of existing visualization types (e.g., animations vs. small multiples) and display environments (e.g., VR vs. desktop). Without such studies, it remains unclear how future visualizations should maximize their strengths and address their weaknesses. A more fundamental gap involves the lack of a deep understanding of analysts' real-world needs that future visualizations should support, such as the tasks they perform with S4D data and the challenges to overcome.

This work aims to answer the following research questions to inform the future design of effective S4D visualization techniques:

- **RQ1**: What are the strengths and weaknesses of different types of visualizations (i.e., animation vs. small multiples) and display environments (i.e., VR vs. desktop)?
- **RQ2**: What are **a)** the analysts' analytical tasks related to S4D data, **b)** their current practices in utilizing visualizations to complete the tasks, and **c)** the challenges they face?
- **RQ3**: What are the research opportunities for designing future visual analytics tools for S4D data?

We conducted open-ended exploratory studies and semi-structured interviews with researchers who regularly analyze S4D data across various domains. Specifically, to answer RQ1, we asked each participant to extract findings from S4D datasets during the open-ended exploratory studies. Each participant used four visualization techniques: VR animation, VR small multiples, desktop animation, and desktop small multiples. It is important to note that our goal was not to determine which technique is superior. Instead,

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we leveraged the four conditions to contextualize participant feedback and explore the strengths and weaknesses of different visualizations and environments. To answer RQ2, we conducted semi-structured interviews to ask participants about their analytical tasks and the challenges they face in daily practice. For RQ3, we synthesized the qualitative feedback from both the exploratory studies and interviews to identify several future research opportunities for advancing S4D data visual analytics.

Our contributions are threefold. First, we conduct an exploratory study involving four S4D visualization techniques, providing insights into the strengths and weaknesses of different visualization types and environments (Sec. 5). Second, we summarize the analytical tasks, challenges, and requirements for S4D data visualization by engaging domain experts across various fields (Sec. 6). Third, we identify multiple future research directions (Sec. 7).

2 Related Work

In this section, we first review techniques for volume visualization, which form the basis for implementing our four visualization techniques. Next, we examine existing S4D data visualization techniques, which motivated the selection of the four techniques investigated in our exploratory study. Finally, we review the current understanding of S4D data, focusing on tasks, practices, challenges, and opportunities.

2.1 Volume Visualization

Volume visualizations can represent 3D scalar fields, enabling users to explore patterns and understand internal features within 3D data [8]. There are two major categories of rendering techniques based on the visualization results: direct volume rendering and isosurface rendering. In direct volume rendering, a volumetric effect is generated by accumulating optical properties along view rays as they sample the 3D volume [24]. In contrast, isosurface rendering requires the extraction of isosurfaces to visualize geometric structures within the data [28]. Existing research on direct volume rendering primarily focuses on improving rendering performance. These efforts include designing a time-space partitioning tree to enable sparse data traversal [32], utilizing temporal occlusion coherence to identify visible subvolumes [14], and proposing a shear warp factorisation algorithm to reduce data storage and detect spatiotemporal coherence [2] for time-varying volumetric data. More recently, researchers have developed neural representations, such as learnable features [38], adaptive grids [41], and hash tables [27], for modeling single large-scale scalar fields. Similarly, prior work on isosurface rendering has mainly aimed to speed up the isosurface extraction process [37, 22, 11, 39] to enable interactive visualization of large-scale fields.

While these algorithmic advancements are essential for the efficient generation of volume visualizations, they do not address the downstream challenge of how the resulting outputs should be presented to and interpreted by users. In contrast to these performance-oriented approaches, our work investigates how users analyze an S4D dataset presented as a series of rendered volumes using animation versus small multiples.

2.2 S4D Data Visualization Techniques

As summarized in Table 1, existing visualization techniques for S4D data can be categorized by the visualization type (animation vs. small multiples) and the display environment (desktop vs. VR).

Animation. With each S3D data instance visualized as a volumetric cube, animation [1, 9, 18, 19] displays one cube at a time and plays them sequentially over time. In **desktop** environments, a template-based animation tool named AniViz [1] integrates animation creation into data exploration across spatial, temporal, and variable aspects, demonstrating the power of animation in enhancing the communication and understanding of complex scientific data.

Table 1: Overview of existing S4D visualization techniques, categorized by display environment and visualization type (DT = Desktop; VR = Virtual Reality; Anim. = Animation; S.M. = Small Multiples).

Reviewed Paper	Environment		Vis. Type	
	DT	**VR**	**Anim.**	**S.M.**
Akiba et al. [1]	✓		✓	
Jankun-Kelly and Ma [18]	✓		✓	✓
Angelelli and Hauser [4]	✓			✓
Gu et al. [15]	✓			✓
Lu and Shen [25]	✓			✓
Maries et al. [26]	✓			✓
Fouché et al. [13]		✓		✓
Coffey et al. [9]		✓	✓	✓
Johnson et al. [19]		✓	✓	✓
Our study	✓	✓	✓	✓

Moving to **VR**, Coffey et al. [9] investigated visualizations for complex motion data, highlighting how the different integration of interactive control and animation of spatial and temporal dimensions influences motion analysis, spatial perception, and communication.

Small multiples. In contrast to the temporal sequencing of animation, small multiples [18, 13, 19, 4, 15, 25, 26] present multiple S3D volumetric cubes simultaneously by arranging them side by side in a structured layout, such as a grid or a curve. For example, in **desktop** settings, Jankun-Kelly and Ma [18] introduced a spreadsheet-like interface where each cell represents a fixed point in the multidimensional parameter space, enabling side-by-side comparisons and collaboration. To overcome the screen space limitations of desktops, researchers have utilized the unlimited display space of **VR**. Fouché et al. [13] extended the timeline design space into immersive 3D environments, using small multiples to juxtapose temporal snapshots in VR for enhanced spatial perception and exploratory analysis of S4D data. Johnson et al. [19] developed the Bento Box, a VR system that combines zoomable, interactive grids with small multiples to support detailed comparative analysis of complex spatial relationships like fluid-structure interactions.

While the works in Table 1 demonstrate technical feasibility, empirical studies evaluating all four visualization techniques together are lacking. We address this gap through an open-ended exploratory study to characterize their strengths and weaknesses (RQ1).

2.3 Analytical Tasks, Current Practices, Challenges, and Future Opportunities for S4D Data Analytics

Analytical Tasks. The works in Table 1 support various analytical tasks for S4D data. Most of them focus on specific tasks, such as *"finding the first occurrence of multiple similar events"* [9], *"analyzing complex spatial relationships, such as subtle differences in 4D vortical structures"* [19], and *"exploring the evolution of coherent structures or identifying similar structures"* [15]. However, these works lack a characterization of the broader analytical tasks. Other studies [10, 13] classify analytical tasks for time-varying spatial data based on general visualization tasks, such as lookup, comparison, relation-seeking, browsing, and locating. However, these categorizations were primarily used to evaluate proposed techniques, with the tasks being relatively simple and potentially failing to capture the complex demands of real-world S4D analysis. GRACE [26] represents the most relevant effort regarding task understanding, categorizing seven analytical tasks based on interviews with domain experts. However, their taxonomy focuses on correlations between spatial and non-spatial variables, rather than the spatiotemporal perspectives central to our work.

Current Practices, Challenges, and Future Opportunities. A recent survey [20] reviews 41 papers on S3D and S4D data analysis,

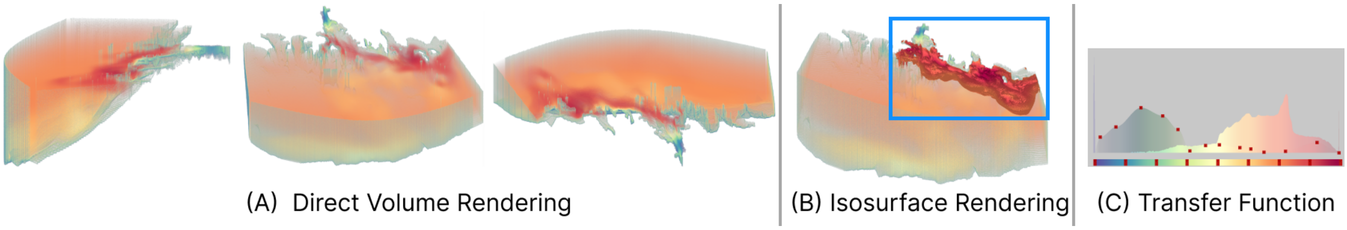

Figure 1: Visualization of a single S3D cube: (A) Direct volume rendering of the S3D cube from multiple perspectives, (B) highlighted isosurfaces using isosurface rendering, and (C) the underlying transfer function.

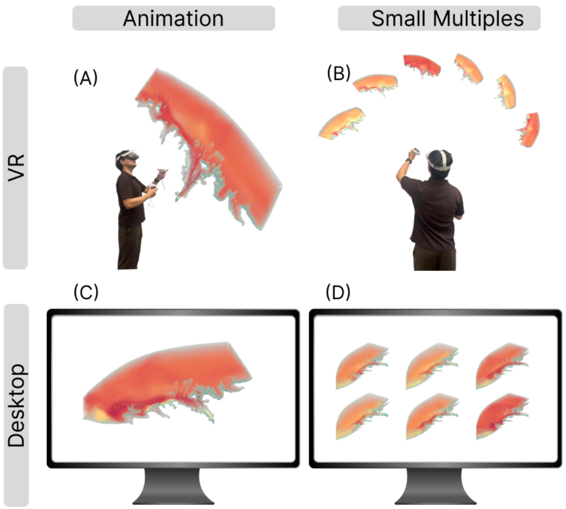

Figure 2: Illustrations of four visualization techniques for S4D data: (A) VR animation, (B) VR small multiples, (C) desktop animation, and (D) desktop small multiples.

categorizing existing visualization techniques into four types: juxtaposition, superimposition, interchangeable, and explicit encoding. In this context, the animation and small multiples investigated in our work are variations of the interchangeable and juxtaposition techniques, respectively, for S4D data with more than two timestamps. The survey highlights occlusion and perceptual challenges in S4D analysis and notes that current techniques are insufficient for addressing analysts' diverse needs; however, it stops short of summarizing what those specific tasks are. While the survey suggests future directions such as hybrid designs and VR-specific visualizations, the authors explicitly state that their recommendations derive from a literature review and call for user studies to empirically understand the needs and future directions for S4D data.

Our work complements existing studies and the survey with empirical findings derived from observing analysts using the four visualization techniques and interviewing them about their daily practices. We offer a deep understanding of analytical tasks, current practices, challenges (RQ2), and future opportunities (RQ3).

3 Study Rationale

We designed and implemented four visualization techniques, which serve as stimuli to elicit contextualized and concrete feedback from domain experts and inspire them to envision more effective visualizations. This section describes the S4D data we focus on and the four visualization techniques.

3.1 S4D Data Description

In this study, we focus on time-varying spatial 3D (S4D) data, which consists of a sequence of Spatial 3D (S3D) data over time. Specifically, S3D data can be represented as a function $v(x,y,z)$, where (x,y,z) specifies a point in 3D space, and v represents the value of a property (e.g., temperature, pressure, or density) at that location. S4D data builds upon this by introducing a temporal dimension t. It can be expressed as $v(x,y,z,t)$, representing the value of the property at the 3D point (x,y,z) at time t. It is important to note that (x,y,z) represents real-world spatial dimensions, capturing the relative positions, distances, and orientations of points in 3D space, which play a fundamental role in the analysis and interpretation of such data.

3.2 Four Visualization Techniques

Since S4D data consists of a series of S3D instances, we first visualize each S3D instance as a cube using volume rendering, with optional isosurfaces displayed via surface rendering. S4D data is visualized through animation, playing S3D instances in time order, and small multiples, arranging instances in a grid. Both techniques are available in VR and desktop environments, resulting in four visualization techniques with a shared set of interactions. This section describes the S3D visualization, the four S4D visualizations, and the interactions.

3.2.1 S3D Visualizations

Figure 1 shows a whole S3D visualization cube and an isosurface at a specific iso-threshold.

S3D Cube. Since S3D data can be regarded as volume data, we adapt the recent volume-based Space-Time Cube (STC) [10] to develop our S3D cube. In the original volume-based STC, the x and y axes represent 2D geographical information, while the z axis encodes timestamps. However, since S3D data is collected from 3D space, we modify the z axis to encode depth, with the timestamp represented either as an animation or through small multiples, as discussed later. Colors are used to encode the values of the property. Specifically, we use direct volume rendering and employ a reversed rainbow transfer function [12] to map data values to colors, where the values decrease progressively from red, orange, yellow, and green to purple. To prevent occlusion and differentiate between colors, we adjust the opacity accordingly.

Isosurface. To overcome occlusion and make it more convenient for experts to analyze data at specific values, we implemented an isosurface rendering mode based on [10] as a filtering method. Given an iso-threshold λ_s, we extract an isosurface whose value is equal to λ_s and visualize it. The isosurface rendering result will be incorporated into volume rendering, as shown in Fig. 1-(B). The mixture rendering offers both global (i.e., displaying patterns across various spatial space via direct volume rendering) and local (i.e., illustrating one structure via isosurface rendering) information. Users can adjust the iso-threshold to obtain different isosurfaces using a slider available in both Desktop and VR environments.

Implementation details. In direct volume rendering, we use ray marching to sample the values in the volume along the ray and a transfer function map the sampled voxel values to corresponding colors and opacities. At each ray, we accumulate the color and opacity (also referred to as alpha) until we reach either the early ray termination condition or a fully opaque result. Color and opacity

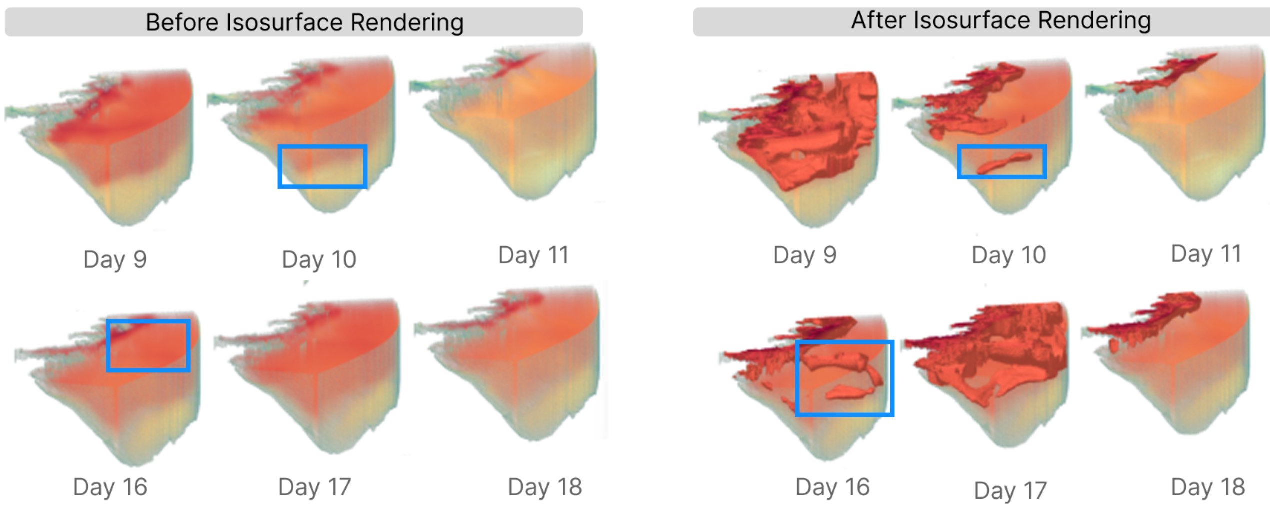

Figure 3: A use case of desktop small multiples. It helps identify specific patterns in ocean data, such as regions with higher values in the middle ocean depths that are disconnected from upper levels, as seen on days 10 and 16 (highlighted by blue boxes). While these patterns can be detected using the direct volume rendering, isosurface rendering makes them more distinct and easier to interpret.

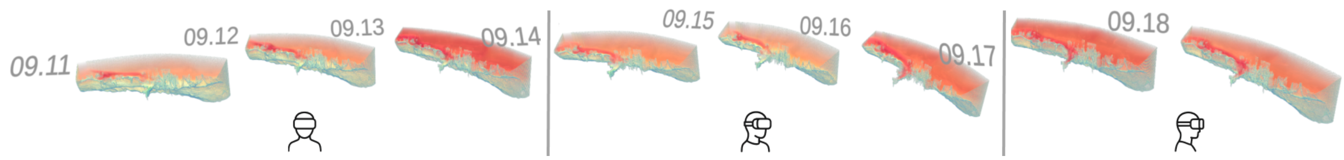

Figure 4: A use case of VR small multiples. It enables users to explore ocean data on an enlarged scale, uncovering spatial and temporal details. For instance, on September 16, a high-oxygen region was observed flowing outward and deflecting to the left due to the Coriolis force. The immersive effect allows users to view the surrounding data simply by turning their heads.

are composited from all voxels in a ray from front to back [31, 10], as defined below:

$$C_i = (1.0 - \alpha_{i-1}) \cdot C_{\text{sample}} + C_{i-1}$$
$$\alpha_i = (1.0 - \alpha_{i-1}) \cdot \alpha_{\text{sample}} + \alpha_{i-1}$$

Here, C_i and α_i represent the accumulated color and opacity from i samples in the front-to-back compositing process, while C_{sample} and α_{sample} are the sampled color and opacity from the current voxel.

For isosurface rendering, we visualize each isosurface with a fully opaque appearance rather than a transparent one, thereby highlighting the geometric structures and preventing confusion when interpreting information across different spatial regions and levels. In both isosurface rendering and direct volume rendering, Phong illumination model is applied to simulate the lighting effects.

3.2.2 S4D Visualizations

We visualize S4D data as a series of the above S3D cubes using four techniques, whose specific designs are informed by existing literature [23, 7]. As shown in Fig. 2, the four techniques are:

VR animation: The S3D cubes are placed in the same location, at the center of the field of view. Each cube appears for one second and then disappears one after another in time.

VR small multiples: Multiple S3D cubes are arranged in a horizontal half-circle wrapping around the user. The half-circle layout is chosen because previous studies [23] show that it strikes a balance between providing a clear overview of multiples and reducing the physical effort required to navigate them in VR.

Desktop animation: It is similar to VR animation, but the cubes are placed in the center of the desktop screen.

Desktop small multiples: Multiple S3D cubes are arranged on a flat grid on the screen. This design follows common practices for creating small multiples in 2D visualizations on a desktop [7].

We present two cases with desktop and VR in Fig. 3 and Fig. 4.

3.2.3 Interactions

Based on practices from relevant research [10, 23], we provide a unified set of interactions for all four conditions, affecting all S3D instances within the S4D data. Specifically, users can adjust clipping planes of S3D instances along the x, y, and z axes to reveal internal data, manipulate cubes by scaling and rotating for better analysis, and set time ranges to focus on specific temporal slices. Additionally, users can reset cube positions and take screenshots to capture specific views.

4 Study Design

4.1 Participants

We recruited 12 participants (nine males and three females; aged 22–31) from local universities, including eight Ph.D. students and four Master's students. Their backgrounds encompassed diverse fields, including ocean science, atmospheric science, 3D medical imaging, urban analysis, biological sciences, and computer science, providing a wide-ranging perspective on practices and needs. They all had experience analyzing spatiotemporal data in their research or studies. On a seven-point Likert scale, participants reported an average familiarity of 5.4 (STD=1.0) with data visualization, 5.2 (STD=0.7) with spatiotemporal data analysis, and 5.0 (STD=1.5) with using data visualizations for spatiotemporal data analysis. Additionally, their average familiarity with VR was 4.0 (STD=1.4).

4.2 Data

A real-world S4D dataset from the ocean domain, following the characteristics described in Sec. 3.1, was utilized in this study. The

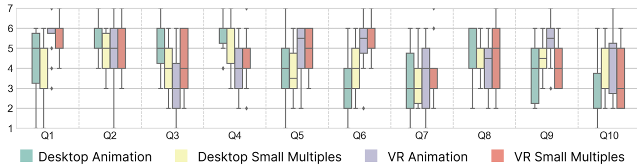

Figure 5: User ratings on the four conditions. Higher scores are better for Q1–Q4, and lower scores are better for Q5–Q10. The questions Q1-Q4 assess immersion, enjoyment, ease of use, and easy of learning, respectively. The Q5–Q10 are NASA-TLX questions, including mental demand, physical demand, temporal demand, performance, effort, and frustration. The user ratings present high variability, reflecting the diverse experiences and preferences of participants.

dataset spans 30 days and includes daily records of dissolved oxygen levels in the seawater of a bay. The entire S4D dataset is denoted as $V_1, V_2, \cdots, V_{30}$, where each $V_i = v(x, y, z)$ represents a S3D data corresponding to a daily record. Each S3D data is stored in a 3D grid structure, with layers ranging from the surface (depth 0) to the seafloor (depth -30). Each layer is formatted as a 400 × 441 grid and includes a mask to model the topography of the continental shelf. After preprocessing, the S4D dataset has a minimum value of 0.1907 and a maximum value of 10.4103. This dataset was selected because it captures the pre-typhoon, during-typhoon, and post-typhoon periods, offering valuable insights into how typhoons impact oxygen levels across various ocean locations over time.

4.3 Procedure and Tasks

We implemented the four conditions on a PC with an NVIDIA GeForce RTX 4060. The two desktop conditions were displayed on the PC, while the two VR conditions were accessed using a Quest 2 headset connected to the same PC. The study was conducted with each participant individually in three stages:

Introduction (10 mins): We began by explaining the study's purpose and overall procedure to the participants. Next, we described the dataset, including a brief background on the ocean phenomenon it represents (i.e., typhoon and oxygen). Lastly, we introduced the S3D visualization, providing instructions on how to interpret its visual encodings and relate them to the underlying data.

Open-ended exploratory study for RQ1 and RQ3 (80 mins): Each participant tested all four visualization techniques (Sec. 3.2.2) in a counter-balanced order. Although we aimed to explore the strengths and weaknesses of different visualization types and display environments, our intent was not to rank them or determine which technique was the best or worst overall. Instead, we used these conditions to elicit user feedback on the specific pros and cons associated with each technique. Therefore, we did not require participants to perform closed-ended tasks, such as measuring completion time or accuracy. Instead, we adopted an exploratory study design, following the practice of a previous study comparing small multiples and animation [7]. Specifically, participants were tasked with analyzing the data using each visualization and identifying as many findings as possible. Each condition lasted approximately 20 minutes. For the first 10 minutes of each condition, we explained the interactions and allowed participants to familiarize themselves with the technique. In the remaining 10 minutes, participants freely explored the dataset interactively and were asked to explicitly report their findings to the experimenter, who documented them. Participants were encouraged to think aloud throughout the process. Their exploration processes were video-recorded. After completing each condition, they filled out a 7-point Likert questionnaire to assess the condition in terms of user experience, usability, and workload. We also gathered feedback on the pros and cons of each condition.

Semi-structured Interview for RQ2 and RQ3 (30 mins): The interview focused on their routine research experiences, such as their common analytical needs, current practices, and challenges faced. Participants were also encouraged to suggest improvements for the four conditions or ideas for designing other visualizations to better support their needs and address challenges. All interview sessions were audio-recorded and transcribed for later analysis.

Ethics Statement: The study was reviewed and approved by the Human and Artefacts Research Ethics Committee of the Hong Kong University of Science and Technology. We obtained consent forms from participants before they attended the study.

5 RQ1: Strengths and Weaknesses of Visualization Types and Display Environments

To answer RQ1, we report the results of the exploratory study by analyzing the strengths and weaknesses of visualization types and display environments. First, we discuss the shared benefits and limitations of the four S4D visualization techniques in Sec. 5.1 and Sec. 5.2, respectively. Next, we compare the two visualization types (i.e., animation and small multiples) in Sec. 5.3 and the two display environments in Sec. 5.4.

5.1 Shared Strengths of the Four S4D Visualizations

Across conditions, participants affirmed the value of 3D representations for S4D data. Two key themes emerged:

Effective Pattern Overview Before Detail Analysis: These techniques allow them to capture the overall patterns of the datasets before diving into specific details. This capability is particularly valuable when analyzing sparse data, where relationships might not be apparent in the 2D representations currently used in their practices. For example, P1 noted, *"3D visualization helps in selecting appropriate slopes for analysis. Besides, using 3D allows us to first identify continuous changes."*

Essential for Multi-Dimensional and Non-Planar Data: Participants emphasized that 3D visualizations are essential for tasks involving three or more variables or dimensions, especially when dealing with data that have inherent spatial relationships or geometries, such as volumetric distributions or irregular spatial shapes. Without 3D, critical spatial information could be lost in 2D representations. As P8 explained, *"Some values are not distributed on a plane but spread across the entire space, possibly in irregular shapes. In such cases, 3D is necessary."*

5.2 Shared Weaknesses of the Four S4D Visualizations

Figure 5 shows the user ratings on the four conditions, which reveal two shared weaknesses of the S4D visualization techniques:

High Cognitive and Effort Overhead: Across all four conditions, participants reported moderate-to-high levels of Mental Demand (Q5) and Effort (Q9), with median scores ranging between 3.5 and 5.5. This indicates a shared weakness: these visualizations do not fully alleviate the cognitive burden required to interpret complex S4D data.

High Variability in User Adaptation: A visual inspection of the boxplots, particularly for Ease of Use (Q3), Temporal Demand (Q7), Performance (Q8), and Frustration (Q10), reveals large interquartile ranges and wide variances (whiskers spanning from ratings of 1 to 7). This high variability suggests that the current visualization methods fail to deliver a consistent user experience, and their success may depend on individual user capabilities such as spatial ability or VR familiarity. This underscores the need for more robust designs that accommodate a broader range of users.

5.3 Strengths and Weaknesses of Animation vs. Small Multiples

5.3.1 Animation

Strengths: Animation enables iterative play-and-pause interaction to effectively observe continuous changes. Participants often played and paused animation repeatedly to follow changes over

Table 2: A task characterization for S4D data analysis informed by participants' routine research practices.

Category	Subcategory	Description	Example Tasks
Single Subspace + Fixed Time	Single-State Analysis	Discover patterns or outliers within a single subspace of the original 3D space at a fixed time point.	*Examining the spatial distribution of pollution hotspots within a subspace at a specific time.*
Single Subspace + Dynamic Time	Temporal Trends and Patterns	Discover and annotate temporal changes or trends within a spatial subspace.	*Analyzing seasonal temperature changes in a specific location.*
Multiple Subspaces + Fixed Time	Spatial Distribution Analysis	Compare spatial distributions or dependencies across different subspaces at a single moment in time.	*Analyzing the spatial extent of storm surge during a typhoon.*
Multiple Subspaces + Dynamic Time	Spatial-Temporal Phenomena Tracking	Derive and annotate lifecycle patterns of phenomena that evolve across different subspaces and over time.	*Tracking a typhoon's path and associated atmospheric and oceanic variables over time.*
	Temporal Evolution of Spatial Distributions	Discover and compare how spatial patterns evolve dynamically across regions over time.	*Examining the spatial progression of cold air phenomena over time.*
	Event-Centric Analysis	Analyze the temporal dynamics of specific events and their impacts across different subspaces over time.	*Examining atmospheric and oceanic variables before, during, and after a typhoon.*
	Multi-Scale Spatial Analysis	Compare spatial patterns across varying geographic scales and observe their evolution over time.	*Analyzing temperature changes at regional and national spatial scales.*

a certain period. P7 explained, *"I watch the animation cycle repeatedly and pause to analyze what's happening."* Similarly, P11 noted, *"I notice a period where values look unusual, pause, and then examine specific days to understand the details."* Therefore, animation excels at showing how phenomena evolve continuously over time. P10 highlighted that animation *"helps observe the evolution of phenomena over time, such as the movement of oxygen levels."* P12 further emphasized, *"Animation makes it possible to see how phenomena change dynamically over time in a way that's not possible with static visualizations."*

Weaknesses: Animation struggles to locate exact time points and perform direct comparisons. Animation often lacks precision when users need to pause at exact time points or analyze subtle details. P12 noted, *"It's hard to pinpoint specific moments in time when using animation."* Additionally, animation is less effective for direct spatial comparisons across different times, as P7 observed, *"It's hard to notice subtle spatial differences or trends in less prominent areas."* This limitation arises because animation presents one frame at a time, requiring users to rely on memory to compare frames.

5.3.2 Small Multiples

Strengths: Small multiples support broad scanning and enable direct comparisons across discrete time points. Small multiples allow users to scan the entire set of 3D cubes to quickly identify areas of interest and then zoom in for detailed comparisons. P1 explained, *"I first look at the whole visualization to see if anything stands out, then zoom in to analyze specific areas."* Similarly, P3 noted, *"I look at the whole time series first, focusing on time, and then lock in on specific spatial patterns."* After scanning, small multiples provide a comparative perspective, enabling users to observe spatial and temporal relationships simultaneously across discrete timestamps. As P3 noted, *"Small multiples allow me to directly compare spatial details at different time points,"* making them particularly effective for identifying spatial anomalies and trends.

Weaknesses: Small multiples require users to physically shift their focus and mentally connect changes. The fragmented layout of small multiples forces users to compare spatial and temporal patterns across separate 3D cubes. As P4 noted, *"It requires shifting eyes back and forth on specific areas to extract meaningful insights."* Beyond this physical effort, participants highlighted the cognitive demand of mentally mapping changes between 3D cubes. For example, P11 stated, *"Animation makes temporal changes feel more natural, whereas small multiples require users to mentally piece together spatial and temporal changes."*

5.4 Strengths and Weaknesses of VR vs. Desktop

5.4.1 VR

Strengths: VR may support internal spatial exploration and detailed observation of volumetric structures. Participants were interested in the potential of VR for an inside-out inspection of the data. P4 noted, *"VR allows me to enter the interior of data and look up and down to observe internal flows."* Participants also described a strong desire for engaging interaction metaphors, such as the ability to *"swim in the sea"* (P3) or *"treat myself as a submarine and examine the data from a first-person view"* (P1). Furthermore, participants reported *"enhanced depth perception"* (P12), enabling them to uncover subtle spatial phenomena, such as *"how oxygen concentration changes vertically"* (P12).

Weaknesses: VR struggles with providing temporal overviews due to visual overload. Participants noted that small multiples in VR could exceed their field of view, making it *"harder to see the overall data"* (P7) across multiple timestamps simultaneously. This fragmentation forced users to rely heavily on spatial memory when comparing non-adjacent time steps. Additionally, the extensive head-turning required to scan the data was described by participants as *"dazzling and chaotic"* (P10).

5.4.2 Desktop

Strengths: Desktop environments facilitate temporal navigation with precise parameter control. Participants noted that desktop interfaces allow for *"easy and precise interaction"* (P11), enabling them to efficiently *"locate specific time points or adjust temporal parameters without the physical constraints encountered in immersive environments"* (P11).

Weaknesses: Desktop environments struggle to fully convey complex 3D spatial relationships and restrict observation angles. Since 2D screens flatten volumetric structures, participants found it difficult to perceive depth-dependent data such as *"internal flow patterns"* (P5) or *"occluded density changes"* (P3). Some participants also faced difficulties in view rotation; as P9 stated, *"Switching the viewing angle is not intuitive compared to the natural head movements in VR, and thus observing data from different angles is difficult."*

6 RQ2: Understanding of Current S4D Data Analysis

To answer RQ2, this section presents the results of semi-structured interviews with our participants, providing a holistic understanding of their current analytical tasks, practices, and challenges. Specifically, we categorize the analytical tasks that analysts usually perform with S4D data (Sec. 6.1). Next, we summarize their current practices in utilizing visualizations to achieve these tasks (Sec. 6.2). Finally, we identify the challenges they face in completing these tasks within their current practices (Sec. 6.3).

6.1 RQ2a: Analytical Tasks

Categorizing analytical tasks provides insights into analysts' real-world needs and thereby offers guidance for developing future visualizations. Based on participants' responses, we categorize the tasks along two key dimensions: spatial focus (i.e., single subspace vs. multiple subspaces) and temporal scope (fixed time vs. dynamic time). A single subspace refers to tasks that consistently focus on one specific region within the 3D space throughout the analysis. In contrast, multiple subspaces involve examining or comparing different regions or subsets of the 3D space, such as analyzing pollution across various cities or tracking a typhoon as it moves through multiple regions. On the temporal side, fixed time refers to tasks that analyze data at a single timestamp, whereas dynamic time involves studying trends and changes over a period of time.

Based on the two dimensions, we characterize tasks into four main categories: Single Subspace + Fixed Time, Single Subspace + Dynamic Time, Multiple Subspaces + Fixed Time, and Multiple Subspaces + Dynamic Time. Each category captures distinct combinations of spatial and temporal characteristics, and within these, additional subcategories highlight specific analysis goals. For example, tasks in Single Subspace + Dynamic Time focus on identifying temporal trends in a fixed region, such as seasonal temperature changes in a specific location. The details of each subcategory and their examples can be found in Table 2. These characterizations provide an overview for understanding the diverse range of spatial-temporal analysis tasks and their real-world applications.

6.2 RQ2b: Current Practices

Having identified the spatiotemporal tasks that analysts typically perform, we next investigate how they utilize visualizations when accomplishing these tasks. Two key themes emerge: the roles that visualizations play in their workflows (Sec. 6.2.1) and a two-step process analysts typically adopt to simplify and manage the complexity of S4D data (Sec. 6.2.2).

6.2.1 Roles of Visualizations

Our participants shared that visualizations serve three primary roles in their S4D data analysis workflows: exploration, validation, and communication.

Exploration. Our participants frequently rely on visualizations to explore their data at the early stage of their analysis. As P1 noted, *"Visualization is essential for initial analysis to understand patterns and trends in the data, and inform what to analyze with our simulation or numerical analysis methods. For example, I plot 2D heatmaps or line charts after data pre-processing with Python or Matlab."* P4 also described using visualizations as *"overviews to observe spatiotemporal changes, such as plotting flow curves with line graphs, analyzing energy distributions using spectral analysis, and summarizing patterns"*. This process not only aids in understanding but also highlights potential research directions. For example, P5 further emphasized that visualizing vertical and horizontal variations *"saves time and helps identify specific areas in the ocean worth investigating."*

Validation. Our participants used visualizations to validate their computational models. For example, P1 used visualizations to check *"whether simulation or deep learning algorithms work as expected by comparing results."* P14 shared, *"Using simple visualizations helps identify parameter correlations and anomalies, ensuring the reliability of findings."*

Communication. Our participants also used visualizations to present insights and communicate effectively with others. They used visualizations to condense spatiotemporal phenomena into intuitive maps, diagrams, or animations, enabling effective communication across teams with varying levels of technical expertise.

6.2.2 A Two-Step Approach to Visualize S4D Data

Since S4D data contains massive amounts of detail that exceed human cognitive ability to process directly, most participants typically adopted a two-step process in their visual analytics: dimensionality reduction to 2D spaces, followed by detailed and overview analyses based on the selected subspaces.

Step 1: Dimension reduction to 2D Subspaces. The first step in analyzing S4D data involves simplifying the 3D spatial dimensions by reducing them to 2D subspaces. This reduction is essential to make the data manageable and interpretable. Two primary approaches are commonly used to define these 2D subspaces: plane-based selection and semantic-based selection.

Plane-based selection focuses on using *"standard xyz planes"* (P7) or *"customized irregular planes"* (P1). These planes are typically selected based on spatial characteristics, and their choice does not necessarily carry semantic meaning. For example, analysts might select a specific subspace based on the region of interest, such as a site-specific area or a spatially significant plane. Depending on the research goal, the clipping plane may be aligned with standard axes or customized to explore irregular surfaces or rotate around a specific point for a 360-degree view. In contrast, **semantic-based selection** identifies subspaces with both spatial and semantic significance. Analysts may prioritize regions like *"sea surfaces and off-band areas"* (P8) that align with the focus of their study. These regions allow analysts to narrow their scope and focus on critical aspects of the data, avoiding irrelevant details.

Regardless of whether the reduction is plane-based or semantic-based, the selection process heavily depends on *"manual inspection"* (P6) and *"domain-specific knowledge"* (P3). As P1 shared, *"We rely on our existing understanding of the data and the research context to determine the most meaningful subspaces."*

Step 2: Detailed and overview analysis based on subspaces. After dimension reduction, they conduct both detailed and overview analyses on the selected subspaces to extract meaningful insights. For detailed analysis, temporal dynamics within the reduced 2D spaces are explored using animations, *"small multiples of heatmaps, or line charts"* (P1), which help reveal fine-grained spatiotemporal patterns. For an overview, analysts often employ aggregation techniques to summarize broader trends across the dataset. As P9 stated, *"By focusing on overall patterns, this approach allows us to identify dominant characteristics or trends without being overwhelmed by details."*

6.3 RQ2c: Challenges

While the two-step visualization approach in Sec. 6.2.2 facilitates S4D analysis, our interviews reveal that relying on selecting 2D subspaces to investigate 3D spaces over time is insufficient. This disconnect between complex 3D phenomena and their 2D reduction leads to the following challenges.

6.3.1 Difficulty in Efficiently Narrowing Down Areas for Investigation

One major challenge in analyzing S4D data with 2D subspaces lies in efficiently selecting subspaces for investigation. Our participants often struggled to determine where to focus, relying heavily on trial-and-error methods. For example, as P12 said, *"Selecting a vertical cross-section (e.g., along the z-axis) requires repeated attempts to locate a meaningful plane."* When determining specific axis values for clipping planes, they generally relied on experience or predefined rules. For instance, oceanographic studies tend to focus on the surface layers, as P3 explained, *"The most dynamic activity occurs near the surface in the ocean."* Alternatively, they may sample axis values at regular intervals, such as *"every 10 units"* (P1), to ensure consistent coverage. However, fully exploring depth data remains challenging due to the large scale of the dataset. In medical imaging, similar challenges arise. Doctors often analyze 3D images ((e.g., 500×500×100) slice by slice, which is both time-consuming and prone to missed features. As P6 noted, *"Lymph nodes can appear anywhere and have a wide spatial range, making it difficult to decide where to focus without extensive manual inspection."*

6.3.2 Limitations of 2D Representations for Inherently 3D Structures

Representing 3D data in 2D slices introduces significant limitations, especially when dealing with complex spatial structures. Certain features, such as volumetric distributions or irregular shapes, are inherently 3D and cannot be fully captured in 2D representations. For example, in oceanographic studies, phenomena like water masses, defined by density, salinity, and temperature, often require a 3D view to understand their interactions. As P1 explained, *"The changes between water masses are too abstract in 2D, but in 3D, their spatial volume and interactions become clear."* Besides, in medical imaging, important distinctions between features can be lost in 2D. For example, P6 shared, *"Lung nodules and blood vessels may both appear as points in a 2D slice, but in 3D, nodules appear as points while blood vessels are lines."* However, current practices in 3D medical imaging often rely on viewing a single 2D plane at a time, making it difficult to identify such distinctions.

7 RQ3: Future Research Directions

To answer RQ3, we synthesize the results of our exploratory study (Sec. 5) and interviews (Sec. 6) to outline future opportunities. First, the strengths and weaknesses observed in Sec. 5 motivate refined visualization designs (Sec. 7.1). Second, the characterization of analytical tasks (Sec. 6.1) underscores the need to consider the unique properties of S4D data (Sec. 7.2). Third, the difficulty analysts face in manually identifying relevant subspaces (Sec. 6.3.1) highlights the need for intelligent support to guide investigation (Sec. 7.3). Finally, limitations in representing complex 3D structures within 2D slices (Sec. 6.3.2) call for techniques that reduce cognitive overwhelm while preserving spatial context (Sec. 7.4).

7.1 Enhance Visualization Designs and VR Utilization

This section outlines potential directions to address the limitations of each technique identified in Sec.5.3 and Sec.5.4. Next, we discuss how to leverage the advantages of VR identified in Sec. 5.4.1.

7.1.1 Improvements on Each Technique

Desktop animation should better leverage the inherent strength of desktops in precise control to address difficulties in locating exact time points. Furthermore, to support direct comparisons, it would benefit from features like side-by-side comparisons or overlays to highlight differences between adjacent time steps. Desktop small multiples require improvements to reduce the cognitive load of physically shifting focus and mentally connecting changes. Rather than relying solely on time-sequential arrangements, designing customizable sorting and grouping mechanisms may help users manage the density of information. Additionally, interactive features like filtering or zooming could be included to reduce visual clutter and improve user focus without sacrificing the ability to scan the overall dataset. VR animation needs enhanced VR interaction designs, such as finer temporal control, to address the difficulty of locating exact time points without disrupting the workflow. VR small multiples require enhancements to balance the strength of immersive observation with the weakness of visual overload. Improvements could include better organization of visual information to keep data within a comfortable viewpoint, and more intuitive controls for exploring spatial data across multiple frames.

7.1.2 Improvements on the VR Usage

To make use of the advantages of VR identified in Sec. 5.4.1, we highlight two directions for enhancing VR usage in S4D data analysis: supporting inside-out inspection and designing specific embodied interactions.

First, a major potential advantage of VR is its ability to immerse users inside data, facilitating the intuitive exploration of internal spatial relationships. Future research needs to investigate efficient mechanisms for observing and exploring S4D data from the inside out in VR, addressing challenges like occlusion and helping analysts uncover subtle phenomena that are difficult to detect on desktops, such as internal flow patterns.

Second, our results and previous research have shown that VR offers advantages in creating more natural and intuitive interactions compared to traditional desktop interfaces [36, 42]. However, the current interaction designs in our two VR conditions have substantial room for improvement to fully leverage these benefits. Since S3D and S4D data are more complex than visualizations such as node-link graphs [34] and 3D bar charts [23] commonly investigated in the literature, dedicated research is needed to determine which types of embodied interactions are most effective for S3D and S4D data visualizations. In addition to general interactions, such as grabbing, rotating, or resizing, VR also offers opportunities for advanced data annotation and exploration, such as the use of embodied tools like 3D lasso selections for marking areas of interest or gesture-based highlighting to emphasize specific regions within a dataset. Since patterns in S3D instances of an S4D dataset may appear across time, it remains unclear how to enable annotations created in VR to persist across multiple slices, allowing users to conduct comparative analyses efficiently.

7.2 Support Analytical Tasks by Addressing Unique Data Characteristics

Table 2 summarizes the analytical tasks for S4D data, categorized by their temporal scope and spatial focus. To effectively support these tasks, particularly those involving *Dynamic Time* and *Multiple Subspaces*, future research needs to address the challenges imposed by the spatiotemporal and large-scale nature of S4D data.

Supporting tasks related to Dynamic Time requires addressing the specific challenges of temporal evolution. S4D data involves spatial features that may grow, shrink, disappear, or emerge as new entities across time steps. This necessitates methods for robust spatiotemporal feature tracking to ensure these changes are consistently captured and analyzed. Additionally, the temporal shift in feature values makes designing transfer functions challenging, as a function effective for one timestamp may obscure features in another. Therefore, ensuring temporal consistency in transfer function design is critical for accurately visualizing evolution trends.

Similarly, supporting tasks related to Multiple Subspaces require addressing the large spatial scale of S4D data, which often spans vast geo-spatial regions. This large-scale introduces computational and visualization challenges that can hinder the efficient comparison of different subspaces. Future research should explore multi-scale representations that allow users to seamlessly navigate between global analyses and localized subspace investigations. Such approaches would enable analysts to observe broad patterns while maintaining the ability to examine fine-grained details efficiently.

7.3 Embed Intelligent Support to Find Subspaces Deserving Investigation

The reliance on manual selection and knowledge-driven decisions, as mentioned in Sec. 6.3.1, highlights the need for interactive semi-automated and automated methods to effectively identify meaningful subspaces. Future work could focus on improving these visualizations and incorporating more diverse interactions, such as expanding subspace selection, as proposed in previous literature [5], from S3D to S4D. Mixed-initiative methods, which involve collaboration between users and AI systems, could also be explored. While such methods have been successfully applied to 2D visualizations [40], their application to S4D data remains an open challenge. Fully automated approaches [16], on the other hand, could leverage small datasets to identify areas with potential patterns, train models to understand relationships between patterns and other variables, and detect meaningful patterns across larger datasets.

7.4 Reduce the Overwhelms while Maintaining 3D Structures

To address the challenge in Sec. 6.3.2, it is crucial to explore visualization techniques that balance clarity with the preservation of 3D spatial relationships and structures. Hybrid 2D/3D visualizations and multiscale visualizations are two promising solutions. Immersive analytics systems have explored how to incorporate 2D and 3D visualizations across various domains, as detailed in existing surveys [21, 17]. Specifically, hybrid visualizations enable users to combine 2D slices or projections with full 3D visualizations, facilitating focused exploration of specific data dimensions while maintaining the broader spatial context. However, for time-varying S4D data, it remains an open question how to extend current hybrid designs to effectively capture and represent temporal dynamics. Multiscale visualizations in our context refer to smooth transitions between overarching 3D spaces and specific localized sub-3D regions. They may allow analysts to investigate large-scale patterns alongside fine-grained details. A key challenge lies in tracking the dynamic changes of phenomena with inherent spatial relationships or geometries over time. This includes identifying relevant sub-3D regions, visualizing their evolution, and ensuring that spatial and temporal relationships are preserved.

8 Limitations

8.1 Participant Demographics and Sample Size

We acknowledge several limitations regarding participant composition and sample size. First, the relatively small number of participants (N = 12) may limit the comprehensiveness of our findings. Second, all participants were Ph.D. and Master's students rather than senior domain experts. Although their self-reported familiarity with spatiotemporal data analysis (mean = 5.2 on a 7-point Likert scale) indicates that they possessed relevant analytical experience and were able to share their tasks and practices, their responses might lack variety and omit more nuanced expert requirements. Future studies should include a larger and more diverse cohort of seasoned domain experts. Third, while two of our participants were senior Ph.D. students dedicated to working on data visualizations for spatiotemporal data analysis, involving more experts in data visualization would further validate the utility of the techniques and suggest future directions.

8.2 Dataset Diversity and Finding Generalizability

Our study primarily relied on a single oceanographic dataset, characterized by continuous and dense volumetric fields. Although this dataset exhibits key characteristics of S4D data, such as temporal continuity and volumetric spatial structure, it may not represent the full spectrum of S4D data found in other fields (e.g., atmospheric science, medical imaging, urban analytics). For instance, some S4D datasets may feature more discrete temporal events or different spatial scales, and our findings regarding the strengths of animation and small multiples may not fully generalize to these datasets. Consequently, our design recommendations should be interpreted within the context of continuous volumetric S4D data. Additionally, the oceanographic dataset did not align closely with the specific academic backgrounds of some participants (e.g., computer science). While the dataset served effectively as context to elicit feedback, and participants were able to connect the visualization techniques to their own research contexts (e.g., medical imaging, urban analysis), future research should incorporate different types of S4D datasets from diverse domains to enhance the robustness and generalizability of our findings. Such cross-domain, multi-dataset studies would help uncover more universally applicable design principles and validate the transferability of the techniques proposed in this work.

9 Conclusion

This work advances the understanding of analytical tasks, challenges, and requirements in time-varying spatial 3D (S4D) data visual analytics. By engaging domain experts from various fields, we provide a summary of the key needs for S4D visualization. Through an exploratory study of four representative visualization techniques across VR and desktop environments, we highlight how different approaches influence analytical processes and outcomes. Finally, we identify future research opportunities, such as improving the current four techniques to efficiently handle S4D data with a single variable, embedding intelligent support to identify subspaces for investigation, reducing the sense of overwhelm while maintaining 3D structures, and supporting S4D data with multiple variables. These contributions pave the way for more effective S4D visualization strategies in the future.

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