Towards Multimodal and Multiresolution Descriptive and Learning-Based Environmental Analytics in the Smart City Digital Twin

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Abstract. Environmental data analysis at the urban scale is a key component of digital twins for smart cities. This paper presents the main research challenges involved in implementing descriptive and learning-based analytics for environmental data. It also explores how the availability of precomputed statistical summaries at different levels of granularity can help address these challenges.

Keywords: Smart City · Environmental data · Data exploration · Deep Learning · Digital twin.

1 Introduction

The development of digital twins for smart cities requires monitoring and modeling infrastructures that depend on environmental data. However, the intrinsic characteristics of these data present significant challenges for descriptive and learning-based analytics. Specifically, environmental data exhibit high volume, considerable heterogeneity, and complex spatial and temporal structures.

This paper identifies the main challenges associated with the interactive exploration of environmental datasets and the development of deep learning models. It also describes the expected functionality of an interactive interface for environmental data analysis. In addition, it shows how precomputed statistical summaries at multiple levels of granularity across relevant dimensions can support more efficient implementations. These structures are also expected to improve the performance of deep learning applications.

The remainder of this paper is organized as follows. Section 2 discusses the motivation and related challenges. Section 3 presents the proposed vision. Finally, Section 4 concludes the paper and analyzes the potential impact of the results.

2 Motivation and research challenges

Environmental data exhibits distinctive characteristics that present significant challenges [5].

- Environmental datasets are typically large, including observations from increasingly sophisticated IoT sensor infrastructures and outputs from prediction and simulation models.
- Observation data is highly heterogeneous, comprising time series from fixed stations, in-situ measurements along trajectories, and remote sensing products such as linear scans and rectangular scenes.
- Environmental data has a complex structure, including metadata describing provenance and spatial-temporal context, both essential for analysis.
- Data may be continuously or discretely distributed across geospatial, vertical, and temporal dimensions, generating both dense and sparse datasets.

Interactive exploration of environmental datasets through descriptive statistics is essential for identifying patterns and relationships. However, implementing dashboards that support these characteristics remains challenging. In particular, computing aggregations over large, heterogeneous datasets across spatial and temporal dimensions with interactive response times surpasses the capabilities of conventional business intelligence systems. Spatial precomputed aggregates are partially supported by formats such as GeoTIFF [3]. Other approaches include spatial-indexes with aggregates [9], progressive query processing [7], and Approximate Query Processing (AQP)[2]. Nevertheless, none efficiently addresses the complete range of challenges posed by environmental data.

Following exploration, data scientists often perform classification, segmentation, and regression tasks using learning-based methods. Spatial, temporal, and spatio-temporal prediction is required in many domains. Recurrent networks are commonly applied to time series, whereas convolutional networks operate across spatial and temporal dimensions. The U-Net architecture, originally developed for pixel-level image segmentation, has been adapted for segmentation and regression of spatio-temporal data [10, 8]. Hybrid U-Net and transformer approaches have also been proposed to develop foundation models for Earth systems [1]. However, the volume and heterogeneity of environmental data, particularly under spatial sparsity, remain major challenges for model development. Precomputed aggregated statistical structures are expected to help mitigate these limitations.

3 Vision of the proposed solutions

A general-purpose environmental data exploration dashboard should support navigation across all relevant dimensions. In particular, it should enable zooming and panning in the spatial dimension, using color-scaled maps to display aggregates of environmental properties (e.g., maximum, minimum, average, and standard deviation). Similar capabilities should be available for the temporal and

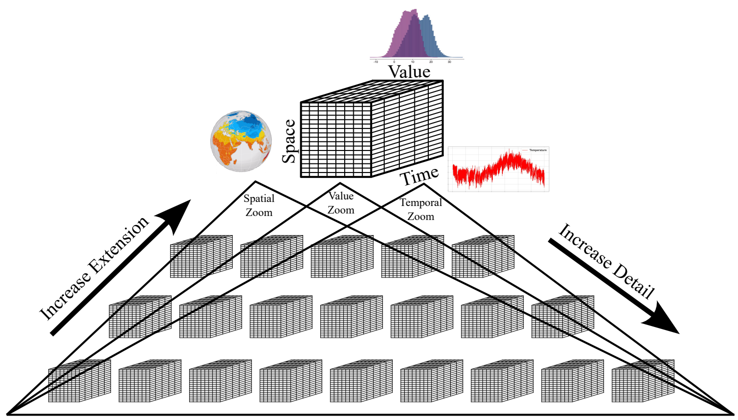

Fig. 1. Illustration of the multiresolution environmental data structures.

height dimensions, allowing visualization at different levels of detail and extent. The distribution of property values within selected regions of space, time, and height should also be represented through histograms. In addition, maps, time series, and vertical profiles can be displayed for selected ranges and values of the property under analysis. Finally, supporting zooming and panning along the property-value dimension using histograms as a reference can further improve the exploration of variable distributions.

An initial prototype that precomputes histograms at multiple spatial and temporal resolutions for an HF radar dataset is presented in [6]. Figure 1 illustrates the required multiresolution structures. Additional optimizations are necessary to manage both dense and sparse distributions across dimensions. Support for exploring pairs of variables through scatter plots is also needed to identify correlations.

An alternative to storing collections of histograms is the use of function-based models. A limited set of distribution functions, such as the normal distribution, can approximate histograms, while polynomial functions can model variations of property values over space and time [4].

Regarding learning-based analytics, training neural network models on precomputed structures at multiple resolutions is expected to provide substantial benefits for environmental data mining pipelines. For example, using histograms instead of averages at coarse resolutions enables prediction of output distributions rather than scalar values. Furthermore, depending on the application, progressive training from lower to higher resolutions along selected dimensions may provide an effective balance between training time and model accuracy.

4 Conclusion

This paper has identified the main challenges in developing descriptive and learning-based analytics for environmental data. It argues that general-purpose statistical summaries precomputed at multiple levels of granularity can facilitate interactive exploration and improve the development of accurate and robust AI models. The resulting technologies can enhance existing services, foster new business models, and contribute to a more sustainable urban quality of life.

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