Year-Long Time-Varying 3D Air Quality Data Visualization

Aidong Lu, Wei Chen, William Ribarsky, and David Ebert

Abstract. Understanding air quality data is important for many environmental and climatic applications that are crucial to our daily life. It is often challenging to handle these 3D datasets due to their large number of time steps and multiple interactional chemicals. In this paper, we design and generate knowledge templates for visually analyzing multi-field, time-varying 3D air quality data. Specifically, we design a set of multi-level knowledge templates to capture important statistical data properties based on the distribution features of air quality data. We develop a fast template synthesis method to generate suitable templates according to user intentions. We have also developed an integrated visualization system for visually comparing multiple templates and volume datasets. Our approach can automatically synthesize suitable knowledge templates to assist the visualization and analysis tasks of multiple related datasets. The experimental results demonstrate that appropriate knowledge templates can significantly improve the exploration and analysis processes of air quality data by encapsulating long-time range knowledge into understandable visual formats.

Aidong Lu
University of North Carolina at Charlotte
e-mail: aidong.lu@uncc.edu

Wei Chen
Zhejiang University
e-mail: chenwei@cad.zju.edu.cn

William Ribarsky
University of North Carolina at Charlotte
e-mail: ribarsky@uncc.edu

David Ebert
Purdue University
e-mail: ebertd@purdue.edu

Z.W. Ras and W. Ribarsky (Eds.): Advances in Information & Intelligent Sys., SCI 251, pp. 289–306.
springerlink.com

1 Introduction

Air quality data are important for many environmental and climatic applications that are crucial to our daily life. They can be used to study multiple air quality issues, including tropospheric ozone, fine particles, toxics, acid deposition, and visibility degradation. Many of the air quality data are multi-field time-varying datasets and they are generally composed of a large number of time steps and hundreds of variables. Although both multi-field visualization and time-varying visualization have attracted much attention from visualization researchers, it is very challenging to effectively visualize these year-long air quality data and develop a convenient analysis system for scientists to use.

In this paper, we concentrate on providing a visual analysis solution for 3D air quality data. Our data are generated from the community multi-scale air quality (CMAQ) [1] and the sparse matrix operator kernel emissions (SMOKE) [2] modeling systems. SMOKE is also one input source of the CMAQ system, which simulates various chemical and physical processes that are important for understanding atmospheric transformations and distributions. One important challenge for analyzing these air quality data is the large number of involved datasets, since both modeling systems can produce data at the rate of an hour for years. Additionally, at each time step, there are hundreds of chemicals that may interact with each other. The total number of involved datasets can be easily over one million, which requires a significant amount of user effort to understand them. It is obviously too time consuming to ask scientists to visualize each time step and chemical respectively for such a large number of datasets.

Therefore, we have developed a statistical visualization approach to assist scientists in analyzing a large number of related datasets. Our main motivation comes from the statistical properties of air quality datasets that change over time, which are common among many environmental data and scientific simulations. First, most air quality data have similar appearances, which make it especially challenging to compare datasets from different time steps or chemical variables. Second, major data properties change very slowly over time except under abnormal conditions, in the sense that data at the same time of different years are expected to be similar. According to these two data properties, we can use accumulated knowledge from historical datasets to explore general data features and predict future events. Similar things happen in weather forecasting, in which record high, record low, average high, and average low are used to provide a general knowledge about the temperature and precipitation around a certain time period. Therefore, suitable visualizations that combine information collected from multiple relevant datasets can greatly improve the data analysis process of air quality studies.

In this paper, we present a method to visualize multi-field, time-varying air quality datasets through designing and generating knowledge templates that can capture statistical arithmetic and geometric distributions of multiple datasets. Specifically, We generate multi-level templates with different level-of-detail to effectively visualize statistical information at appropriate levels for visual analysis tasks. We develop a user-guided template generation method to synthesize appropriate templates according to regions-of-interests during user interactions. We have also integrated a multiple template synthesis method for visually analyzing volume datasets using various knowledge templates. We have received positive feedback from our collaborators on using knowledge templates to improve the data comparison and analysis processes in their air quality studies.

The remainder of the paper is organized as follows: we first summarize previous work related to the topic of multi-field time-varying air quality data visualization in Section 2. Section 3 describes the generation method of knowledge templates with different level-of-details. Section 4 presents an automatic template synthesis approach to generate appropriate templates according to user selections. In Section 5, we describe our integrated system for exploring and analyzing 3D air quality data. We conclude and discuss the future work in Section 6.

2 Related Work

2.1 Time-Varying Data Visualization

Time-varying data visualization is a challenging topic because of the large data volume. Many approaches have been explored to improve the efficiency of rendering algorithms, such as fast data compression [15] and hardware-accelerated rendering [10]. Most relevant work to this paper are data comparison and composition approaches. For example, Verma and Pang [17] proposed comparative visualization tools for analyzing vector datasets based on streamlines. Woodring et al. [22] composed visualizations for providing contextual cues to compare multi-variate, time-varying datasets. The main difference of this paper from previous work is that we design knowledge templates for representing statistical data distributions from a large number of related datasets.

2.2 Multivariate Visualization

In multivariate information visualization, many methods have been explored to visualize data in reduced dimensions to improve the understanding of users. For example, Guo et al. [8] integrated computational, visual, and cartographic methods to develop a geo-visual analytic approach for exploring and understanding multivariate patterns. Weimer et al. [18] developed a co-triangulation method that represented dependent data from multiple sets of scattered data. Wilkinson et al. [19] proposed statistical measures for discovering outliner patterns with multivariate displays.

2.3 Knowledge Visualization

The term "knowledge visualization"[5, 6, 24] is gaining more attention among visualization researchers. For example, Chen and Hsieh [6] presented a generic method to visualize citation information. Burkhard [5] introduced a mediating framework that brought together isolated research directions and defined the new research focus knowledge visualization. There are also works that combine the topic of knowledge visualization with a specific application. The interdisciplinary approach presented in [11] discussed the benefit of collecting the input data and aggregating over very large data sets. Wong et al. [20] introduced an interactive graph generator, GreenSketch, to facilitate the creation of descriptive graphs required for different visual analytics tasks.

2.4 Environmental Visualization

Many visualization approaches have been proposed to explore environmental datasets. For example, Wood et al. [21] explored modular visualization environments over the World Wide Web that could monitor multiple gases and pollution sources. Treinish [16] employed critical point analysis and simple band pass filtering of wind fields for streamline calculations and an encapsulation of nested computational meshes for general visualization. Riley et al. [13] developed a multi-field visualization that used physically-based calculations for accurate weather visualization. Yuan et al. [23] presented a high dynamic range volume visualization method for data with both high spatial and intensity resolutions. Song et al. [14] developed an integrated atmospheric visual analysis and exploration system for interactive analysis of weather datasets. Qu et al. [12] presented an information visualization method to analyze air pollution problems in Hong Kong. In this paper, we concentrate on 3D statistical visual analysis approaches for air quality datasets.

3 Multi-Level Knowledge Templates

To overcome the data analysis and visualization difficulties caused by a large number of datasets, we design sets of knowledge templates that can incorporate statistical information of air quality data in interactive visualization processes. The statistical data distributions are crucial for analyzing air quality data, since all the datasets from different time steps and chemical variables share similar appearances. In air quality studies, data relations and distributions play important roles as well as the 3D data structures of single datasets. Our knowledge templates are designed specially for capturing data distributions among such a large number of related datasets.

Our design principle of knowledge templates is to synthesize relevant information with appropriate level-of-details for effective visual analysis and comparisons. We believe that it is essential to combine information from multiple sources for analyzing a large number of air quality data, since it is too tedious for users to visualize every dataset and visually compare all of them. We use knowledge templates as effective visual formats of statistical measurements with additional information of 3D object structures. The knowledge templates will be further used as general knowledge of historical air quality data that allows users to visually analyze 3D

Spring Summer Autumn Winter

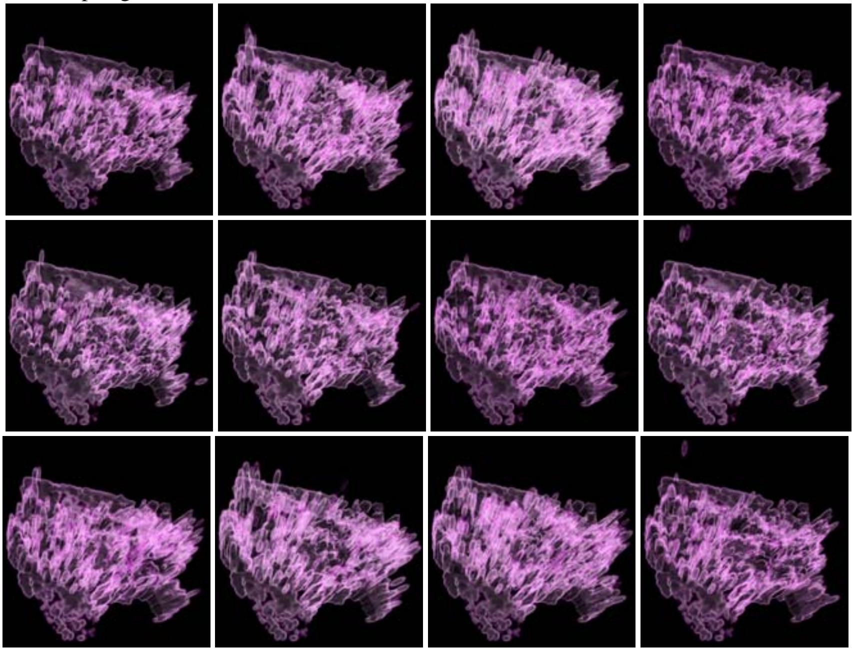


Fig. 1 Sample volume renderings of air quality datasets show very similar structures. The images from top to bottom are from morning, noon, and night respectively. Generally, each data is similar in terms of chemical shapes. In each day, the density is low around noon and high in the morning and night. Throughout a year, the density is generally high in Summer and Autumn and low in Spring and Winter.

data distribution and discover abnormal cases. We designed several data composition and simplification methods to generate knowledge templates for representing various statistical data properties. We also designed knowledge templates with different levels-of-details so that visualizations with appropriate amount of information can be further generated for visual comparison and analysis tasks.

3.1 Data Processing

We first explore sample air quality datasets with a single data visualization method, as shown in Figure 1. First, all these datasets have very similar appearances, which make it especially challenging to compare all of them, and their heights play an important role in the data analysis process. Second, we can see two strong distribution trends: noon datasets generally have lower chemical levels than morning and night and chemicals are generally sparse in spring and winter while dense in summer and autumn. Our knowledge templates are designed based upon these two data features.

Since the original format of air quality data (IO-API [3]) is not convenient for interactive visualization, we convert and organize all the datasets as regular structured volume data indexed by time and chemical variables. The original datasets include layers at multiple pressure levels, which start from 1000hPa and gradually drop to 100hPa. We use the standard atmosphere table [4] to calculate the actual height for each layer and generate regular volume datasets by linearly interpolating between adjacent layers. We also change all the data values using a log function to enlarge the data variances for clearer chemical structures. Finally, we normalize all the data values to the same 0-1 range for all the chemicals and time steps so that we can measure their statistical information and relations accurately.

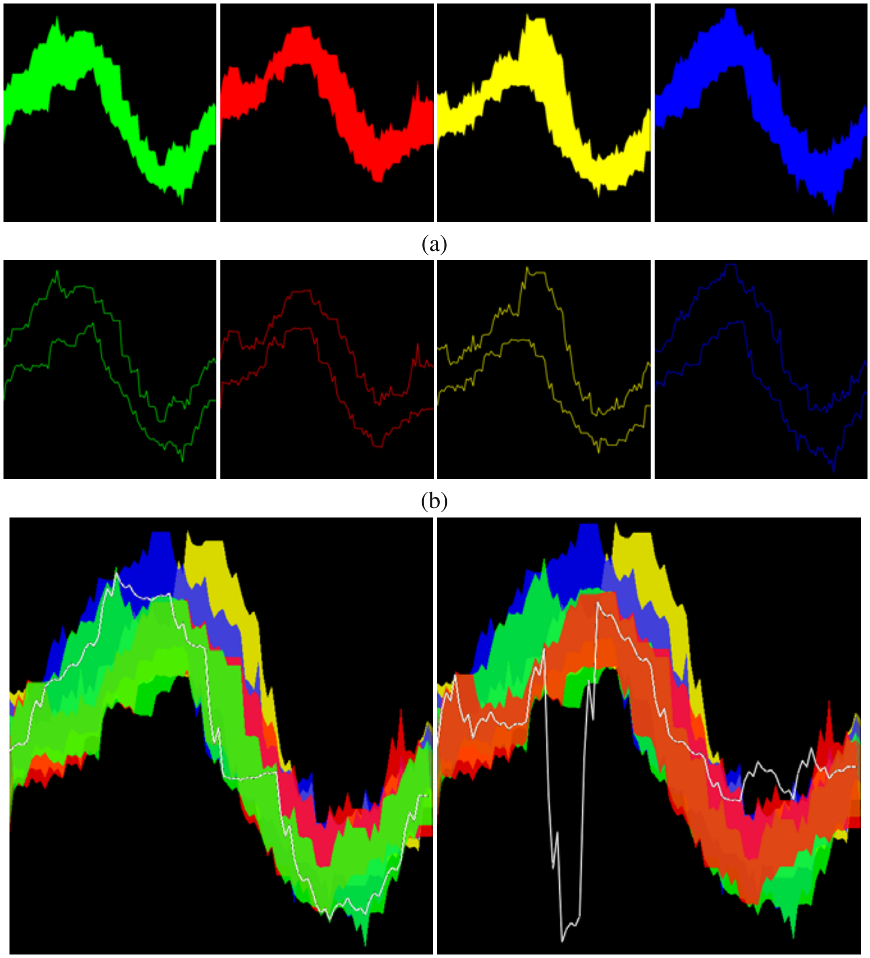
Since knowledge templates are designed to represent "typical" data distributions, it is ideal to reduce the effect of abnormal datasets, such as hurricanes, in our templates. According to the distribution features of air quality data, we use the majority rule to filter out datasets that are significantly different from the average data behaviors across a long time range. A simple threshold is set to remove all these datasets and thereby removing rare cases in a long term.

3.2 2D Height Templates

We use 2D height templates to demonstrate the usage of general statistical knowledge templates. According to regions-of-interest, we collect the highest and lowest height values from all the datasets in a time range. We select one day as the template size, since it can clearly show the periodic data distributions. For every hour, we calculate the statistical information of heights, such as average, and generate knowledge templates by connecting adjacent data points, as shown in Figure 2. To effectively visualize statistical information, we render templates with two modes: value mode and edge mode. The value mode is rendered by filling the space between highest and lowest values with polygons and the edge mode only renders the top and bottom boundaries. Suitable modes are automatically selected for synthesizing comprehensive knowledge templates (section 5) during user interactions.

3.3 3D General Templates

Scientists are especially interested in 3D data distributions, so that they can analyze the intersection relationships among multiple chemicals across different time range. We generate several types of 3D knowledge templates to represent various statistical data distributions. To generate a 3D general template, we collect data values from all the related datasets (including multiple time steps and chemicals) at each sample point position and calculate their statistical values to compose a volumetric dataset. We can also design time transfer functions that assigns a color to each time step to compose volumetric color datasets. We have used several common statistical



(a)

(b)

(c) (d)

Fig. 2 The value mode (a) and edge mode (b) of 2D templates. The bottom row provides examples of using 2D templates for analyzing air quality data, in which the white line renders special data. Abnormal datasets can be easily recognized (d) compared to the normal cases (c). The background templates are automatically adjusted according to the regions-of-interest.

measurements, as shown in Figures 3, 4 and 5. The four templates in Figure 4 and the first two templates in Figure 5 are self-explanatory by their names. The frequency template measures the appearance number of selected objects and time template is composed by assigning colors according to the sequence of time steps. We can use data and time colorbars to represent all the general templates as color volumes, which require more effective ways to visualize their 3D data distributions.

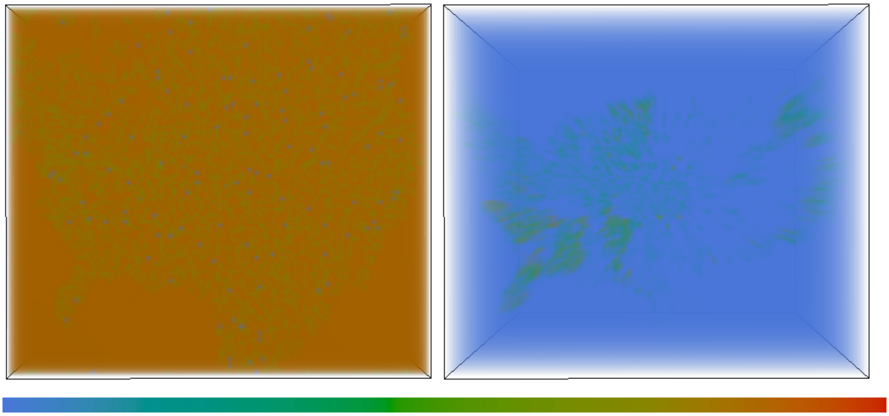


Fig. 3 Examples of 3D general knowledge templates: the mode and variance of NH3 in June. The same color transfer function is used for showing data values in the templates.

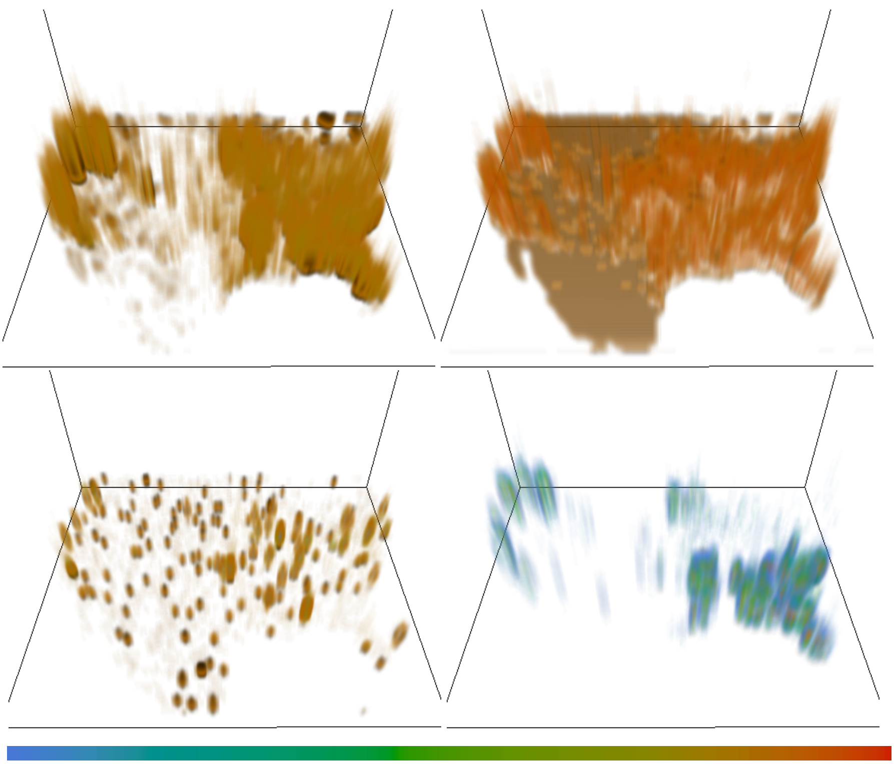


Fig. 4 Several examples of 3D representative templates: mean, median, mode, variance. With the colorbar shown on the bottom, we can directly visualize 3D statistical data distributions among a large number of datasets.

3.4 3D Representative Templates

To effectively visualize 3D general templates and combine datasets and templates for visual analytics tasks (section 5), we generate 3D representative templates to preserve important information in a general template and reduce the occupied 3D space, similar to the edge mode of 2D templates. This allows us to visualize statistical data information from more time or data ranges, with the cost of reduced details in the templates.

Since we concentrate on 3D structures of air quality data, we design representative templates as the composition of several important interval volumes [7] for visualizing data distributions in the space. For the best effect, the interval volumes should be equally spaced, so that they can cover most of the valid regions. We have developed an automatic approach to choose sample data values according to a user-specified size of interval volumes. The first data value is selected as the value that appears the most frequently in a general template. We mark the selected interval volume regions and expand them with a 3D region growing method. Then, we calculate the next sample data value by averaging all the data points around the surface of grown marks. We throw away the data values whose gradient magnitudes are below a threshold (0.1) for enhancing prominent surfaces. This process is repeated until most of the 3D space or valid data ranges are covered. The opacity values are calculated according to the data values in general templates. As shown in Figures 4 and 5, representative templates occupy much less 3D space than general templates and still demonstrate important data distributions.

3.5 3D Simplified Templates

We have also explored methods to simplify 3D knowledge templates to surfaces for emphasizing particularly important surfaces in the data, e.g., the highest and lowest height boundaries can be used to indicate normal 3D location range. The simplified templates can clearly represent certain data values and locations, thus they are useful for visualizing small and important regions that may be easily neglected in the general and representative templates.

As shown in Figure 6, to strengthen small pieces of information, we generate a complete surface that can embed accurate data points and have adjacent regions connected. We find that these smooth surfaces can provide better visual cues than simple points, especially when multiple types of templates exist at the same time in a 3D space. We assign opacity values in the rendering to indicate the accuracy of different surface regions.

After we collect all the information from relevant datasets according to regions-of-interest, we use the following procedure to generate surface templates. For example, a height table is first collected for generating the highest location surface. We find the data values to be preserved by searching for the local extreme locations, which can be determined by locating points that have the maximum or minimum values within a surrounding region, and store a flag table. Then, we generate

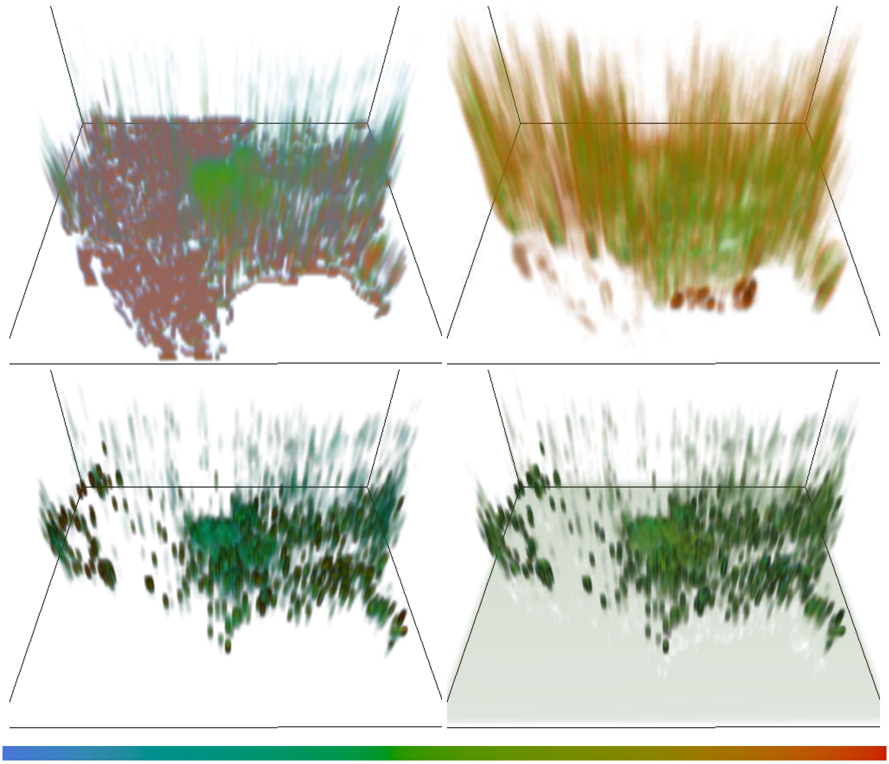


Fig. 5 Several examples of 3D representative templates: height, correlation, frequency, and time. With the colorbar shown on the bottom, we can directly visualize 3D statistical data distributions among a large number of datasets.

a smooth surface, initialized around half of the highest local extreme height, by smoothing the height table with a weighted Gaussian kernel.

$$T'(x,y) = \sum_{i,j} flag(x,y) \times Gaussian(i,j) \times T(x,y) \tag{1}$$

This can quickly generate smooth surfaces with dozens of iterations and preserve the accurate data points well.

4 User-Guided Template Synthesis

While the 2D and 3D knowledge templates provide general statistical information of multiple datasets, we are more interested in generating templates according to the time and data ranges selected by users. The user-guided templates can provide more useful information for visually analyzing individual data features. For example, users can choose a dataset, select their regions-of-interest, and it is ideal

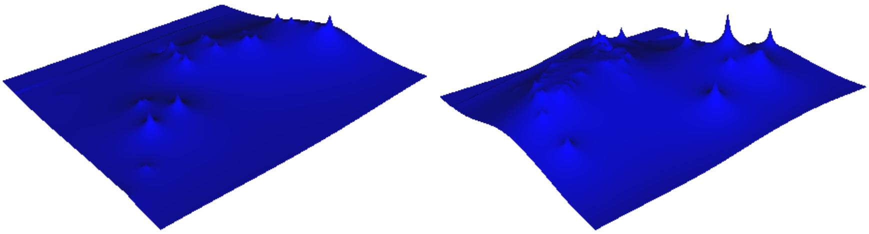


Fig. 6 Two surface templates generated with the smoothing method using local extreme template values.

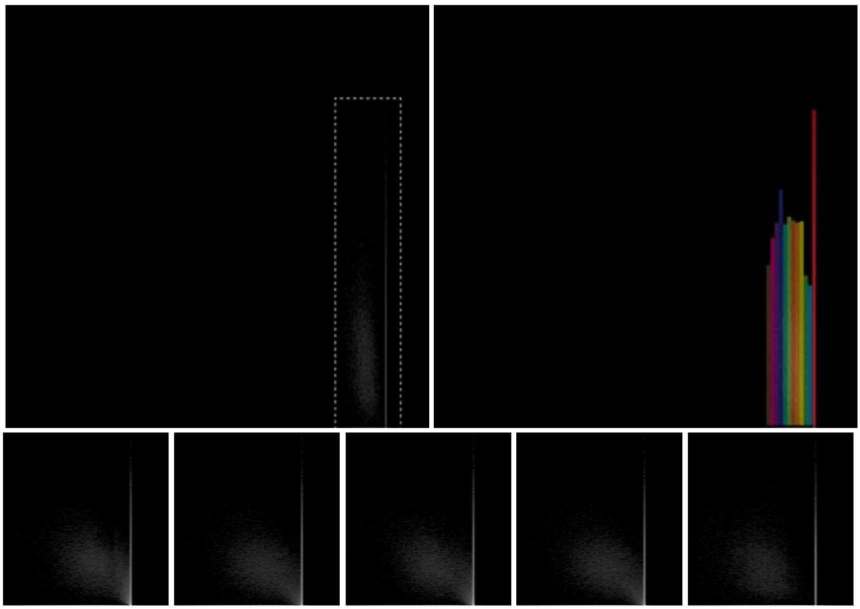


Fig. 7 (Top) Accumulated histogram and the division for basic templates, with a colored rectangle represents an interval volume. (Bottom) Enlarged region of histograms from different time ranges are similar, therefore we can generate appropriate statistical information with basic templates.

to generate templates around the selected data values within a close time range for visualizing the specialty of this dataset comparing to general statistical information.

Since the generation of knowledge templates require us to go through all the datasets within the range, it is not practical to generate templates during user interaction. Instead, we carefully select basic templates based on valid data ranges. During the interactive visualization process, the closest combination of basic templates will be accessed and composed to synthesize an appropriate template. This allows users to select their interested data and time ranges freely.

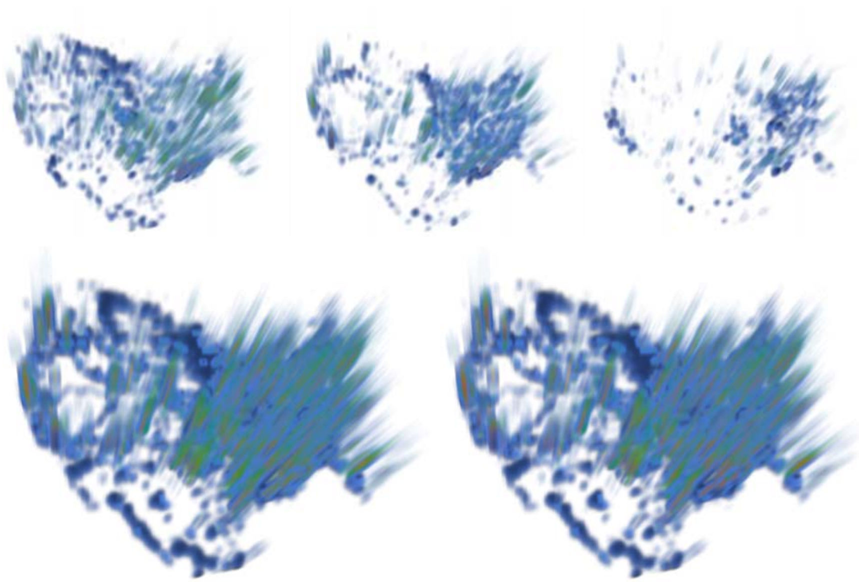


Fig. 8 The top row shows three basic frequency templates. The left image on the bottom row is synthesized with the three basic templates. It is very close to the actual templates shown on the bottom right.

This method relies on the similar data properties of individual air quality datasets. As shown in Figure 7, the histograms generated with data value and gradient magnitude [9] from different time ranges, including a time step, a day, a week, a month, and a year, are very similar to each other. Also, the objects our scientists mostly interested in are surface structures, which can be represented as the sum of multiple interval volumes. Therefore, we can synthesize new knowledge templates with basic ones.

During interaction, a general knowledge template is assembled with the basic templates according to the regions-of-interest a user selects. We first measure the overlap degrees of each rectangle and regions-of-interest on the histogram. Then, we use the overlap degrees as weights to summarize all the related interval volumes. Different summation methods are used according to the meaning of templates, e.g., frequency templates can be combined as weighted sum of basic templates. The template on the bottom left of Figure 8 is calculated as $0.8T1 + T2 + 0.6T3$, with $T1$, $T2$, and $T3$ correspond to the three basic templates on the top. Generally, we generate knowledge templates on the data value space and visualize them as color volumes.

The selection of time range is uniformly processed at three levels: bi-week, month, and season. Since templates from smaller time range are generated with less data, they are expected to include more subtle details than larger templates. Figure 8 shows that the synthesized template is very close to the template calculated according to the regions-of-interest.

5 Integrated Visualization System

We have developed an integrated visualization system by incorporating specialized visualization tools to effectively use knowledge templates to explore and analyze air quality datasets. In the visualization process, knowledge templates can be visualized individually to represent general statistical information or combined with single datasets for analysis purposes. We are especially interested in the latter, since it is more effective to visualize and compare a large number of related datasets. With various knowledge templates generated from previous sections, we develop visualization tools to compose multiple relevant templates to provide comprehensive information for users to understand and analyze individual datasets.

Our system allows users to interact with both 3D air quality datasets and knowledge templates, including selecting regions-of-interest, adjusting level-of-details of knowledge templates, and performing common 3D visualization interactions. Suitable knowledge templates are automatically synthesized according to user selections during interactive visualization processes.

From our experience with knowledge templates, we find that it is very useful to synthesize one comprehensive template from various information and provide convenient interaction methods for users to adjust it. The major difficulty is to reduce the information amount to an appropriate level, so that the synthesized template won't produce over-crowded visualization. We control the composition process and select level-of-details of templates to synthesis suitable comprehensive templates.

Two major factors, time range and template type, are involved of composition parameter selection for knowledge templates. The time range defines the size of time window and only the datasets within the time window will be considered as relevant. We use a value $(0-1)$ to indicate user-desired time range, with 1 represents smallest and closest time window. This value is used as weights to controls the interpolation between our bi-weeks, month, and season templates. The importance values of template types can be used to show their relevancy to the selected dataset and we use one value for each template type. We provide an interface for users to select the combination of knowledge templates and adjust their weights for composition.

We use the multiplication of time range indicator and template type importance as the weight for each relevant template. This weight is further used to automatically select level-of-details of templates, with larger weights correspond to more details in the representative templates. The surface templates are generally selected for one template type to emphasize important details and we let users to select surfaces based on their tasks.

Figures 9 and 10 shows example usages of 3D templates. Figure 9 (top) is a synthesized template from multiple basic templates. It can be used to measure the 3D height specialty of single datasets. Figure 9 (bottom) visualizes a NH3 chemical with the combination of average, variance, frequency, and height templates. The dataset is highlighted as red and the templates are generated with the blue to green colorbar for difference. It is clear that most of the red data portions are within normal

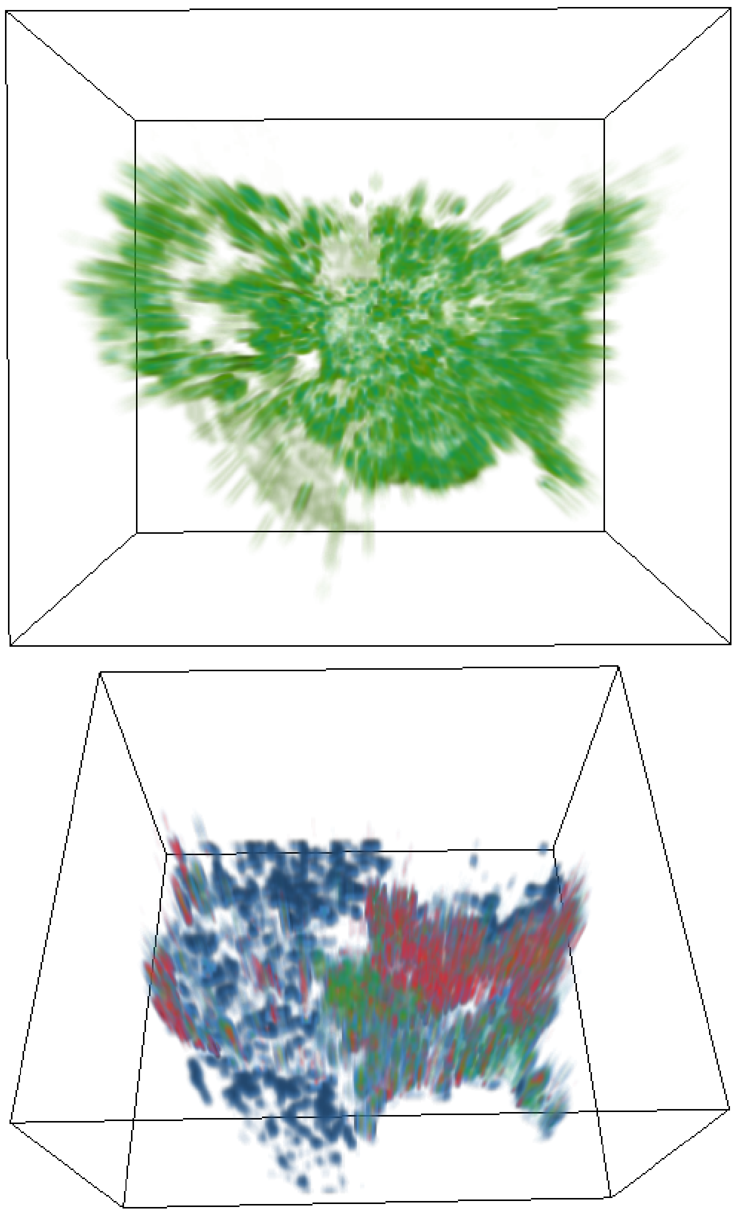


Fig. 9 Usage of 3D templates for air quality studies. With the statistical information provided by knowledge templates, users can visually analyzing 3D data distribution features and detecting interesting regions.

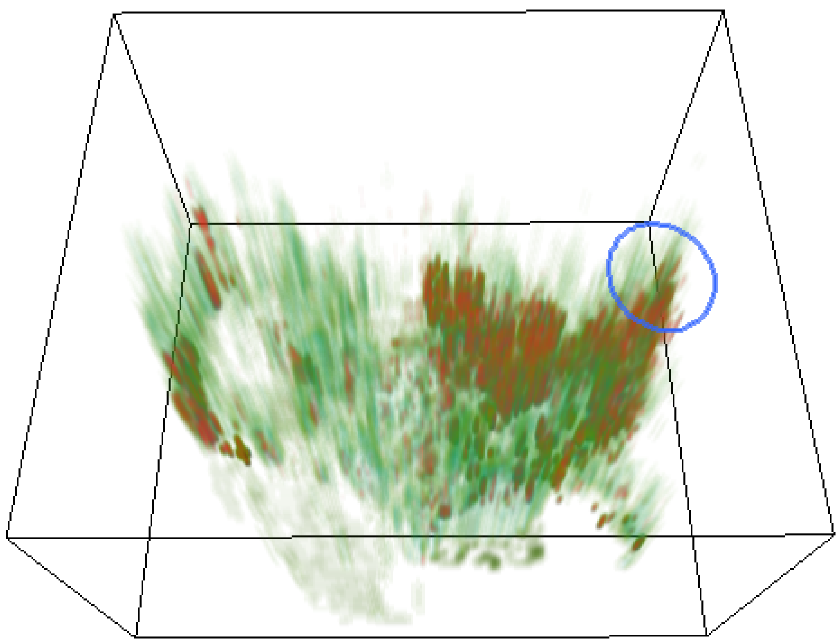


Fig. 10 An example of detecting abnormal regions, such as the circled region (right).

distributions. Figure 10 shows a PAR chemical mixed with correlation (with NO2), variance (PAR), and average (PAR). The red region above the surface indicates an abnormal case and it can be picked out easily during visualization. These examples demonstrate that the templates provide effective 3D statistical information that are difficult to achieve with single data visualization methods.

For 2D cases, we convert a dataset to a point (or 24 datasets per day to a line) in the same way as templates. Since 2D templates are rendered as transparent polygons in a 3D space, we switch the distance of templates according to their time differences to the selected time stamp to emphasize most relevant information. Figure 2 show the usage 2D templates in analyzing air quality data.

During our studies, the most common interactions are to select template types and adjust composition results, which can be achieved in real-time. The user-guided template generation significantly shortens the required time and has been found to be endurable (several seconds when users change regions-of-interest). The preparation of basic templates only need to run once before all the studies. The rendering time of templates and combined templates and datasets are real-time. All the processed datasets and templates are organized according to the information of year, month, day, hour, and chemical type, which allow us to access any data combination easily.

6 Conclusions and Future Work

This paper presents an efficient data visualization and exploration method through generating knowledge templates for 3D multi-field time-varying air quality data. We design knowledge templates to capture statistical data distributions from a large number of related datasets and use them in interactive visualization to save numerous human efforts on visualizing and comparing multiple air quality datasets. The usage of knowledge templates can accelerate the data analysis process and provide useful comparison and overview capabilities to explore new datasets. Our method integrates the special features of air quality data to develop a practical visualization system for visual data analysis in environmental applications. The experimental results demonstrate that appropriate knowledge templates can significantly improve the exploration and and analysis processes of air quality data by encapsulating long-time range knowledge into understandable visual formats. The design of knowledge templates can also be used for similar related time-varying or multi-field datasets, since these data features are shared among many other environmental datasets and scientific simulations.

To assist data exploration and visualization processes, we design several methods to generate knowledge templates by incorporating statistical data features among a large number of air quality datasets. We have presented methods to synthesize appropriate general and user-guided knowledge templates that can effectively represent historical knowledge of 3D data distributions. We designed the knowledge templates at multiple levels, so that they can be flexibly combined during interactive visualization processes. We have also developed a multiple template synthesis approach specialized for analyzing 3D air quality datasets using knowledge templates. With the integrated system, users can freely explore their interested data and time ranges based upon the statistical information provided by multiple knowledge templates without visualizing every relevant single dataset. Our scientists provide positive feedbacks on using knowledge templates in their studies comparing to single data visualization methods.

Our future work includes designing knowledge templates to incorporate environmental models and chemical principles of air quality variables. We are interested in exploring illustrative visualization methods to highlight information in the knowledge templates and the 3D relations between volume data and templates. To assist environmental applications involved of air quality data, we plan to integrate GIS data into our system, which will provide more accurate geographic and additional 2D information, such as population, average age, etc. We also plan to expand the analysis functions of our system though designing additional visualization tools for common environmental tasks, such as city planning and location selection. We believe that the concepts of multi-level knowledge templates and interactive template synthesis can be applied to other multi-field time-varying datasets and we will explore more of their applications.

Acknowledgements. This work was supported by the VisualGrid project at UNC Charlotte from EPA. The authors would like thank for the discussions with Sunyoung Bae, Hilary Inyang, Walt Martin, and Brian Etherton.

References

1. http://www.cmascenter.org/
2. http://www.smoke-model.org/index.cfm
3. http://www.baronams.com/products/ioapi/
4. http://www.usatoday.com/weather/wstdatmo.htm
5. Burkhard, R.: Learning from architects: the difference between knowledge visualization and information visualization. In: Eighth International Conference on Information Visualization, pp. 519–524 (2004)
6. Chen, T., Hsieh, L.: Uncovering the latent underlying domains of a research field: Knowledge visualization revealed. In: Information Visualization, 2006, pp. 252–256 (2006)
7. Fujishiro, I., Maeda, Y., Sato, H., Takeshima, Y.: Volumetric data exploration using interval volume. IEEE Transactions on Visualization and Computer Graphics 2(2), 144–155 (1996)
8. Guo, D., Chen, J., MacEachren, A., Liao, K.: A visualization system for space-time and multivariate patterns (vis-stamp). IEEE Transactions on Visualization and Computer Graphics 12(6), 1461–1474 (2006)
9. Kindlmann, G., Durkin, J.W.: Semi-automatic generation of transfer functions for direct volume rendering. In: IEEE Symposium on Volume Visualization, pp. 79–86 (1998)
10. Lum, E., Ma, K.-L., Clyne, J.: Texture hardware assisted rendering of time-varying volume data. In: Proceedings of IEEE Visualization, pp. 263–270 (2001)
11. Mansmann, F., Vinnik, S.: Interactive exploration of data traffic with hierarchical network maps. IEEE Transactions on Visualization and Computer Graphics 12(6), 1440–1449 (2006)
12. Qu, H., Chan, W.-Y., Xu, A., Chung, K.-L., Lau, K.-H., Guo, P.: Visual analysis of the air pollution problem in hong kong. IEEE Transactions on Visualization and Computer Graphics 13(6), 1408–1415 (2007)
13. Riley, K., Ebert, D., Hansen, C., Levit, J.: Visually Accurate Multi-Field Weather Visualization. In: Proceedings of IEEE Visualization, pp. 279–286 (2003)
14. Song, Y., Ye, J., Svakhine, N., Lasher-Trapp, S., Baldwin, M., Ebert, D.: An atmospheric visual analysis and exploration system. IEEE Transactions on Visualization and Computer Graphics 12(5), 1157–1164 (2006)
15. Sutton, P., Hansen, C.: Isosurface extraction in time-varying fields using a temporal branch-on-need tree (T-BON). In: Proceedings of IEEE Visualization, pp. 147–154 (1999)
16. Treinish, L.: Multi-resolution visualization techniques for nested weather models. In: Proceedings on IEEE Visualization, pp. 513–516 (2000)
17. Verma, V., Pang, A.: Comparative flow visualization. IEEE Transactions on Visualization and Computer Graphics 10(6), 609–624 (2004)
18. Weimer, H., Warren, J., Troutner, J., Wiggins, W., Shrout, J.: Efficient co-triangulation of large data sets. In: Proceedings on IEEE Visualization, pp. 119–126 (1998)
19. Wilkinson, L., Anand, A., Grossman, R.: High-dimensional visual analytics: Interactive exploration guided by pairwise views of point distributions. IEEE Transactions on Visualization and Computer Graphics 12(6), 1363–1372 (2006)

20. Wong, P., Foote, H., Mackey, P., Perrine, G., Chin, K.: Generating graphs for visual analytics through interactive sketching. IEEE Transactions on Visualization and Computer Graphics 12(6), 1399–1413 (2006)
21. Wood, J., Brodlie, K., Wright, H.: Visualization over the world wide web and its application to environmental data. In: Proceedings of IEEE Visualization, pp. 81–86 (1996)
22. Woodring, J., Shen, H.-W.: Multi-variate, time-varying, and comparative visualization with contextual cues. In: Proceedings of IEEE Visualization (2006)
23. Yuan, X., Nguyen, M., Chen, B., Porter, D.: Hdr volvis: high dynamic range volume visualization. IEEE transactions on Visualization and Computer Graphics 12(4), 433–445 (2006)
24. Zeiller, M.: A case study based approach to knowledge visualization. In: Ninth International Conference on Information Visualization, pp. 377–382 (2005)