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# The Impact of Climate Change on Urban Transportation Resilience to Compound Extreme Events

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**Abstract:** Global warming, sea-level rise, and rapid urbanization all increase the risk of compound extreme weather events, presenting challenges for the operation of urban-related infrastructure, including transportation infrastructure. In this context, some questions become important. For example, what are the temporal and spatial distribution and development trends of transportation resilience when considering the impact of multilpe extreme weather events on the urban transportation system? What is the degree of loss of urban transportation resilience (UT resilience) under different extreme event intensities, and how long will it take for the entire system to restore balance? In the future, if extreme weather events become more frequent and intense, what trends will urban transportation resilience show? Considering these problems, the current monitoring methods for transportation resilience under the influence of extreme events are lacking, especially the monitoring of the temporal and spatial dynamic changes of transportation resilience under the influence of compined extreme events. The development of big data mining technology and deep learning methods for spatiotemporal predictions made the construction of spatiotemporal data sets for evaluating and predicting UT resilience-intensity indicators possible. Such data sets reveal the temporal and spatial features and evolution of UT resilience intensity under the influence of compound extreme weather events, as well as the related future change trends. They indicate the key research areas that should be focused on, namely, the transportation resilience under climate warming. This work is especially important in planning efforts to adapt to climate change and rising sea levels and is relevant to policymakers, traffic managers, civil protection managers, and the general public.

**Keywords:** transportation resilience; compound extreme weather events; climate change; spatiotemporal dynamic evolution; future trends

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## 1. Introduction

Global climate change will increase the occurrence of extreme weather events such as typhoons, storm surges, heavy rains, floods, high temperatures, heat waves, and droughts. The processes that cause these extreme weather events usually interact and depend on each other in space or time [1]. In recent decades, we have also witnessed compound events such as high-temperature heat waves, droughts, and typhoon storm surges with heavy rain and flooding [2]. Such instnces of two or more extreme weather events occuring simultaniously or successively are called extreme compound weather events. [3,4]. Compared with extreme weather events that occur in isolation, the damage to socioeconomic and ecological systems of such compound extreme weather events tends to be greater [5].

Global warming, rising sea levels, and rapid urbanization have made coastal cities vulnerable to heavy rains and floods, especially during typhoons and storm surges. The risks of compound extreme weather events (typhoon surges, heavy rainfall, and flooding) are increasing, severely challenging the operation of urban infrastructure [6]. Events such as Super Typhoon Meranti landed in Xiamen in 2016, Super Typhoon Mangkhut hit Guangzhou in 2018, and Super Typhoon Lekima struck in Taizhou in 2019. After these typhoons made landfall, they caused disasters such as storm surges, heavy rains, and floods, which damaged urban transportation infrastructure, blocked roads, and paralyzed bus lines [7–9]. This reveals the vulnerability of the transportation system to compound extreme weather events. In the next few decades, transportation infrastructure may face huge challenges due to climate change because these transportation systems have been designed for historical conditions and predictability [10].

UT resilience reflects the ability of the transportation system to maintain its basic functions and structure through its resistance, mitigation, and absorption under extreme conditions (such as public incidents, terrorist attacks, and natural disasters), called static resilience, or the ability to restore the original equilibrium or a new equilibrium state within a reasonable time and cost, called dynamic resilience [10,11]. Currently, there is, however, no reliable method that can accurately reveal the spatiotemporal evolution of UT resilience when subjected to compound extreme weather events and scientifically clarify the impact of global climate change (the frequency and intensity of extreme weather events caused by climate warming) on UT resilience. This article, therefore, reviews the existing research on UT resilience, summarizes the research progress on UT resilience, identifies the deficiencies in the existing research, and proposes the countermeasures for future complex extreme events under conditions of climate change. The recommendations on UT resilience research provide new ideas for future research.

## 2. Overview of UT resilience Research

The research on UT resilience began in the 1970s [12], and the research on transportation system resilience has been steadily increasing since the 1990s. Based on transportation resilience papers published by Web of Science over the years (Figure 1), there has been a definite increase in the number of published papers, from a few in 2000 to 278 in 2020, and the percentage of publications has also jumped from less than 1% to about 25%, especially since 2010. From 2014 to 2020, research papers on transportation resilience showed explosive growth, which further reflects that with the deepening of research, the importance of transportation resilience is increasingly being recognized.

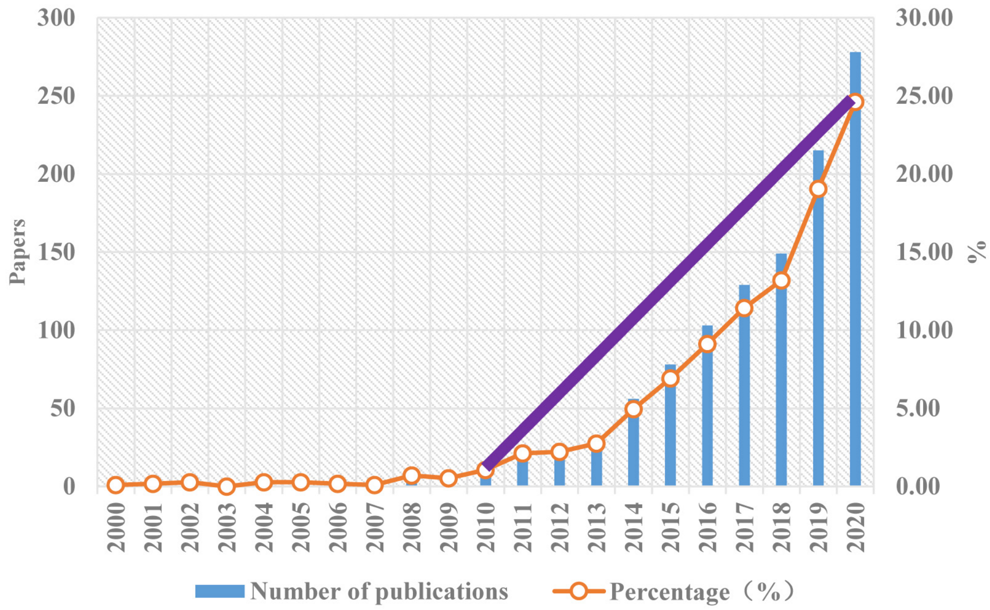


**Figure 1.** Time series distribution and percentage of transportation resilience-related research publications over the years. The purple trend line indicates the period of the rapid growth of research papers on transportation resilience.

The current research on UT resilience mainly focuses on conceptual frameworks, indicator systems, quantitative evaluations, and emergency and disaster response to extreme weather events and has achieved fruitful research results in related fields [10]. The above research involved the construction of a transportation resilience index system, analysis of the impact mechanism of extreme weather events on transportation resilience, exploration of the relationship between climate change and UT resilience, and the evaluation and prediction of the intensity of transportation resilience. The following is a description of the domestic and foreign research present situation from the above aspects.

### *2.1. Constructing the Transportation Resilience Index System*

Urban transportation systems are always disturbed by extreme events such as natural disasters (typhoons, storm surges, heavy rains, floods) or man-made events (terrorist attacks, cultural incidents, strikes, and system failures caused by human mismanagement). The impact on urban transportation system functions may be the same as that of other urban system functions [13–15]. Due to the increased risk of extreme events in cities, the resilience of urban transportation systems has become the focus of transportation resilience [16,17]. The resilience of the transportation system not only refers to the ability to prevent the system from malfunctioning due to interference but also refers to the ability of the system to avoid, adapt to, and reduce the impact of catastrophic local events or the failure of the entire system [10]. During the construction of the transportation resilience-measurement system, it should be considered that the resilience of the transportation system should reflect the system's ability to mitigate the impact of extreme weather events and maintain its own functions. In addition, the time it takes for extreme weather events to disrupt the full function of the transportation system and the time it takes for the system to return to normal function should also be considered.

The indicator research on the definition of transportation resilience is a necessary step to construct a measurement system. Relevant research has adopted a series of concepts and definitions, which play a crucial role in the construction of the measurement system. The transportation resilience index system mainly includes the Redundancy, Adaptation, Efficiency, Robustness, Interdependence, Preparedness, Flexibility, and Rapidity of the system. Redundancy refers to the replaceable components of the system with the same function, such as the ability of certain components to take over the failed components without compromising the function of the system itself [18–25]. Adaptation refers to the system's ability to flexibly adjust its form, structure, or function according to changes in the external environment to deal with new pressures [25–30]. Efficiency refers to the ability to maintain the level of service and connectivity during an extreme event causing a system interruption [18,27,31–33]. Robustness refers to the ability of the system to resist and respond to external shocks [16,25,34–44]. Interdependence is the connectivity between system components, including the connectivity of the relational network between system components [45], while preparedness is the ability to prepare certain measures before the system is destroyed and to enhance the resilience of the system by reducing the potential negative effects of destructive events [22,29,46,47]. Flexibility refers to the ability of the system to respond to the impact of emergencies and adapt to changes through contingency plans after the system is interrupted. It is also called the ability to reconfigure resources to deal with uncertainties [16,19,23,34,39,45]. Rapidity is the ability of the system to achieve the goal of controlling losses promptly in accordance with priorities and avoiding future system outages [16,25,48,49]. Most of the above research only uses one or several of these concepts as the evaluation indicators of transportation resilience. Moreover, travel time and traffic flow (driving speed, etc.) are the main performance variables that reflect the above indicators, and they are also important measurement variables for changes in UT resilience under external and internal threats [10,50].

### *2.2. Analysis Mechanism of the Impact of Extreme Events on Transportation Resilience*

Extreme weather events have many adverse effects on the transportation system, including high social, economic, and environmental costs [26]. Due to global climate change, extreme weather events occur more frequently than decades ago [51]. In this context, the ability of the transportation system to adapt to extreme weather becomes important [52]. Table 1 shows the possible direct physical impacts of extreme weather events on transportation infrastructure.

**Table 1.** The possible direct physical impact of extreme weather events on transportation infrastructure (from [16]).

| Types of Extreme Events | Impact on Transportation | Authors |
|---|---|---|
| Extreme heat events | Asphalt cracking<br>Asphalt aging/oxidation<br>Migration of liquid asphalt<br>Asphalt softening rutting<br>Railway bucking<br>Catenary wire sag<br>Failed expansion joints<br>Concrete pavements blowups | [16,53–55] |
| Season shift in temperatures | Increased damage from freeze-thaw cycles<br>More frequent landslides/mudslides | [16,56,57] |
| Extreme precipitation events | Flooding of roadways<br>Overloading of drainage systems<br>Roadway washout<br>Bridge scour/washout<br>Reduced structural integrity from soil moisture<br>More frequent landslides/mudslides | [11,16,55,56,58–60] |
| Droughts | Greater chance of wildfire<br>Road closure from wildfire & reduced visibility<br>Increased flooding in a deforested area<br>More debris in stormwater management systems<br>Reduced pavement integrity due to ground shrinking | [16,55] |
| Sea Level Rise/Storm Surge/Coastal Flooding | More frequent/intense floods in low-lying areas<br>Erosion of road base<br>Erosion of bridge supports/bridge scouring<br>Land subsidence | [11,16,55,57,59–63] |

Currently, scholars study the damage and loss (quantitative and economic quantitative analysis), reliability, and vulnerability of urban transportation system facilities to various extreme events (earthquakes, tsunamis, typhoons, rainstorms, floods). Extreme events damage transportation infrastructure, impact commuting time and cost and cause road congestion, traffic accidents, and casualties [64–69]. Even though the abovementioned analysis is quantitative, it essentially only measures the vulnerability of the transportation system rather than its resilience [51]. Current transportation resilience research focuses on the impact of extreme events on traffic volume, mileage, punctuality, and driving costs, as well as the time required for the transportation system to return to equilibrium or the speed of recovery after extreme events [19,27,70,71].

### *2.3. Mining the Relationship between Climate Change and Transportation Resilience*

The United Nations Intergovernmental Panel on Clime Change (IPCC) Fifth Assessment Report once again pointed out that over the past 100 years, the global climate system has experienced significant changes from global warming, which has increasingly affected human survival and development [72]. In the coming decades, transportation infrastructure (and other infrastructure systems) may face major challenges: they are largely unable to adapt to changes in external conditions and adjust their subsequent financial support, their use often far exceeds their expected lifespan, and they are becoming increasingly interconnected and complex [6]. The unstable changes of the global weather patterns due to climate change may exacerbate transportation infrastructure challenges (including aging, insufficient funding, historical conditions, and predictability), thereby seriously threatening the transportation infrastructure [55]. Although uncertain about the impact of future climate change, climate models indicate that extreme events and gradual changes in climate and hydrology may become more severe even under conservative scenarios, even with a significant reduction in greenhouse gas emissions in the short term [72,73]. Complicating this challenge is the inability to predict current or future conditions based on past trends [74]. Research has, however, been conducted on the robustness of the transportation system in response to climate change by strengthening its ability to adapt to climate change and other threats, and improving its control, prevention, and consolidation capabilities to prevent the destruction of transportation infrastructure [55,58,75]. A small number of scholars have also evaluated the impact of extreme weather events on UT resilience under the influence of climate change (the resilience recovery rate) and prediction studies and proposed standard indicators for the impact of climate change. These studies help researchers understand the influence of weather on transportation infrastructure and operations, how climate change will change the frequency and magnitude of these extreme events, and how synchronized technological and socioeconomic development may shape the future transportation network and improve or exacerbate the impact of climate change [76].

### *2.4. Evaluation and Prediction of Transportation Resilience Features*

The analysis of the temporal and spatial evolution of UT resilience and intensity features relies on data sets with high precision, high resolution, and complete temporal and spatial coverage. Current research on the impact of extreme weather events on transportation resilience mainly focuses on the use of topological methods to quantify the resilience of the transportation system [77–79]. Topological resilience research usually simulates transportation resilience scenarios by continuously deleting nodes in the traffic network according to various scenarios in which extreme weather events occur and then measuring its resilience by the degree of node deletion for each scenario. Based on this research, it was found that the resilience of the transportation system can still be maintained at a high level when the traffic nodes are randomly deleted, but when the traffic nodes are deleted under specific extreme weather events, the resilience of the transportation system is reduced. Data-driven analysis is another important and effective method for studying UT resilience after extreme weather events. Big traffic travel data (such as taxi trajectory data and public transportation travel data) can be used through traditional statistical models, frame calculations, and emerging big data mining technologies to construct and evaluate internal threats based on urban traffic (such as traffic accidents and man-made technical failure) of the transportation resilience process. Analyzing the formation and development process of traffic resilience under the abovementioned specific events is currently common practice [20,30].

Recently, Deep Learning technology has shown great potential for predicting traffic resilience. It has performed well in transportation research because of its flexible model structure and powerful learning capabilities [80–82]. The recurrent neural network method has proved itself to be excellent in capturing long-term time dependence and has been widely used in daily traffic and transportation forecast analysis [81–85]. However, the recurrent neural network model ignores the proximity factors in the transportation system and cannot represent the spatial correlation. A convolutional neural network prediction model that can extract spatiotemporal features and consider the Euclidean space in grid structure data (such as images) is therefore proposed for prediction [86,87]. The traffic volume in the transportation system contains complex non-Euclidean and directional correlations and, at the same time, has stronger topological characteristics instead of general European space dependence. For this kind of spatial structure data, the original convolutional neural network method is not applicable. To solve the above problems, a graph convolutional neural network was developed to extend the convolution operator to any grid image. The graph of the convolutional neural network is applied to daily traffic predictions, such as the traffic speed in the traffic sensor network, the station-level demand in the shared bicycle network, and the real-time parking occupancy rate in the parking fee network, have achieved good results [88–91].

## 3. Challenges in Current UT resilience Research

Research on UT resilience has achieved fruitful results in developing conceptual frameworks, indicator systems, quantitative evaluations, and emergency and disaster responses to extreme weather events. The development and construction of high-precision and high-resolution transportation resilience evaluation and prediction methods to accurately reveal the temporal and spatial evolution of UT resilience intensity under the influence of compound extreme weather events scientifically clarifies the impact of global climate change on UT resilience and other related issues. The above research, however, still has the shortcomings discussed below.

### *3.1. There Is No Unified Quantitative Index to Measure the Intensity of Transportation Resilience*

It is generally believed that Redundancy, Adaptation, Robustness, Preparedness, and Rapidity are the main indicators that best reflect the resilience of the transportation system [10]. However, in the design of the index system, there are too many different indicators that are too comprehensive, gradually leading to a broader research direction, with no unified standard [10]. Transportation resilience is a measure of the ability of the urban transportation system to resist external interference. The strength of its resilience and its temporal and spatial distribution features determine the performance of the urban transportation network. Selecting the appropriate indicators is, therefore, the key to constructing a system that reflects the resilience of the urban transportation system. Current research has, however, severely restricted the overall global understanding of the features of the intensity of transportation resilience.

### *3.2. The Methods of Analysis of the Impact of Extreme Weather Events on Transportation Resilience Are Limited*

Only a few studies on the frequency and intensity of extreme weather events affecting the urban transportation system and the current research is limited to the impact of a single extreme weather event on UT resilience. There are even fewer studies on the impact of compound extreme weather events on UT resilience [16,26,92]. With global warming, the frequency and intensity of compound extreme weather events will increase, which will undoubtedly further increase the pressures on urban transportation systems, and which will seriously restrict the temporal and spatial features that increase UT resilience [92]. It is therefore important to understand the mechanism and the impact of extreme weather events on UT resilience, especially for compound extreme weather events. Current research on the impact of extreme events on transportation resilience is, however, limited to individual conditions and cannot fully describe the regular features related to the impact of extreme events on transportation resilience.

### *3.3. Limited Research Has Been Conducted on the Resilience of Transportation Systems to Global Climate Change and Extreme Weather Events*

The current roads, dams, and other transportation infrastructure are designed to meet specific extreme event-level standards (such as a 100-year storm surge event, the transportation infrastructure can withstand any situation under 1% probability of occurrence of the event intensity), but it must be determined how robust this infrastructure is to extreme weather events. The transportation system, however, also faces other indirect and nonphysical impacts linked to climate change that are difficult to quantify [16]. For example, when extreme events become more frequent and intense, how can we design and improve the resilience of transportation systems? If a road is designed to, for example, withstand a 100-year storm surge event, but the driver has only experience for dealing with a 50-year storm surge event, how can traffic interruptions and traffic accidents most effectively be avoided, and the rate of traffic recovery be optimized? With global warming, more and stronger typhoons may be generated in coastal areas of China, which will change the intensity of storm surges, heavy rains, and floods [93,94]. This poses a huge challenge to UT resilience in terms of changes in time, space, and trends. The future impact of climate change and its temporal and spatial evolution must, therefore, be further clarified, including how the spatial features of future transportation resilience will change, which areas will need to be strengthened for better traffic emergency control, and how the future transportation resilience will change over time [16].

### *3.4. Research on Transportation Resilience Cannot Accurately Assess and Predict the Impact during Extreme Weather Events*

Although topological resilience can be used to study transportation resilience under extreme events and can identify the weak links in transportation systems under such conditions, this method still has difficulties in studying the intensity of transportation resilience and cannot effectively reflect the real situation of transportation resilience after the occurrence of extreme weather events, because of the many factors that affect traffic system resilience and their complex relationships [11,95]. Only a few studies have tried to apply data-driven methods to evaluate the resilience of transportation networks under external threats, especially for catastrophic extreme events [63,95] because it is difficult to accurately describe the resilience features of urban transportation under external threats (such as terrorist attacks, strikes, severe weather conditions, and natural disasters). Most of the current data-driven research only provides research cases for a single or some catastrophic extreme weather event, and it is difficult to obtain the results and conclusions of the temporal and spatial features of the impact of extreme events with obvious regularities on UT resilience [11]. Although the abovementioned deep learning methods are gradually solving various problems in the research process of UT resilience, they cannot fully predict the temporal and spatial evolution of transportation resilience in the face of extreme weather events, especially the reliability and accuracy of the temporal and spatial prediction results of traffic intensity. The current topological quantification methods, therefore, have limitations in terms of realistic simulation, and data-driven and deep learning methods cannot fully meet the requirements of the analysis and prediction of UT resilience evolution on temporal and spatial scales.

## 4. Research Direction of Future UT resilience

The IPCC fifth assessment report, once again, indicated that the global climate system has been undergoing significant changes characterized by global warming over the past 100 years. Entering the 21st century, the frequency of global extreme climate events will increase rapidly, and the scope of their influence will expand [5,16]. In the context of future global climate change, the impact of compound extreme weather events on the temporal and spatial evolution of transportation resilience must be further clarified, including how the spatial features of future transportation resilience will change, which areas must be strengthened in terms of traffic emergency control in the future, and how the future transportation resilience intensity will change. There are no clear and definite answers to these questions [76]. Therefore, against the background of climate warming, there is no clear and complete framework for studying the spatiotemporal features of the impact of compound extreme events on transportation resilience. In this context, the author believes that the following aspects should be considered to address current shortcomings.

### *4.1. Mechanistic Studies on How Extremes Impact Transportation Resilience*

UT resilience is dynamically balanced with its surrounding environment in the process of adaptation and evolution. Whether it is a single extreme weather event, such as torrential rain, flood, typhoon, storm surge, or a compound extreme event (typhoon storm surge with heavy rain and flooding), it deviates from the normal commuting environment that the transportation system has been adapted to. This inhibits the orderly organization of traffic, which leads to traffic paralysis and further affects the city's social and economic development [3,51]. The transportation system also has a certain degree of adaptability and resistance to extreme weather [10,95]. Even if the intensity and frequency of extreme events do not exceed the tolerance limits of the transportation system, extreme events usually significantly reduce the efficiency and capacity of the entire transportation system. When the intensity and frequency of extreme events exceed the tolerance limits of the transportation system, they can cause widespread paralysis of the transportation system. In short, extreme events usually have a negative impact on the balance of the transportation system [93]. The precise quantitative description of this impact depends on scholars' in-depth understanding of the impact of extreme events on transportation resilience, including how to improve the recovery time and speed of the transportation system and the accurate description of the mechanism of resistance to extreme events [63]. Most of the past work has, however, focused on the description of the phenomenon, and there is still a lack of in-depth analysis of the driving mechanism behind it.

We, therefore, need to explore and improve our understanding of the features of transportation system resilience and further clarify how extreme events can affect transportation resilience, especially extreme compound events (Figure 2). We must also determine how to choose the appropriate transportation resilience indicators to accurately reflect the impact of single and combined extreme events on the traffic system, to prepare for the traffic system before the interruption, and to aid recovery actions after such interruptions. We must create a comprehensive traffic system resilience-assessment method and continuously adjust the assessment plan by combining virtual and actual traffic resilience assessments to be able to scientifically describe the entire evolution of the transportation system under the influence of extreme events, from the initial balance to relative imbalance, imbalance, and finally the restoration of the initial balance. [10]. Sensitivity analysis can also be carried out to determine the priority of each indicator, with special emphasis on the adjustment of indicator weights to enhance the scientific accuracy of the assessment of transportation resilience. Together with studying how extreme events affect transportation resilience, we can also consider integrating travel behavior/mobility models to provide additional insights and analysis on the changes in transportation resilience.

For example, we can use the relevant indicators in Figure 2 to build a transportation resilience-measurement system, carry out quantitative research on transportation resilience, and propose a comprehensive indicator of transportation resilience. We can analyze the impact of the intensity of extreme weather events on the temporal and spatial evolution of the strength of transportation resilience through the statistics of the impact of previous extreme weather events on the strength of transportation resilience and analyze the impact of the frequency and intensity of extreme weather events on the strength of transportation resilience on the interannual scale. Thus, an attempt can be made to reveal the mechanism of the impact of climate change-extreme weather events on the strength of transportation resilience.

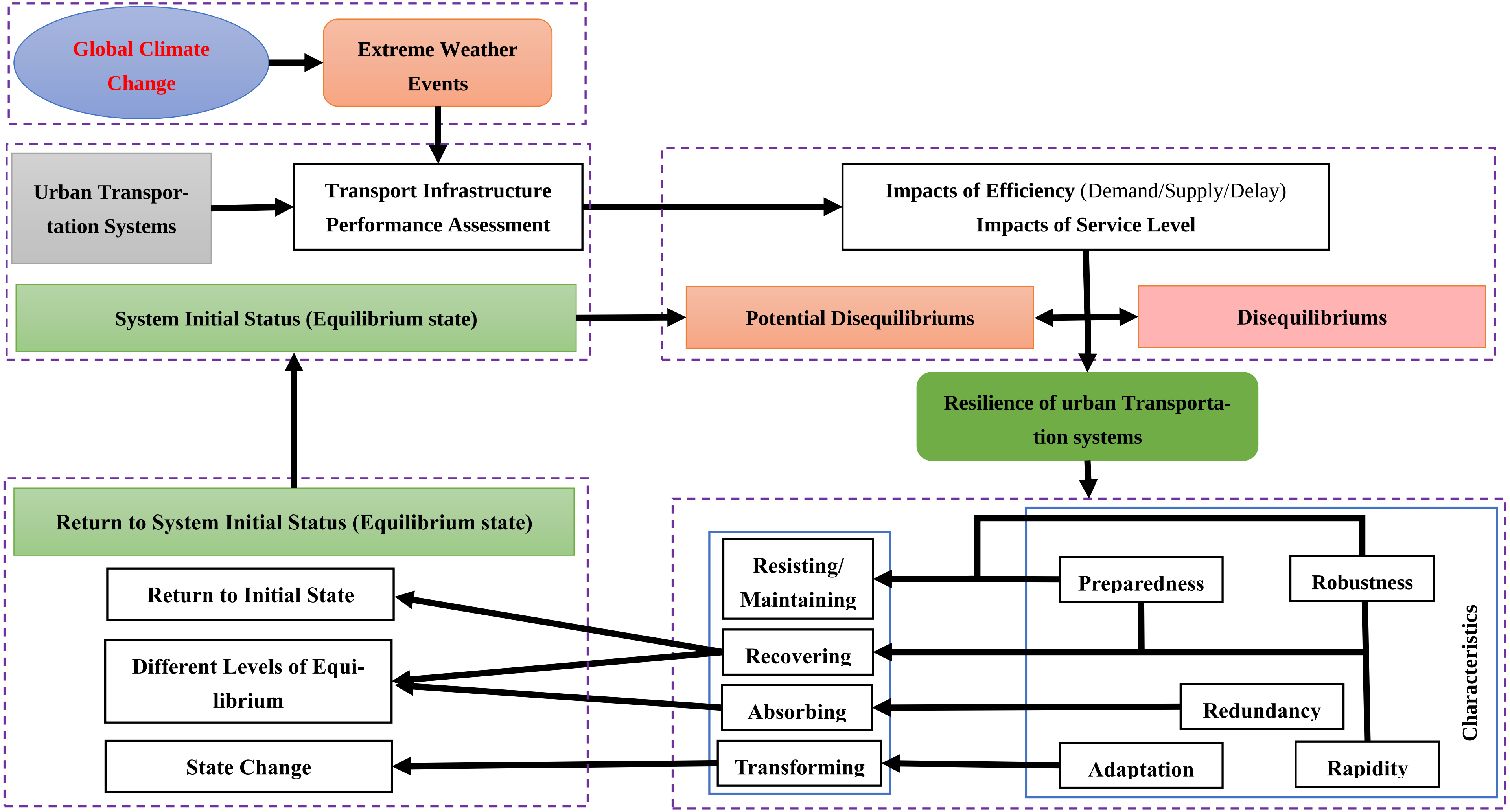


**Figure 2.** Framework diagram of the research mechanism on the impact of extreme events on UT resilience (from [10]).

### *4.2. Evaluating and Predicting Transportation Resilience for Climate Extremes Using Multisource Data Fusion*

Current climate change forecasting tools have not been developed to address transportation and other sectors. The transportation sector (and to some extent the energy sector) is, however, vulnerable to extreme short-term events not currently captured by existing weather generators. Spatial continuity and the reproduction of real weather are also very important future requirements for forecasting tools because transportation is susceptible to weather events, which can simultaneously affect multiple traffic nodes in space [3]. Given that big data analysis has proven to be a valuable method to assess traffic system performance, the traffic system needs to play a more active role, applying this technology to guide „accurate planning" in emergency situations [76]. We can, therefore, use multisource heterogeneous big data (floating car GPS, video surveillance, mobile phone signaling, urban road network, satellite remote sensing, meteorological observation, and tidal observation data) to construct a high-precision UT resilience intensity-evaluation index system and through deep learning and big data mining algorithms, construct an evaluation and prediction method to assess the impact of compound extreme weather events on UT resilience intensity (Figure 3). The deep learning prediction model of the joint graph convolutional neural network and Geographic Information System(GIS) technology can also be combined and integrated to standardize the data structure of model calculation. Comprehensive application component technology, data object access technology, and dynamic link library technology can be used to establish transportation resilience spatiotemporal dynamic simulation, which can be closely integrated with embedded GIS technology. In the future, transportation resilience models will be fully integrated with GIS, Remote Sensing(RS), and database management systems to integrate UT resilience spatial data management, numerical model calculations, and spatial data visualization. This will assist researchers in scientifically recognizing the temporal and spatial changes of UT resilience intensity under compound extreme weather events, improve the management capabilities of urban road networks, establish comprehensive emergency response measures for extreme weather events, ensure the sustainable development of cities in coastal areas, and build the innovative development of risk management in response to climate change.

For example, according to the reconstructed data of the hourly speed of urban traffic under previous extreme weather events, as well as external feature data, that is, meteorological data (precipitation, wind speed, wind direction, temperature, air pressure, etc.) in Figure 3, we can use a Diffusion Graph Convolutional Recurrent Neural Network (DCRNN) of multivariate spatiotemporal forecasting methods to predict future urban traffic speeds. We can set the network input layer/output layer neurons in the input layer according to the IPCC AR6 5 RCPs path scenarios and use CMIP6 multimode to compare the simulated data to output the overall possibility-change trend of the intensity of future extreme weather events. Thus, we obtain the neural network speed and travel time prediction results, as well as the transportation resilience strength-measurement system based on the above, to predict the spatiotemporal data set of UT resilience strength indicators under extreme weather events in the future. Thus, it can guide the sustainable development of urban transportation under future climate change scenarios.

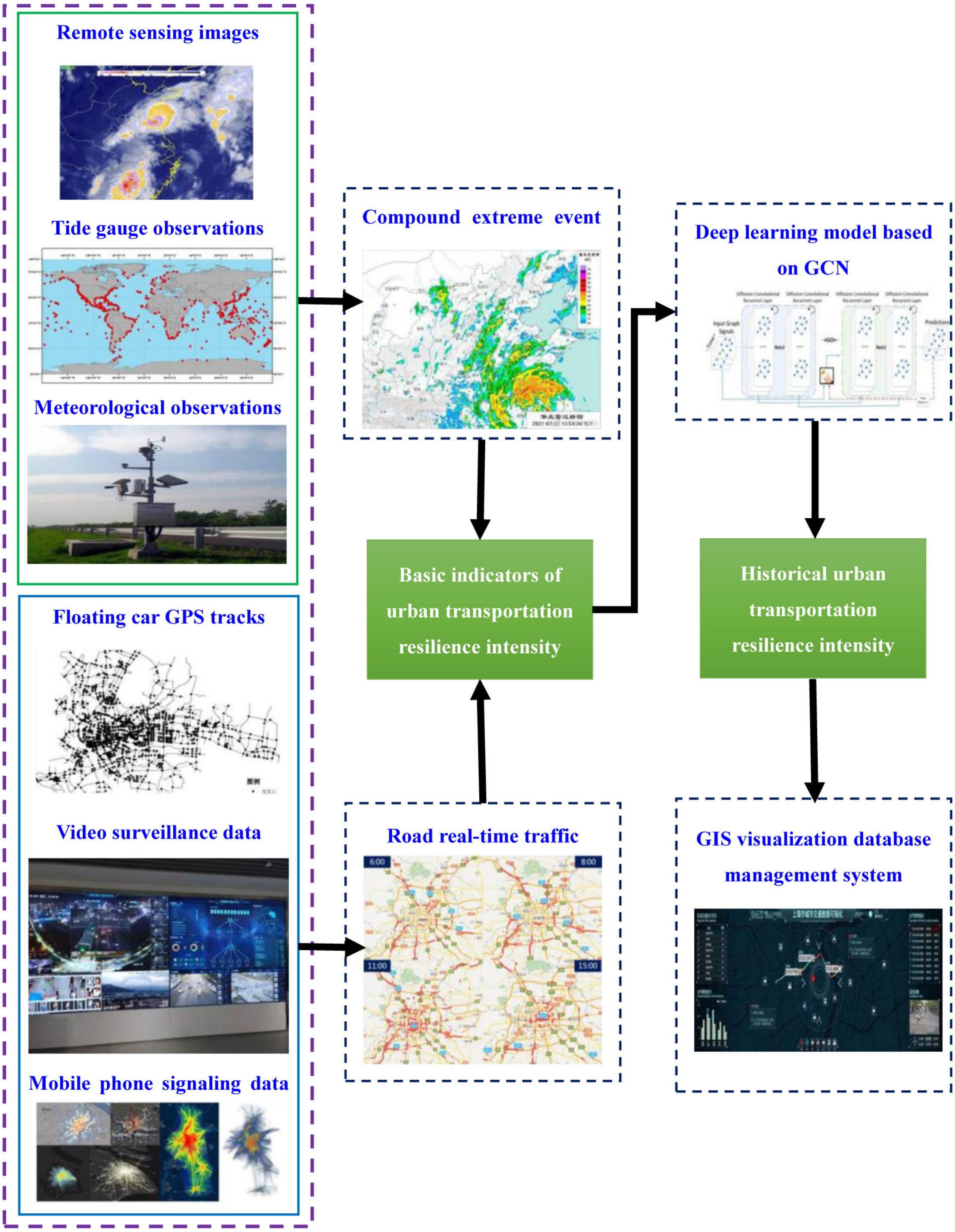


**Figure 3.** Framework diagram of multisource data fusion and transportation resilience tool for evaluating and predicting traffic system performance under the influence of extremes.

## 5. Conclusions

Transportation resilience, including the conceptual framework, index system, quantitative evaluation, and emergency and disaster response to extreme weather events, have been studied for nearly 50 years. However, the development of spatiotemporal dynamic monitoring of the impact of extreme events on transportation resilience is relatively slow due to the limitations of monitoring approaches. From a geographical perspective, in particular, the temporal and spatial features of the impact of extreme events on transportation resilience at a climatic scale and the future trends of temporal and spatial variation should be monitored.

Global warming and the rise of sea levels during the 21st century, extreme weather events (including extreme weather events such as typhoons, rainstorms, and floods) may cause devastating damage to the transportation system, especially in the case of compound extreme weather events (typhoon storm surges with heavy rains and floods). This may even cause loss of life and property and may seriously impact the functionality of urban transportation infrastructure. Global warming also continues to intensify, which has increased the possibility of changes in the frequency and intensity of extreme weather events such as typhoons, rainstorms, and floods and has become the main factor influencing the temporal and spatial evolution of transportation resilience. Many new challenges have therefore emerged in UT resilience monitoring. Big data mining technology and deep learning prediction models can, however, be used to study the temporal and spatial evolution of transportation resilience, understand the patterns and trends of changes in the intensity of transportation resilience under the influence of extreme compound events, and especially focus on monitoring transportation resilience in areas that are subjected to extreme weather events. In the context of global climate change, it is unclear whether there will be new changes in the frequency, intensity, and geographical distribution of future extreme events. To fully understand future extreme events, we need to make full use of existing remote sensing technology, GIS technology, big data mining technology, and deep learning prediction models, combined with model analysis, scenario predictions, and other methods to address the issues in UT resilience monitoring effectively.

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