Building Urban Resilience: A Tensor-Based Simulation Framework for Sensitivity Analysis

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1 Introduction

Cities are dynamic environments, constantly shaped by both routine activities and unexpected disruptions. Events such as natural disasters, major festivals, or sudden surges in tourism can dramatically alter how people move and gather, posing significant challenges for urban planners and policymakers (Batty 2013, Yabe et al. 2020). Understanding these shifts is essential for designing cities that are not only efficient but also resilient in the face of change (Kolda & Bader 2009).

The rise of large-scale mobility datasets, like aggregated mobile phone location data, has opened new possibilities for observing population behavior in real time (Lee et al. 2018). These datasets provide a detailed view of how people respond to different scenarios, but their complexity makes it difficult to extract actionable insights using traditional methods (Kolda & Bader 2009). As a result, there is a growing need for analytical frameworks that can handle high-dimensional data and reveal the underlying patterns that drive urban activity (Cichocki et al. 2016).

Advanced techniques such as tensor decomposition allow engineers and researchers to break down multi-array data into core components, making it possible to identify trends and behavioral shifts across time, space, and demographic groups from the population dynamics data (Kolda & Bader 2009, Cichocki et al. 2016). When combined with forecasting models, these methods can simulate how cities might respond to future disruptions, providing valuable guidance for contingency planning and resilience-building (Hyndman & Athanasopoulos 2018).

This study introduces a simulation-based framework that leverages tensor decomposition and time-series forecasting to analyze and predict urban activity patterns under various disruptive scenarios. By applying this approach to mobile spatial statistics from Kyoto, Japan, the research aims to offer practical tools for urban planners and decision-makers, supporting more informed and adaptive strategies for managing cities in an uncertain world (Yabe et al. 2020).

2 Methods

This study develops a simulation-based framework to analyze how urban activity patterns shift under disruptive scenarios, using aggregated mobile phone location data and tensor decomposition. The process is illustrated in Figure 1, which shows how the core tensor from one condition (e.g., a disruptive event) is exchanged into the factorization structure of another, allowing us to observe changes in reconstructed activity patterns.

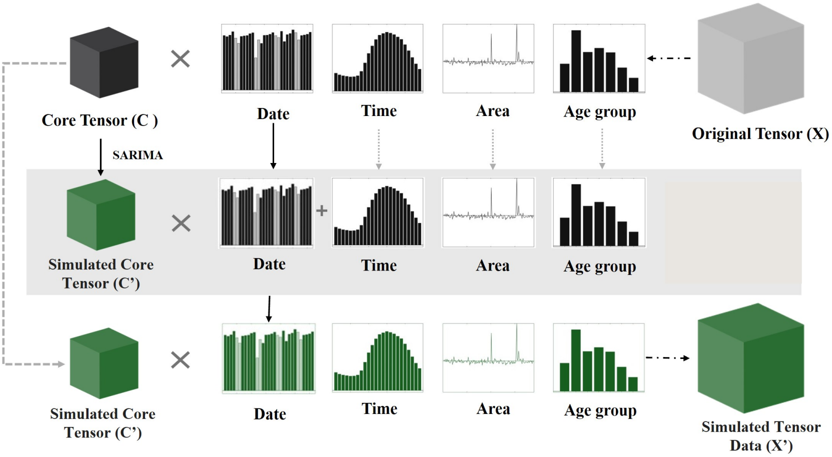

Figure 1: Simulating Tensor Methodology Framework

We use Mobile Spatial Statistics (MSS) data from NTT Docomo, which provides hourly population counts across different areas of Kyoto, Japan. The data are organized as a multi-dimensional array (tensor), with dimensions representing date, time, area, and age group (Yabe et al. 2020).

Tensor Decomposition To uncover latent patterns in the high-dimensional MSS data, we apply Tucker decomposition—a flexible tensor factorization technique widely used in urban mobility research (Kolda & Bader 2009, Gong et al. 2025, Wang et al. 2019), specifically Non-negative Tucker Decomposition (NTD).

Fundamentally, NTD is based on the decomposition of a tensor, which is a multi-dimensional array, into a core tensor and factor matrices along each mode (Shi et al. 2022). The core tensor represents the shared patterns across all modes, while the factor matrices capture the specific patterns unique to each mode (Pelechrinis & Lin 2017). By decomposing the tensor, we can uncover the underlying structure and extract the dominant patterns present in the data.

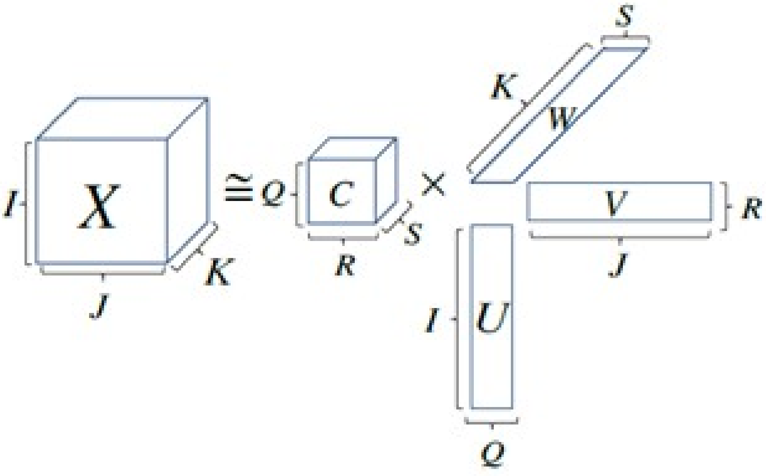

Figure 2: Three-dimensional Tucker Decomposition Approach Example

The method utilized is the Non-Negative Tucker Decomposition (NTD), the features of each dimension (each element axis) are represented by matrices called feature matrices and a core tensor. These are used to capture the characteristics of the data. Figure 2 illustrates the concept of NTD using a 3rd-order tensor as an example. Consider a 3rd-order tensor X with dimensions I × J × K. Dimensional compression involves mapping each element axis to a low-dimensional space. Specifically, it decomposes the dimensions of the I mode into Q ($Q \leq I$), the dimensions of the J mode into R ($R \leq J$), and the dimensions of the K mode into S ($S \leq K$), thereby incorporating information reduction (Kuwano et al. 2017). NTD accomplishes this by decomposing the tensor X, which has three modes given by I, J, and K, into a matrix U of size I × Q that holds information about the I mode, a matrix V of size J × R that holds information about the J mode, a matrix W of size K × S that holds information about the K mode, and a core tensor C of size Q × R × S. This decomposition is known as the rank-(Q, R, S) Tucker decomposition, with Q, R, and S being referred to as the factor numbers for each mode. Specifically, it is formulated by the following equation.

$$X \approx C \times U^T \times V^T \times W^T \tag{1}$$

Here, C represents the core tensor, and U, V, and W represent the feature matrices. Expressing equation (1) element-wise results in equation (2).

$$X_{ijk} \approx \sum_{q=1}^{Q} \sum_{r=1}^{R} \sum_{s=1}^{S} C_{qrs} U_{iq} V_{jr} W_{ks} \tag{2}$$

Furthermore, the number of dimensions to compress (Q, R, S) in the feature matrices is determined at the beginning to find the number of pattern we wanted to extract (Shi et al. 2022, Maeda et al. 2019, Kuwano et al. 2017). NTD has parameters C, U, V, and W, and these parameters are determined by imposing a non-negativity constraint to minimize the squared error (Kim & Choi 2007). In other words, parameter estimation is formulated as the following problem:

$$\min_{C,U,V,W} \left\| X - C \times U^T \times V^T \times W^T \right\|_F^2 \tag{3}$$

$$f(C,U,V,W) = \left\| X - C \times U^T \times V^T \times W^T \right\|_F^2 \tag{4}$$

where f is the Frobenius norm (Shi et al. 2022) or the square root of the total sum of the inside function .

Scenario Simulation by Core Tensor Exchange After decomposing the tensors for both normal and disruptive conditions, we simulate the impact of disruptions by exchanging the core tensor from the disruptive scenario into the factor matrices of the normal scenario. This reconstructs a new tensor that reflects how population patterns would shift if the underlying behavioral 'core' matched that of the disruption, while keeping the usual spatial and temporal context (Gong et al. 2025, Ishii et al. 2022). The resulting tensor allows us to examine plausible changes in congestion, distribution, or demographic activity under simulated conditions.

This approach does not rely on time-series forecasting models, but instead uses the internal structure of the tensor decomposition to explore how changes in the core behavioral patterns affect overall urban activity. The method is inspired by recent work in urban mobility analysis, where tensor decomposition is used to reveal spatial-temporal relationships and simulate alternative scenarios (Gong et al. 2025, Wang et al. 2019).

3 Results

The simulation results, illustrated in Figure 2, provide a detailed view of how population distribution in Kyoto changes under a simulated typhoon scenario during the peak tourist season. By exchanging the core tensors between a normal peak tourism weekday (November 29) and a weekday affected by typhoon conditions (October 12), distinct shifts emerge in patterns across time, area, and age dimensions.

Notably, the time-based profiles indicate altered daily rhythms, with the most pronounced components showing a reduction in activity during typical commuting and leisure hours. Spatially, the area factor matrices reveal a concentration of population in limited districts, suggesting that movement across the city becomes more localized or clustered during disruptive weather. The age dimension shows changes in the activity levels among different demographic groups: for example, certain age groups—possibly older adults or children—display enhanced sensitivity, with sharper decreases in outdoor activity during adverse conditions. Together, these results highlight how severe weather leads to both spatial and temporal reorganization of urban activity, with some populations reducing mobility more than others.

4 Discussion and Conclusion

These findings emphasize the value of a tensor-based simulation framework for anticipating and understanding population redistribution during disruptive events. The ability to swap core patterns between contrasting scenarios demonstrates how urban managers can quickly assess which neighborhoods may become congestion hotspots or, conversely, see reduced activity, simply by observing changes in the core drivers of collective behavior (Kolda & Bader 2009, Gong et al. 2025).

A key practical insight is that standard interventions—such as opening additional shelters, rerouting transit, or communicating targeted advisories—can be informed by these scenario analyses. By capturing not just the overall magnitude but also the demographic and temporal contours of change, planners are better

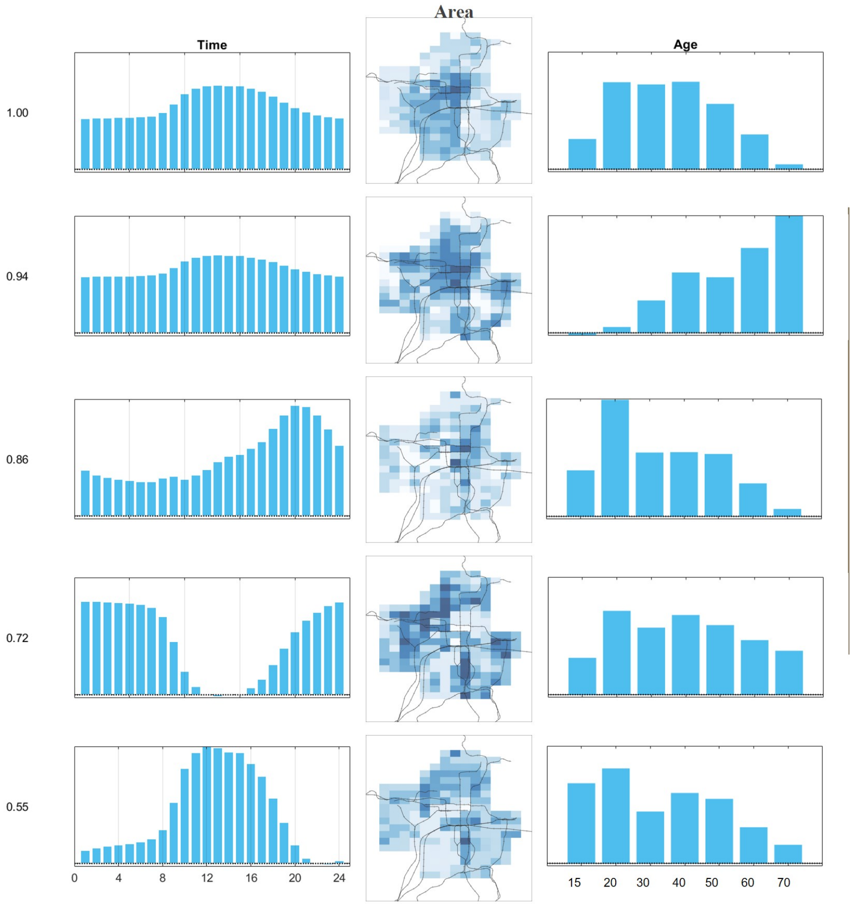

Figure 3: Simulated Typhoon Pattern for Time, Area, and Age group

equipped to design responses that fit real-world urban complexity (Yabe et al. 2020).

Importantly, the simulation approach does not rely on deterministic forecasting but instead leverages the latent structure of real population data to create plausible behavioral alternatives. This flexibility allows stakeholders to proactively explore various ”what-if” conditions and test mitigation strategies in settings where actual disruptive events are unpredictable or rare (Ishii et al. 2022, Shi et al. 2022).

While the current application focuses on tourist and weather disruptions, the framework can be generalized to other types of urban stress, such as major public events, transportation outages, or policy changes affecting urban mobility. Continued refinement, such as integrating more granular demographic or behavioral factors and validating simulated outcomes against additional empirical data, will further enhance the tool’s relevance and utility for urban resilience planning (Gong et al. 2025).

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