

# Urban Resilience Key Metrics Thinking and Computing Using 3D Spatio-Temporal Forecasting Algorithms

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**Abstract.** The vagueness of the concept of resilience makes it difficult to define unanimously, and it becomes even more problematic when it comes to measuring it, while urban resilience metrics can be considered as key indicators transmitting vital information to the decision makers on the observed characteristics about the city. The motivations and goals of such a metric are as different as the proponents who defend them. As for cities, due to growing urbanization in a global context of climate change, the concept of urban resilience is essential and requires scientific attention backed by a methodology with an operational aim. Based on 3D spatio-temporal forecasting algorithms, this paper revisits the concept and presents a novel approach to measuring and computing key metrics of resilience applied to urban systems. Some results show that spatio-temporal forecasting algorithms can significantly improve the accuracy and timeliness of urban resilience metrics compared to traditional methods. Our methodology can help urban planners and policymakers make more informed decisions and enhance the resilience of urban systems. However, the methodology also has limitations and challenges, such as data quality issues and algorithmic complexity, that require further research. This paper contributes to the literature on urban resilience and spatio-temporal forecasting by providing a comprehensive framework for measuring and forecasting key metrics of urban resilience using advanced computational methods.

**Keywords:** Urban resilience · Metrics framework · Forecasting algorithms

## 1 Introduction

It has become undeniable that as we move forward into the 21st century, the increase in world population accompanied by mass urbanization is becoming our reality which constitutes a major challenge [1]. Among other attempts to contain its excesses have led to the theorization of the concept of urban resilience [2–10]. The concept has gained increasing attention in recent years as cities around the world face a range of environmental and social challenges, including climate change, natural disasters, economic disruptions, and social unrest [4, 5, 7–11]. Urban resilience refers to the ability of urban systems to absorb and recover from shocks and stresses while maintaining their essential functions and structures. Measuring and forecasting key metrics of urban resilience is essential

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for identifying potential vulnerabilities and enhancing the adaptability and anticipation of urban systems [9–13]. Traditional methods of measuring urban resilience metrics are often limited by data quality, timeliness, and spatial resolution [14–20]. Census data and land use maps are typically used to measure urban characteristics such as population density and land use diversity [14, 16, 20], but they are often outdated and lack spatial detail. Infrastructure connectivity and social cohesion are more difficult to measure due to the lack of comprehensive data sources [21, 22]. In addition, traditional methods of forecasting these metrics often rely on simplistic statistical models that cannot capture the complex spatio-temporal dynamics of urban systems [17, 18]. Recent advances in spatio-temporal forecasting algorithms [15, 18, 23, 24] and 3D modeling techniques [25] offer new opportunities for more accurate and timely assessment of urban resilience metrics. These methods can combine data from multiple sources and use advanced computational techniques to capture the complex dynamics of urban systems. However, there are still significant challenges in applying these methods to real-world urban contexts, including issues of data quality, algorithmic complexity, and model validation [12, 13, 18, 23].

In this paper, we propose a methodology framework for measuring and forecasting key metrics of urban resilience using 3D spatio-temporal forecasting algorithms, which represents a novel approach to the problem of urban resilience assessment. The primary objective of this study is to develop a methodology for measuring and forecasting key metrics of urban resilience using 3D spatio-temporal forecasting algorithms. To achieve this objective, the following research questions will be addressed: 1) What are the key metrics of urban resilience that can be measured and forecasted using 3D spatio-temporal forecasting algorithms? 2) What data sources and validation techniques are needed to ensure the accuracy and reliability of the forecasting results? 3) How can 3D spatio-temporal forecasting algorithms be used to capture the complex spatio-temporal dynamics of urban systems? 4) How can the proposed methodology be applied to a real-world case study of a medium-sized city?

By addressing these research questions, this study aims to contribute to the field of urban resilience by proposing a comprehensive methodology for measuring and forecasting key metrics using advanced computational methods and real-world data sources. After providing an overview of the concept of urban resilience and its importance for modern cities, we discuss the current challenges faced by urban areas in terms of resilience assessment methodologies and highlight the gaps in the existing approaches in Sect. 2. The rest of the paper is organized as follows according to its main contributions. Section 3 presents our methodology framework for measuring and forecasting key metrics of urban resilience accompanied by the underlying principles, techniques, and key features. Section 4 describes the details about the specific 3D spatio-temporal forecasting algorithms we use, its capabilities and how they contribute to the overall methodology. We discuss the data requirements for the spatio-temporal forecasting algorithms and how one collected and pre-processed the data. Section 5 analyses the results and evaluation of our methodology concerning effectiveness in measuring and forecasting key metrics of urban resilience. We also compare the results with existing major approaches and highlight the strengths and limitations of our approach. Ultimately, Sect. 6 concludes this paper and future work.

## 2 Resilience Concept Background and Related Works

### 2.1 Theoretical Review from Disciplinary Perspectives

The word "resilience" is said to come from the Latin resilire, resilio and the concept has spawned a "long history of multiple and interconnected meanings in art, literature, law, science, and engineering [26, 27]. Semantically, some of its uses invoked a positive outcome or state of being, while others invoked a negative outcome. Before the 20th century, its main meaning was "to rebound" [27]. The notion is widely present in different academic disciplines [10] and now urban planning [3–5, 8, 9]. Another conceptual approach was introduced by Holling [6] in his influential publication "Resilience and Stability of Ecological Systems". The author rejected the idea of restricting resilience solely to the ability of ecosystems to return to their previous state following a disturbance. Instead, he proposed to distinguish resilience more clearly from stability. Indeed, he considers that resilience would be a much more appropriate concept to understand and manage the dynamics of ecosystems, since these systems are defined by multiple states of stability. Another approach to resilience based on the analysis of the interaction of social and ecological systems has been developed [28, 29] by integrating aspects of adaptability, learning and transformation. In this approach, the idea of bouncing has increasingly been replaced by the metaphor of 'bouncing forward'; a view considered more appropriate as it admits the interplay of disturbance and reorganization, as well as long-term societal adaptation processes [30]. More recently, at the level of national and international institutions, the concept has taken a prominent place in the definition and implementation of operational disaster risk management strategies and policies, infrastructure planning, as well as urban development [31]. Urban resilience has also received considerable attention due to other symptoms of crises [30–35]. For example, the financial crisis of 2007/2008 and its repercussions on city budgets, the COVID 19 crisis as well as rapid urban changes and their enormous impacts on urban infrastructure. Most definitions of urban resilience therefore offer suggestions on how to improve the "generic adaptability, flexibility or adaptability" of urban areas [21, 23, 24, 26, 30, 31]. Research continues to explore the concept more deeply and broadly.

### 2.2 Review and Challenges of Current Urban Resilience Frameworks

Urban resilience frameworks have emerged as a useful tool for assessing and enhancing the ability of urban systems and communities to withstand, adapt to, and recover from various shocks and stresses. In recent years, several major frameworks have been developed to guide resilience efforts in cities around the world. Among these frameworks, we can identify the City Resilience Framework (CRF) [36], the Urban Resilience Framework (URF) [37], the 100 Resilient Cities Framework (100RC) [38], the Disaster Risk Reduction Framework (DRR) [39] and the Four-Capital Framework (4CF) [40].

One of the main strengths of current urban resilience frameworks is their holistic approach to assessing and enhancing urban resilience. They recognize that urban systems and communities are complex and interconnected, and they emphasize the importance of addressing multiple dimensions of resilience, such as social, economic, and environmental factors. The frameworks also recognize that cities face different types of shocks

and stresses, including climate change, natural disasters, and economic downturns, and they provide guidance on how to address these challenges. It was possible for us to identify these challenges after scrutinizing each framework in detail. Also, the result of this work is recorded in Table 1.

**Table 1.** Challenges related to the limitations of current urban resilience frameworks.

| Challenge | Description |
|---|---|
| Lack of flexibility and adaptiveness | Current resilience frameworks often rely on predefined indicators and dimensions of resilience, which may not reflect the unique characteristics and challenges of each urban area. This can lead to inflexible approaches that fail to account for the dynamic and complex nature of urban systems and communities. Resilience efforts require a flexible and adaptive approach that can account for the unique characteristics and challenges of each urban area |
| Limited stakeholder engagement | Some frameworks may not effectively engage with diverse stakeholder groups, such as community members and local organizations, in the development and implementation of resilience strategies. This can limit the effectiveness and sustainability of these strategies, as they may not reflect the needs and priorities of these stakeholders |
| Emphasis on shock events | Many frameworks prioritize the ability of urban systems and communities to withstand and recover from acute shock events, such as natural disasters or terrorist attacks. However, chronic stresses, such as poverty, inequality, and climate change, can also pose significant challenges to urban resilience, and may require different approaches and solutions |
| Inadequate consideration of equity | Resilience frameworks may not adequately address the underlying social and economic factors that contribute to vulnerability and inequality in urban areas, leading to uneven resilience outcomes |
| Lack of measurement and evaluation | Resilience frameworks may not provide clear metrics or benchmarks for measuring and evaluating resilience outcomes, making it difficult to assess progress and adjust strategies as needed |

(*continued*)

**Table 1.** (*continued*)

| Challenge | Description |
|---|---|
| Inadequate data and monitoring science | Resilience frameworks may not effectively integrate with other policy areas, such as sustainability, urban planning, or public health. This can limit the potential for synergies and collaboration across these policy areas and may result in fragmented or disjointed approaches to urban development and resilience. Indeed, although they often rely on data and monitoring systems to track progress and identify areas for improvement but do not fully incorporate data science approaches, such as data analytics and 3D spatio-temporal forecasting algorithms, which could enhance the effectiveness of resilience planning and response |

## 3 Novel Methodology Framework

### 3.1 Formalization of Urban System Dynamics Faces to Disruptive Event

Urban systems are complex [41] and dynamic [42], with a range of interdependent components and processes that can be disrupted by various events, such as natural disasters, pandemics, or terrorist attacks. To better understand the behavior of urban systems in the face of disruptive events, it is important to formalize the dynamics of these systems and develop models that can capture their behavior over time. The formalization of urban system dynamics involves the identification of key components and processes within urban systems and the development of mathematical models that can describe the behavior of these components and processes over time. One key challenge in the formalization of urban system dynamics is the incorporation of feedback loops and nonlinear relationships between different components and processes. Figure 1 describes the resilience dynamics of urban system over time.

The starting point of the system's usual state is represented by the initial horizontal line (anticipation state). When a disruptive event occurs (marked by a star icon), the system's performance quickly drops as it absorbs the shock. Once the threat has passed, the system enters the recovery phase. An event is composed of three elements: magnitude, duration, and location. The level of resilience recovered by the system depends on various factors. Limited resources may impede the system from fully regaining its original functionality, while ample resources and wise application of lessons learned may enable the system to attain a greater level of performance. Effective system management should aim to flatten out the entire curve, including vectors Ab, Re, and Ad, to eliminate the disturbance basin during the period dt. Indeed, following a disruption, the initial performance ($U_{res}$) experiences some change ($dU_{res}$) before eventually reaching a new steady state of performance. The time required for recovery after the disruption ($dt$) is a crucial element of resilience. Resilience can be improved by decreasing the magnitude of the disturbance (vector Ab), shortening the recovery period (vector Re) to change the

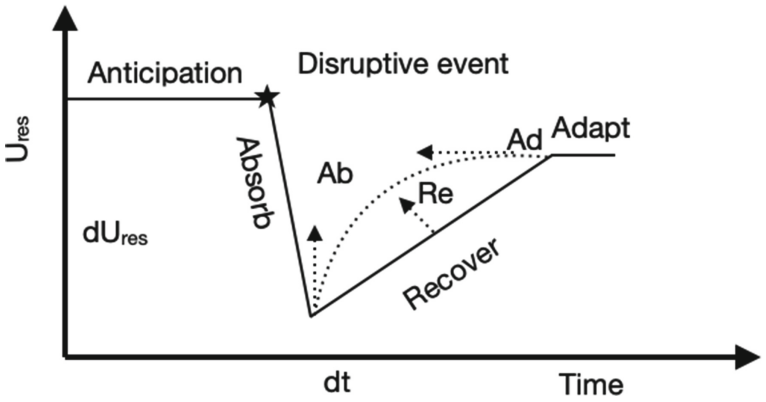


**Fig. 1.** Urban resilience dynamics face to a disruptive event.

shape of the recovery curve to gradually match the level of adaptation to that of before the crisis (vector Ad). Ab, Re, and Ad are keys metrics vectors.

Let E be a disruptive event that affects the urban system. E can be characterized by a set of attributes such as its magnitude, duration, and location (or region).

$$E = \{magnitude, duration, location\} \tag{1}$$

The master equation for the urban system dynamics faces to disruptive event be formalized as follows:

$$\frac{dU_{res}}{dt} = U_{res} - \omega\left(\vec{E}\right) + \varphi(\overrightarrow{Ab}, \overrightarrow{Re}, \overrightarrow{Ad}) \tag{2}$$

$$U_{res}^{t} = \int\left(U_{res} - \omega\left(\vec{E}\right) + \varphi\left(\overrightarrow{Ab}, \overrightarrow{Re}, \overrightarrow{Ad}\right)\right)dt \tag{3}$$

$\frac{dU_{res}}{dt}$ is the rate of change of the urban resilience $U_{res}$ variables over time.

$\omega\left(\vec{E}\right)$ is the impact of the disruptive event according to its magnitude, duration, and spatial location.

$U_{res}^{t}$ is the composite urban resilience at time t.

$\varphi(\overrightarrow{Ab}, \overrightarrow{Re}, \overrightarrow{Ad})$ is the effect of resilience strategies such as emergency response, infrastructure repair, and resource reallocation during the recovery phase depending social, economic, environmental, governance, and physical dimensions of the urban system.

By developing models that capture the complexity and dynamics of urban systems, we can better prepare for and respond to a range of disruptive events and enhance the resilience of our cities and communities. One key challenge in the formalization of urban system dynamics is the incorporation of feedback loops and nonlinear relationships between different major components of dynamics of city and its processes.

### 3.2 Construction of the Urban Resilience Metrics Matrix

The development of the urban resilience metrics matrix is a crucial step towards measuring and enhancing the resilience of urban systems. A resilient city is one that has the capacity to withstand and recover from a range of shocks and stresses, such as natural disasters, economic downturns, or social unrest. To develop an effective resilience strategy for a city, it is important to have a comprehensive set of metrics that can measure the resilience of the city across different domains.

The development of an urban resilience metrics matrix involves the identification of key resilience domains and the selection of appropriate metrics to measure the resilience of these domains. These domains include social, economic, environmental, governance, and physical aspects of the urban system. In constructing the urban resilience metrics matrix (Fig. 2), the focus is on ways to explicitly capture system capacity throughout the timeline of a disruptive event. In the Anticipate column, metrics should be selected to measure the city's ability to anticipate and prepare for potential shocks and stresses. Examples include the city's emergency preparedness plan, the number of trained emergency responders, and the availability of warning systems. In the Absorb column, metrics should be selected to measure the city's ability to absorb and manage the impacts of shocks and stresses. Examples include the capacity of critical infrastructure systems (such as water, power, and transportation) to continue functioning during and after a disruptive event, the availability of emergency shelters, and the accessibility of healthcare services. In the Recover column, metrics should be selected to measure the city's ability to recover from a disruptive event. Examples include the speed and efficiency of debris removal and restoration of critical infrastructure, the availability of financial resources for recovery efforts, and the effectiveness of post-disaster support programs. In the Adapt column, metrics should be selected to measure the city's ability to adapt to changing conditions and to build long-term resilience. Examples include the level of community engagement in resilience planning and decision-making, the adoption of sustainable development practices, and the diversity and flexibility of the local economy.

### 3.3 Urban 3D Data Collection Sources

Data collection is a critical component of any urban resilience strategy, and it involves the gathering of information on a wide range of factors that can influence the resilience of the urban system. Key metrics that are commonly collected as part of urban resilience data collection efforts include demographic data, economic indicators, environmental conditions, infrastructure performance, and social factors. OpenStreetMap 3D [43, 44], CityJSON [45], Cityscapes [45], Google Earth [46], and LIDAR [47] are some of the open databases available for 3D urban data collection. OpenStreetMap 3D provides open-source 3D maps with detailed information on urban infrastructure and buildings, and it can be used for a range of applications, including urban planning and disaster management. CityJSON is a format that allows for the easy exchange of 3D urban data, including buildings, roads, and landmarks. Cityscapes provides high-quality images and semantic annotations of urban scenes [48], which can be used for developing algorithms for urban scene understanding. Google Earth provides high-resolution satellite images and 3D models of urban environments, which can be used to extract building and

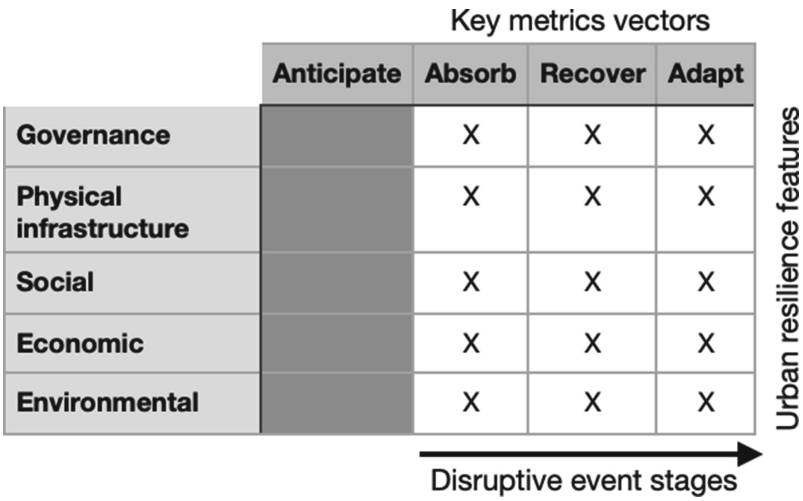


**Fig. 2.** An overview of urban resilience metrics matrix construction.

infrastructure information. LIDAR technology, on the other hand, uses laser scanning to provide high-precision 3D data on urban structures and infrastructure. The combination of these databases can enhance the accuracy and efficiency of 3D spatio-temporal forecasting algorithms for urban resilience analysis.

## 4 Urban Resilience Measurement Algorithm

### 4.1 3D Spatio-Temporal Forecasting Algorithm (STFA) Principles

One of the key challenges in measuring urban resilience is the ability to accurately predict and assess the impact of disruptive events. In recent years, STFA have emerged as a powerful tool for predicting urban system dynamics and identifying critical areas for resilience investments. The motivation of applying STFA is Transfer Learning (TL) from multisource data [49]. The purpose of TL is to mining the potential knowledge within the source domain. In this case, it is the data in line with the matrix of Fig. 2. Simultaneously, multitask learning paradigm [50] is integrated into the design STFA. So, when engaging in multisource transfer learning, it's essential to not only consider the connections between the target domain and multiple source domains as shown in Fig. 1, but also to consider the relationships between the various source domains themselves as depicted in Fig. 2. The general algorithm is deployed according to the following steps: 1) Data preprocessing: 3D dataset provides a large amount of geospatial data on urban areas, including images, point clouds, and semantic annotations. The first step in the algorithm is to preprocess this data and extract relevant features and metrics, such as land use patterns, building heights, and population density. 2) Dimensionality reduction: Given the large size of the 3D dataset, it may be necessary to perform dimensionality reduction techniques, such as principal component analysis, to reduce the complexity of the data and improve computational efficiency. 3) Temporal modeling: Urban resilience

metrics are often dynamic and change over time, so the algorithm will need to incorporate temporal modeling techniques to capture these changes. This may include time series analysis, autoregressive models, or machine learning algorithms such as recurrent neural networks (RNNs) or long short-term memory (LSTM) networks [49, 50]. 4) Spatial modeling: The 3D nature of dataset provides a unique opportunity to model urban resilience metrics in three dimensions. The algorithm will need to incorporate spatial modeling techniques, such as geostatistics or spatial regression, to capture the spatial relationships between different features and metrics.

Forecasting and evaluation: The final step in the algorithm is to use the temporal and spatial models to generate forecasts of urban resilience metrics over time. These forecasts will be evaluated using a variety of metrics, such as Mean Absolute Percentage Error (MAPE), Mean Average Error (MAE) and Root Mean Square Error (RMSE) respectively. The equation defining the n samples is given below.

$$RMSE\left(\widehat{X}_i, X_i\right) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\widehat{X}_i - X_i\right)^2} \tag{4}$$

$$MAE\left(\widehat{X}_i, X_i\right) = \frac{1}{n}\sum_{i=1}^{n}\left|\widehat{X}_i - X_i\right| \tag{5}$$

$$MAPE\left(\widehat{X}_i, X_i\right) = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|\widehat{X}_i - X_i\right|}{X_i} \tag{6}$$

Our STFA relies on three fundamental principles: spatial data modeling, temporal data modeling, and data integration. Spatial data modeling is achieved by representing the urban environment as a 3D grid, where each cell represents a specific location within the city. This approach allows the algorithm to capture the nuances of the urban environment, such as building height, density, and street width, and use this information to make predictions. Temporal data modeling involves analyzing historical data to identify patterns and trends in urban development. This information is then used to make predictions about future changes in the urban environment. Finally, data integration involves combining various data sources, such as satellite imagery, sensor data, and social media data, to create a comprehensive picture of the urban environment.

Several studies have investigated the use of STFA in urban environments. For example, a study by Chen et al. [51] applied a spatio-temporal forecasting algorithm to predict the demand for shared bikes in urban areas. The authors used data from bike-sharing systems and various environmental factors, such as weather, to develop a model that accurately predicted bike usage patterns. Another study by Wu et al. [52] used an STFA to predict air quality levels in urban areas. The authors integrated data from various sources, including satellite imagery, meteorological data, and land-use data, to develop a model that accurately predicted air quality levels in different locations. These studies demonstrate the potential of STFA in urban environments and highlight the importance of integrating various data sources to achieve accurate predictions.

### 4.2 Urban Resilience Key Metrics Computation Algorithm

The STFA for urban resilience metrics vector based on the Cityscapes database will need to incorporate a range of data preprocessing, modeling, and evaluation techniques to capture the complex and dynamic nature of urban resilience metrics. The pseudocode of is presented in detail in Table 2. The algorithm consists of four main steps: preprocessing, model training, forecasting, and evaluation. During the first step, the input data is preprocessed to prepare it for training the model. This includes tasks such as data cleaning, normalization, and feature extraction. Once the data is preprocessed, the algorithm trains a machine learning model on the input data to learn the patterns and relationships in the data. This second step involves selecting an appropriate machine learning algorithm and setting its hyperparameters to optimize the performance of the model. After the model has been trained, it can be used to make predictions on new data. The forecasting step involves feeding the model with new input data and using it to generate predictions. In the final step, the performance of the model is evaluated to determine how well it performs on the task at hand. This step involves using various metrics to assess [53, 55] the accuracy and reliability of the model's predictions.

## 5 Experiments

### 5.1 Experimental City and Dataset

Located in the Auvergne-Rhône-Alpes region of France, the city of Lyon (Fig. 3), has been selected as the experimental area for the implementation of our 3D Spatio-Temporal Forecasting Algorithm. The city is known for its rich cultural heritage, gastronomy, and vibrant urban life. With a population of over 500,000 and an area of 47.87 $km^2$ Lyon is a bustling metropolis with a complex and dynamic urban system. The implementation of the STFA in Lyon will provide a valuable opportunity to test and refine the algorithm in a real-world urban environment. The Cityscapes dataset, along with other available data sources such as OpenStreetMap 3D, CityJSON, and LIDAR, were utilized to collect and process the required 3D spatio-temporal data. Disruptive events such as traffic congestion (TC), extreme weather events (EW), and infrastructure failures (IF) were considered in the development of the key metrics vectors for urban resilience. These metrics were used to train the forecasting model to predict the impact of disruptive events on the urban system in Lyon.

The evaluation of the forecasting results provided insights into the performance of the algorithm and its potential for practical applications in urban planning and management. The insights gained from this experiment aim to contribute to the advancement of the field of urban resilience and the development of effective strategies for managing urban systems in the face of disruptive events.

**Table 2.** Urban resilience key metrics forecasting algorithm.

| |
|---|
| Inputs: |
| - Cityscapes dataset (3D urban model with attributes such as building height, street-layout, and land use)<br>- Other GeoDataset (OpenStreetMap 3D data, CityJSON data, Google Earth data, LIDAR data, ...)<br>- Other data sources (e.g., social, economic, environmental, and governance of the urban system)<br>- Time series data of urban resilience metrics<br>- Spatial boundaries of the study area<br>- Disruptive event characteristics E = {magnitude, duration, location}<br>- Time frame for forecasting |
| Outputs: |
| - Forecasted key metrics vectors $\overrightarrow{Ab}, \overrightarrow{Re}, \overrightarrow{Ad}$ for the urban area affected by the disruptive event.<br>- The composite urban resilience $U_{res}^{t}$ from Eq. (3) |
| 1. Preprocessing: |
| - Load 3D dataset and other relevant data.<br>- Identify the affected area based on the location of the disruptive event.<br>- Extract the relevant 3D spatial and temporal features from input datasets.<br>- Normalize features and split datasets into training and testing sets. |
| 2. Model training: |
| - Train the 3D spatio-temporal forecasting model using the extracted features.<br>- Use the disruptive event characteristics E to adjust the model parameters.<br>- Tune the model hyperparameters to optimize the forecasting accuracy. |
| 3. Forecasting: |
| - Apply the trained model to forecast the key metrics vectors.<br>- Deliver the outputs. |
| 4. Evaluation: |
| - Evaluate the forecasting performance using metrics such as mean squared error or mean absolute error.<br>- Refine the model and forecasting process based on the evaluation results |

To effectively test our algorithm, the dataset includes various socio-economic indicators such as population density, employment rates, public services, and transportation systems. We cover the period from 2000 to 2023. These indicators were collected from official sources such as the National Institute of Statistics and Economic Studies (INSEE), the Urban Community of Lyon (Grand Lyon), Météo France, and the Ministry of Transport. A synoptic view of the data is presented in Table 3. The dataset also includes environmental data such as air quality index (AQI), average temperature (AT), and rainfall.

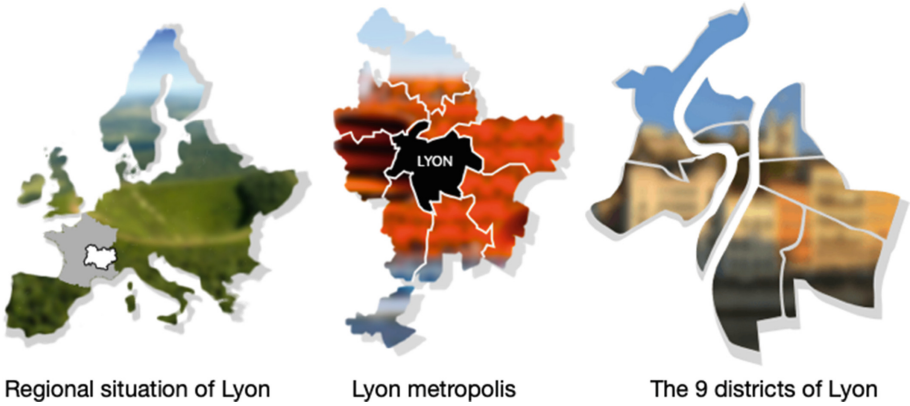


**Fig. 3.** The 9 districts of city of Lyon as study area for urban resilience forecasting computing.

**Table 3.** A synoptic view of the dataset.

| District | 3D GeoData | Population (Average) | Households (Average) | Median Households Income (€) | TC (%) | EW | IF (X) | AQI | AT (°C) |
|---|---|---|---|---|---|---|---|---|---|
| 1st | Available | 30,142 | 16,677 | 29,742 | 18–32 | Rain | 0–2 | 19–35 | 12–19 |
| 2nd | Available | 30,898 | 18,785 | 32,604 | 20–28 | Snow | 1–4 | 20–28 | 11–17 |
| 3rd | Available | 102,752 | 51,304 | 27,839 | 19–27 | Rain | 0–5 | 22–30 | 12–20 |
| 4th | Available | 36,369 | 38,203 | 29,859 | 21–40 | Snow | 2–4 | 18–26 | 9–21 |
| 5th | Available | 50,473 | 23,546 | 29,705 | 18–41 | Snow | 3–4 | 23–38 | 10–21 |
| 6th | Available | 52,568 | 24,925 | 37,768 | 20–38 | Rain | 2–5 | 19–32 | 11–18 |
| 7th | Available | 82,105 | 41,725 | 22,999 | 21–41 | Rain | 1–5 | 23–36 | 9–20 |
| 8th | Available | 86,110 | 41,574 | 24,489 | 23–40 | Snow | 1–2 | 20–29 | 12–19 |
| 9h | Available | 51,262 | 23,282 | 26,673 | 22–39 | Rain | 2–3 | 24–34 | 11–18 |

### 5.2 Experimental Settings

To achieve accurate forecasting of urban resilience, it is crucial to utilize multiple spatio-temporal datasets to their full potential. In recent years, advanced deep learning methods have been introduced for spatio-temporal modeling, but a main challenge remains: designing appropriate neural architectures to effectively fuse multi-scale spatio-temporal data and improve forecasting accuracy. Therefore, extensive experiments were conducted to evaluate a proposed model on real-world datasets from different domains and sources as depicted in Fig. 4. Based on key work in spatio-temporal forecasting [55–59], the effectiveness of STFA was evaluated by comparing it to five reference approaches. Models selected for comparison include Historical Average (HA) [49], XG-Boost [53], ConvLSTM [56], PredRNN [57] and ST-ResNet [58].

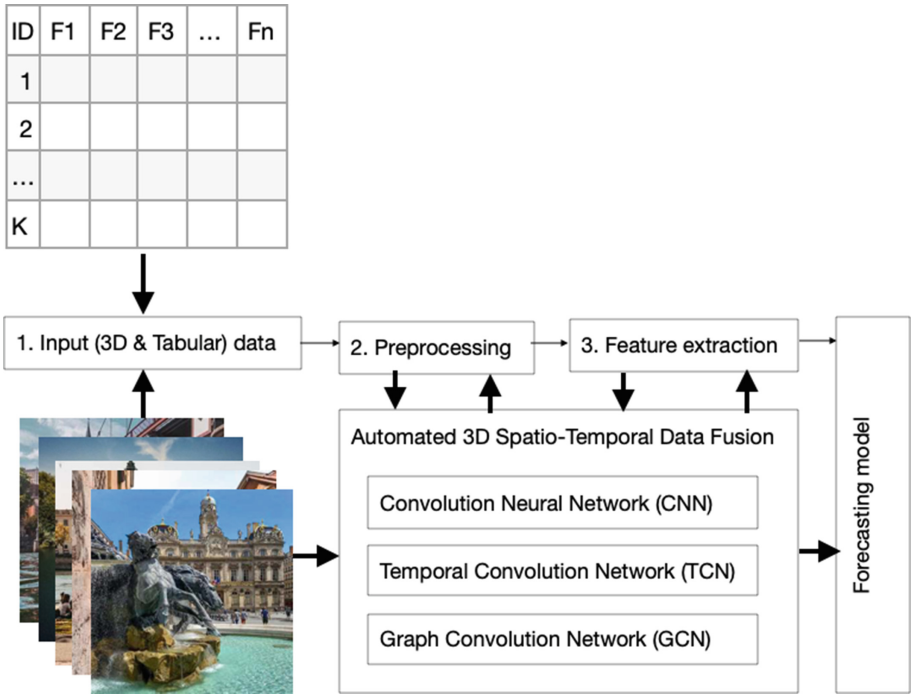


**Fig. 4.** The framework of STFA.

Automated 3D Spatio-Temporal Data Fusion (A3DSTDF) module is the crucial component in our proposed framework on which is developed our STFA (Fig. 4). CNN which has gained remarkable success in image recognition tasks in computer vision, can also be utilized for extracting spatial features in spatio-temporal forecasting. The fundamental learning mechanism of CNN is based on a sliding operation applied to image-like data followed by aggregating neighboring features through a series of filters of fixed size. These filters have learnable parameters and allow the network to automatically learn relevant features at multiple spatial resolutions. When compared to recurrent neural network, TCN is a more efficient method for modeling time series data. Like CNN, TCN's learning mechanism is based on sliding filters with learnable parameters, but the difference is that TCN's filters only slide in the 1D time dimension. GCN is a specialized extension of CNN used to handle structured data in non-Euclidean space. In contrast to a geographic grid map, where spatial semantic relations are defined in a regular Euclidean space, such relations do not exist in non-Euclidean space, and hence GCN is employed for spatial semantic learning. Adjacency matrices are used to represent the spatial semantic relations. HA is a widely used time series forecasting technique, which is simple in nature. It involves averaging the input series and using the resulting average as the forecasted value for the next time step. In this study, the input time step is set at 12. XGBoost is an ensemble learning model that employs decision regression tree models to extract and merge various features from the data in parallel. In our experiment, the input time step is set to 12, while the number of iterations and the maximum depth

of trees are set to 100 and 10, respectively. ConvLSTM is a deep learning model that integrates spatial and temporal information for precipitation prediction by employing convolution operations in LSTM units. The model has 2 layers with the number of hidden dimensions set to [32]. The size of convolutional filters is set to 33, and the input time step is set to 12. The learning rate is set to 0.001. PredRNN is an extension of ConvLSTM that addresses the issue of information loss between different cells by using spatio-temporal memory units. The model also has 2 layers with the number of filters set as [32]. The size of convolutional filters is set to 33, and the input time step is 12. The learning rate is set to 0.001. ST-ResNet is a region-wise spatial-temporal forecasting model that employs the ResNet unit, an improved variant of CNN, to capture spatial-temporal features in different time granularity. In this study, the model only uses the closeness time granularity to ensure its generalizability across different domains. The ResNet unit consists of 4 CNN layers with filter sizes of 3*3. The input time step is set to 6, and the learning rate is set to 0.001.

### 5.3 Experimental Results

We evaluate the effectiveness of our proposed STFA model on three different disruptive events (traffic congestion: TC, extreme weather: EW, and infrastructure failures: IF) in the urban resilience computing of Lyon city. To compare the performance of STFA with five other region-wise spatio-temporal forecasting models, we use three evaluation metrics: Mean Absolute Percentage Error (MAPE), Mean Average Error (MAE), and Root Mean Square Error (RMSE). While MAE and RMSE measure the errors between the forecasting results and actual data, RMSE is more sensitive to outliers. On the other hand, MAPE is a relative error metric that can eliminate the influence of data scale when measuring forecasting accuracy. Lower values for these metrics indicate better performance of the models. Table 4 summarizes the performance of urban resilience forecasting for each disruptive event.

**Table 4.** Performance of our STFA for urban resilience metrics computing

| Method | Traffic Congestion (TC) | | | Extreme Weather (EW) | | | Infrastructure Failures (IF) | | |
|---|---|---|---|---|---|---|---|---|---|
| | RMSE | MAE | MAPE | RMSE | MAE | MAPE | RMSE | MAE | MAPE |
| HA | 1.4782 | 0.4213 | 0.0916 | 0.2265 | 0.0743 | 0.0689 | 0.3895 | 0.1382 | 0.0473 |
| XGBoost | 0.8135 | 0.2707 | 0.0568 | 0.1572 | 0.0514 | 0.0278 | 0.2610 | 0.0866 | 0.0286 |
| ConvLSTM | 0.7458 | 0.2336 | 0.0481 | 0.1146 | 0.0421 | 0.0196 | 0.2201 | 0.0702 | 0.0210 |
| ST-ResNet | 0.7425 | 0.2316 | 0.0471 | 0.1104 | 0.0406 | 0.0193 | 0.2189 | 0.0697 | 0.0204 |
| **PredRNN*** | **0.7378** | **0.2289** | **0.0466** | **0.1083** | **0.0401** | **0.0190** | **0.2174** | **0.0694** | **0.0199** |
| **STFA (ours)** | **0.6146** | **0.1872** | **0.0353** | **0.0864** | **0.0314** | **0.0157** | **0.1814** | **0.0573** | **0.0173** |
| Improvement | +17% | +18% | +24% | +20% | +22% | +17% | +17% | +17% | +13% |

The comparison of different spatio-temporal forecasting methods using three evaluation metrics indicates that the traditional time series model (HA) and statistical learning model (XGBoost) perform poorly compared to other methods, as they fail to capture spatial correlations and consider only temporal information. The results highlight the importance of spatial dependencies in spatio-temporal forecasting. Among the five reference models, PredRNN performs the best, but STFA outperforms all other spatio-temporal deep learning methods and PredRNN in all three evaluation metrics. The performance improvement of STFA can be attributed to three reasons. First, our model captures both Euclidean and non-Euclidean semantic correlations, allowing for better utilization of multi-scale spatial data. Second, STFA employs a TCN approach to capture both short-term and long-term temporal dependencies. This is a significant improvement over other models that focus only on short-term dependencies. Finally, STFA employs the A3DSTDF approach to effectively fuse multi-scale spatio-temporal data, which results in a better adaptation to different data scenarios and superior architectures. Future research will incorporate more refined spatio-temporal learning and fusion operators in the search space of the framework and incorporate additional exogenous information to further improve prediction accuracy.

## 6 Conclusion and Future Work

In this paper, we proposed a novel 3D Spatio-Temporal Forecasting Algorithm (STFA) based on an Automated 3D Spatio-Temporal Data Fusion (A3DSTDF) framework for computing urban resilience metrics. The proposed model was extensively evaluated on three different disruptive events and compared with state-of-the-art baselines using various evaluation metrics. The experimental results demonstrated that the STFA approach outperformed the baselines in terms of forecasting accuracy, highlighting the effectiveness of our proposed method. Furthermore, we presented case studies to illustrate the neural architectures learned by our proposed STFA model for various data attributes. One of the strengths of our framework is its scalability, as it can accommodate various spatio-temporal learning and fusion operators for different urban resilience forecasting tasks. However, we acknowledge that our proposed framework has some limitations. For instance, it currently uses relatively simple modules to fuse multi-scale spatio-temporal data.

To overcome this limitation, we plan to incorporate more refined spatio-temporal learning and fusion operators in the search space of our framework. This will enable us to effectively fuse spatio-temporal data from multiple sources and address large-scale geodata fusion. In addition, we aim to incorporate more exogenous information into the framework to further improve prediction accuracy. Overall, the proposed STFA model and A3DSTDF framework have significant potential for enhancing urban resilience metrics computation, and we believe that our future research will address the limitations and advance the state-of-the-art in this field. Our future research focus on two major directions to further advance the proposed STFA model and A3DSTDF framework for urban resilience forecasting. The proposed framework for urban resilience forecasting could benefit from the integration of more advanced and complex multi-scale spatio-temporal learning and fusion operators. This would enhance the framework's adaptability

and scalability for different forecasting tasks. One such method is the exploration of graph neural networks (GNNs) and attention mechanisms, which can capture semantic and temporal dependencies across multiple scales. Moreover, to improve the accuracy of the predictions, the framework could be extended to incorporate more diverse data sources such as social data and remote sensing data. This could help to capture more comprehensive and diverse urban resilience indicators that are not directly observable, leading to a more accurate forecasting model.

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