# Toward data-driven, dynamical complex systems approaches to disaster resilience

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With rapid urbanization and increasing climate risks, enhancing the resilience of urban systems has never been more important. Despite the availability of massive datasets of human behavior (e.g., mobile phone data, satellite imagery), studies on disaster resilience have been limited to using static measures as proxies for resilience. However, static metrics have significant drawbacks such as their inability to capture the effects of compounding and accumulating disaster shocks; dynamic interdependencies of social, economic, and infrastructure systems; and critical transitions and regime shifts, which are essential components of the complex disaster resilience process. In this article, we argue that the disaster resilience literature needs to take the opportunities of big data and move toward a different research direction, which is to develop data-driven, dynamical complex systems models of disaster resilience. Data-driven complex systems modeling approaches could overcome the drawbacks of static measures and allow us to quantitatively model the dynamic recovery trajectories and intrinsic resilience characteristics of communities in a generic manner by leveraging large-scale and granular observations. This approach brings a paradigm shift in modeling the disaster resilience process and its linkage with the recovery process, paving the way to answering important questions for policy applications via counterfactual analysis and simulations.

disaster resilience | urban science | complex systems | big data

## Increasing Urban Complexity and Disaster Risks

Intensity and frequency of natural hazards have increased across the globe in recent years, due to effects of climate change (1–3), causing ∼1.3 million deaths and leaving a further 4.4 billion people injured, homeless, displaced, or in need of emergency assistance between 1998 and 2017 (4). Over the past 20 y, the total direct economic losses experienced by disaster-affected countries are estimated to be US$2.9 trillion. In addition to climate change, the rapid urbanization trend, where nearly 7 of 10 people in the world are projected to be living in cities by 2050, poses a wide range of challenges for government agencies to build resilient, sustainable, and inclusive urban systems. Almost half a billion urban residents live in coastal areas, and around 90% of urban expansion in developing countries is near hazard-prone areas and built through informal and unplanned settlements, which could exacerbate the negative impacts of natural hazards (5).

Increasing urbanization is reflected in the expansion of urban agglomerations and multiple infrastructure networks to meet the increasing demands for critical infrastructure services (transport, water, wastewater, energy, communications, etc.). The urban infrastructure networks are often geospatially colocated, functionally interdependent, and managed by centralized public/private utilities. Rapid urbanization and growing demands for services, which are often met by drawing on natural resources from distant sources,

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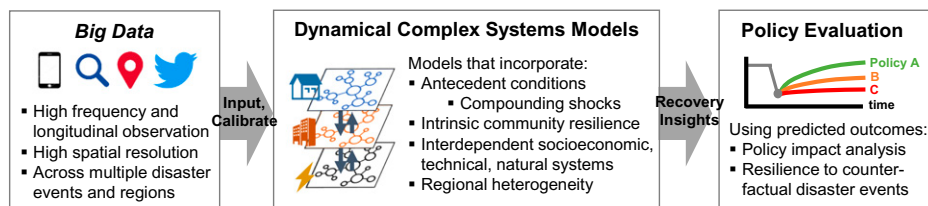
**Fig. 1.** Overview of a data-driven, dynamical complex systems approach to disaster resilience. Big data enable observation of postdisaster recovery dynamics at a high spatial and temporal granularity, from multiple disaster events across regions. Generalizable insights from big data can be used as input to calibrate dynamical complex systems models, which capture various characteristics of the disaster resilience process illustrated in the DROP model (9), such as antecedent conditions, intrinsic community resilience, system interdependencies, and regional heterogeneity. Recovery predictions and insights obtained from the dynamical models can be used for evaluating policy impacts and assessing the resilience of urban systems to counterfactual disaster event scenarios.

increase functional interdependencies among social, economic, and technical systems. Such complex interdependencies could exacerbate the impact of natural hazards and external shocks due to cascading shocks and disruptions and could contribute to unsustainable development (6). Given these increasing threats of natural hazards, reducing people's vulnerability and improving the resilience of communities have become a policy priority among governments and multilateral development agencies (7). Yet, the ability to provide the evidentiary basis for reducing disaster risk through enhanced resilience is constrained by the present inability to characterize, monitor, measure, and model the interdependencies that underlie urban systems (8).

Our analysis focuses on several key questions:

- How can disaster recovery trajectories of diverse urban communities after various disasters be efficiently tracked at multiple spatial and temporal scales?
- How do dynamic conditions, including antecedent conditions, recurring and compounding disaster events, affect the intrinsic resilience of a community and the recovery trajectories?
- How does intrinsic community resilience to disasters relate to the dynamic complex interdependencies between socioeconomic, technological, and environmental systems?
- How can we create a generalizable and quantitative framework based on consistent emergent patterns of recovery for various disaster types and heterogeneous regions?
- How can we right size models that characterize the inherent resilience and its linkage to the disaster recovery process, which may be used to inform urban management and development policy?

Fig. 1 shows the overview of a data-driven, dynamical complex systems approach to disaster resilience. Large-scale disasters, such as hurricanes, earthquakes, and pandemics, generate heterogeneous impacts among the urban communities with different abilities to recover in the affected regions. We first highlight the availability of high-resolution spatial and temporal mobility data and advances in big data analytics, which can be used to quantitatively measure the recovery trajectories of communities across regions after such diverse disaster events. This opportunity motivates us to develop data–model frameworks that can infer the inherent resilience of communities and further be used to model the dynamics of the disaster recovery process. We then discuss the need for data–model integration and cross-comparison of multiple modeling approaches of urban community resilience. We close with a discussion of opportunities and challenges for translation of models and data to urban management, policy, and development.

## Measuring Recovery Trajectories Using Big Data

With the ubiquity of mobile devices and low-cost sensors, we are now capable of collecting various types of data from individual users at an unprecedented scale, including mobile phone location data (for reviews, see refs. 10 and 11), satellite imagery data (12), and social media data (13), which have been leveraged for numerous disaster recovery and resilience applications. In particular, recent studies have used mobile phone location data to analyze and quantify disaster recovery trajectories, such as the population displacement patterns after the Nepal earthquake in 2015 (14), migration patterns in regions stressed by climate shocks in Bangladesh (15), and evacuation behavior after several earthquakes in Japan (16). Lu et al. (17) revealed the predictability of displacement destinations from behavioral patterns observed prior to the Haiti earthquake in 2010. Other studies have developed machine-learning approaches to predict the population flow after disasters using real-time location data in an online manner (18). Yabe et al. (19) studied the spatial heterogeneity in population displacement and recovery patterns after five disaster events, including Hurricanes Maria and Irma, earthquakes, floods, and tsunami using mobile phone global positioning system (GPS) datasets from Japan and the United States. Apart from population recovery and migration analysis, mobile phone location data have been used to quantify the recovery of businesses, hospitals, and schools using foot traffic counts (20).

Often, such measurements obtained from big data sources are fed into state-of-the-art machine-learning and artificial intelligence (AI) models to predict future outcome trends [e.g., predicting disaster evacuation dynamics using long short-term memory (LSTM) models (21)]. Although studies have shown the high predictability of postdisaster dynamics with such models using selected case studies, such models are "black box" and often lack interpretability that is crucial for informing policy making. This is exacerbated by the fact that disaster resilience is a complex process, with heterogeneity in outcomes and the long-range nature of the recovery trends, due to multiple types of dynamic interdependencies across infrastructure and socioeconomic system components (22). Therefore, we need to move beyond simply fitting machine-learning models to measurements collected via big data and embrace the complexity of the disaster resilience process.

Despite the increasing availability and the abundance of studies using large-scale mobility data sources for analyzing disaster displacement and recovery, there are still very few works that combine such insights to understand the holistic disaster resilience process and its relationship to the recovery trajectories. This is a huge missed opportunity, when big data allow us to quantitatively measure the recovery processes of social, technical,

**Table 1. Summary of disaster resilience modeling approaches**

| Modeling approach | Utility/advantages | Limitations | Examples (refs.) |
|---|---|---|---|
| Index based | Comparison and ranking of regions | Neglects dynamical process of resilience | (29, 30, 32) |
| System dynamics | Compartment process based; dynamic, scalable | Aggregated; parameter estimation | (27, 33, 34) |
| Agent-based models | Based on microscopic interactions; high resolution | High computational cost; parameter estimation | (35–39) |

economic, and institutional dynamics after disaster events in an unprecedented scale. Moreover, big data enable us to collect data from multiple disaster events of different types (e.g., hurricanes, wildfires, floods, earthquakes) across regions and cities with low cost. Cross-comparative analysis of various disaster events across cities and countries would contribute toward a more generalized understanding of the dynamical processes of disaster resilience and the recovery trajectories.

## Communities as Dynamical Complex Systems

During the past couple of decades, urban agglomerations (communities and cities) have been perceived as complex systems, composed of heterogeneous components—social, technical, institutional, and natural—with dynamic interactions and interdependencies (23, 24). Several disaster events have revealed that the complexity and uncertainty lead to drastically heterogeneous recovery trajectories across communities and regions after disaster events (19, 25). Understanding the interplay between the physical infrastructure systems and social systems and their impacts on urban recovery after large-scale disasters is essential for developing policies that could enhance effective population recovery in communities and foster sustainable development in hazard-prone areas (26). Moreover, "shocks" are not limited to acute events (e.g., earthquakes, hurricanes), but also include various chronic stresses that are less severe in intensity but are more persistent. Recurring and compounding sequences of stochastically occurring chronic and acute shocks may exacerbate the disaster impacts and could contribute to the loss of resilience of urban systems (27). The dynamic nature and spatiotemporal contingency of the disaster resilience process, as well as the complex interdependencies among heterogeneous components in urban systems, were first conceptualized in the disaster resilience of place (DROP) framework (9). A recent article argued for the need to consider complexity in infrastructure resilience (28). We further argue the need for dynamical, complex systems models that capture emergent patterns that can be observed using large-scale observations.
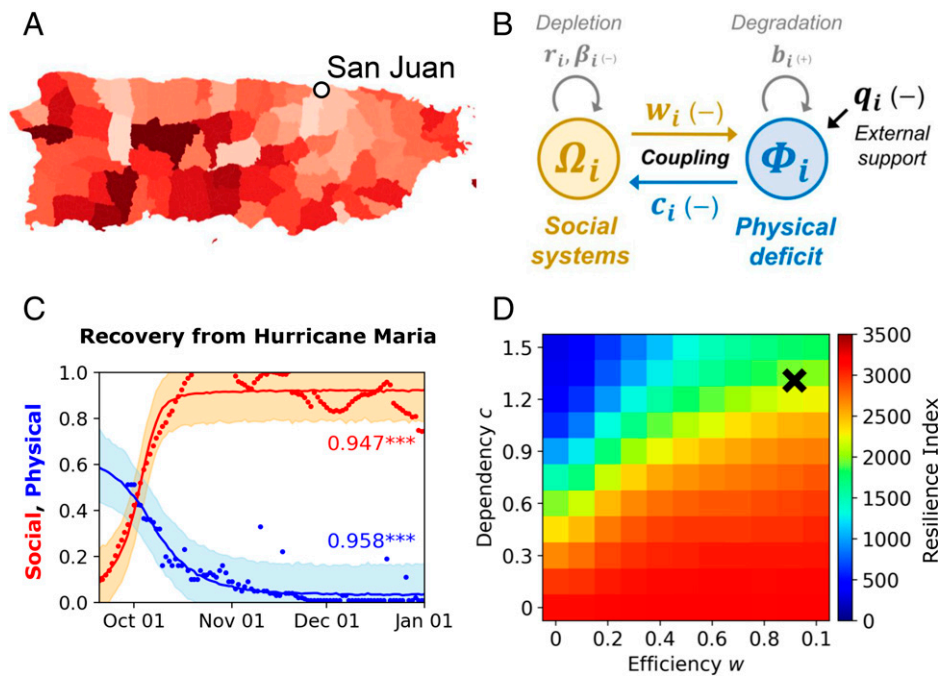
Despite the complex and dynamic conceptualization of resilience in the DROP framework, the study was followed by a plethora of studies that measure the disaster resilience of communities using static indexes (29, 30). Such index-based approaches attempt to quantify the inherent resilience of communities using a predefined list of measures including ecological, social, economic, institutional, and infrastructure variables. However, such index-based approaches have three significant drawbacks: 1) Index-based approaches do not account for complex interdependencies (feedbacks and cascading effects) among urban social, physical, institutional, and natural components during the disaster recovery process. 2) They do not account for the dynamic process of resilience, which could result in neglecting potential critical thresholds of urban systems (as shown in ref. 31). 3) They are difficult to validate and test. To fully connect such measures of inherent resilience with other contributing factors of the resilience process including socio-technical–natural

interdependencies, antecedent conditions, shock characteristics, and adaptive capacity, multiple modeling approaches have been proposed and tested (summarized in Table 1). Despite such advancements in modeling the dynamic complex urban systems' resilience, existing studies are calibrated and tested based on relatively small datasets often collected by household surveys or secondary data sources such as censuses.

Interestingly, global analyses of cities, enabled by big data, have revealed striking similarities, where various urban metrics (e.g., gross domestic product, total road mileage) scale superlinearly with the population of the city (40). Such scaling relationships are prevalent in urban infrastructure networks, such as water pipe networks (41), road networks (42), human settlement with respect to river networks (43), and urban heat island topology (44). Global similarities are observed after disaster events as well, where population displacement and recovery patterns after different types of disasters (e.g., floods, earthquakes, hurricanes) occurring in different regions around the world (e.g., Puerto Rico, Florida, Tohoku, Mexico City) all followed exponential decay dynamics (19). This emergence of consistent patterns across geographical regions and disaster events motivates us to pursue a generalizable framework for modeling the disaster resilience process and recovery trajectories.

## Modeling the Dynamical Resilience Process

To bridge this gap, a recent study proposed a framework to understand the dynamical disaster resilience process using the recovery trajectories measured from big data, shown in Fig. 2 (34). The framework operationalizes the dynamical process of resilience, integrating socio-technical–natural antecedent conditions and interdependencies, event characteristics (intensity and frequency), coping capacity, and adaptive resilience (many of the elements in the DROP model) with recovery trajectories (which are measured using big data). The dynamical complex systems model was composed of two coupled differential equations, each representing the social and physical system states, respectively. In this model, there are four parameters that characterize the functionality of the systems, two parameters describing the strength of coupling between social and physical systems, and a parameter representing external shocks (i.e., natural hazards) that affect the system. A control is used to gauge how much the social systems are affected by external shocks. The cities may be connected with each other via a network matrix term (e.g., using an adjacency matrix) to capture any spillover effects and interdependencies across cities. Moreover, each system may be disaggregated into different subcomponents, which could characterize intracity heterogeneities (e.g., income inequality). While the general model formulation has substantial flexibility, the key principles of such dynamical complex systems models are to construct a set of ordinary differential equations for each system variable of interest (e.g., social systems, economic performance, physical infrastructure deficit). Each system equation is constituted by the 1) replenishment, 2) depletion, 3) external shock factors, and 4) any network effects, and they are coupled

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**Fig. 2. Application of data-driven, dynamical complex systems approach.** (*A*) The data–model approach was tested using data from Puerto Rico, which was devastated by Hurricane Maria. Darkness of red color indicates housing damage rates in each municipio. (*B*) Proposed dynamical model of coupled socio-physical systems. (*C*) Model estimation results (solid line) had high agreement with actual social and physical recovery data collected from mobile phones (dashed line). (*D*) Resilience of San Juan under different policy levers can be evaluated using the dynamical model. (Figures obtained and modified from ref. 34.)

with each other via coupling model parameters. The functional forms and the ways in which the systems are coupled should be determined based on the characteristics of the systems being studied.

Large-scale mobile phone location data were used to estimate the recovery trajectories of various social systems across different regions in Puerto Rico. The dynamical complex systems model was used to estimate the regional intrinsic resilience characteristics using the measured recovery trajectories after Hurricane Maria. As a result, the model revealed high but regionally heterogeneous interdependencies between social and physical systems, and the estimated recovery trajectories matched well with the measured outcomes from big data. The dynamical complex systems model allows the investigation of various counterfactual scenarios of recovery trajectories when the community's inherent resilience and coping capacity are changed through policy interventions.

By fully leveraging the two scientific advancements in dynamical complex systems modeling and big data analytics, we are able to substantially push the boundaries of disaster resilience modeling and measure dynamic outcomes of recovery. Compared with big data analytics approaches, the data-driven, dynamical complex systems modeling approach has three main advantages:

1) better understanding of the underlying disaster resilience process (e.g., antecedent conditions, system interdependencies, impacts of shocks, absorptive capacity, and adaptive resilience);
2) prediction of the disaster recovery trajectories and revealing the underlying mechanisms across a large spatial and temporal timeframe, allowing comprehensive cross-regional comparisons and time series analysis of recovery and urban resilience; and

3) counterfactual scenario analyses using various system model parameters and shock sequences as input information, and potential search for tipping points of urban complex systems.

Data-driven, dynamical complex systems modeling allows us to estimate the inherent resilience of communities and the dynamical resilience process by leveraging the recovery trajectories observed using big data. This approach provides high interpretability and accountability of outputs, which are essential for informing policy decision making. The outputs of evaluating counterfactual scenarios could benefit in identifying locations that are in most need for investments and conducting cost–benefit analysis of multiple policy levers. Moreover, this approach has substantial flexibility in design, implementation, and validation, depending on the characteristics of the systems of interest, available data sources, and computational power. A big-data–enabled, dynamical complex systems approach represents a paradigm shift in modeling the disaster resilience process, enabling us to return to and to operationalize the complex characteristics of the disaster resilience process conveyed originally in the DROP framework (9).

## Future Steps and Challenges

***Moving Toward Dynamical, Complex, and Generalizable Frameworks.*** The DROP framework introduced the key concepts of disaster resilience, including the dynamic nature and complex interdependencies among heterogeneous entities. The revolution in the spatiotemporal granularity and scale of the available data after disaster events poses significant opportunities to make a paradigm shift in modeling the disaster resilience process, by using the measured recovery trajectories to infer the inherent community resilience characteristics. To further capture the complex and interdependent dynamics among social, economic, technical, and natural systems, mobile

phone location data can be integrated with various other datasets that capture different dimensions of urban dynamics, including satellite imagery data (e.g., to monitor changes in built environment), household survey data (e.g., to unravel behavioral adaptations of households and communities), and social media data (e.g., to understand opinion and sentiment dynamics). Big data have revealed the emergence of a wide range of consistent patterns in urban characteristics across different cities and disaster events (19). Such consistent patterns across geographical regions and disaster events motivate us to investigate generalizable frameworks for modeling the disaster resilience process and recovery trajectories.

***Right Sizing the Model for Policy and Management.*** While the usage of big data and dynamical complex systems models presents immense opportunities, there exist significant challenges in right sizing the models for the intended applications and stakeholders. Models could be designed to include a wide spectrum of complexities, ranging from parsimonious systems models to spatially explicit agent-based models. The coupled socio-physical model (34) and its applications to water systems resilience (45) are examples of parsimonious models where social and physical systems were aggregated over regions (with ~500,000 residents) and cities. Empirical evidence has revealed that cities are "fractal" (44, 46), and Verbavatz and Barthelemy (47) have modeled the growth of urban agglomerations. Seeking the right approaches for modeling resilience in the future as cities and populations grow is an important research question.

The aggregation levels and specification details of the model can be designed with the intended applications and use cases in mind, so that the model outputs can lead to effective policy prescriptions. For example, the coupled socio-physical systems model described in the previous section can be used by policy makers to predict the recovery trajectories of social systems including local businesses and education systems (e.g., schools) over time. Such information can be used to prescribe various policies during the disaster recovery phase, such as allocation strategies of reconstruction subsidies for local micro-, small, and medium enterprises and determining the locations and capacities of temporary school facilities for areas where schools were not able to continue due to heavy structural damage. To inform policy makers in the power infrastructure sector, we may emphasize the effects of interdependencies between physical and cyber systems (wireless sensor networks and power grids) that connect households and vehicles during disaster recovery ("cyber-social–physical systems"), to assess the resilience of cyber systems to future shocks (48). To account for the needs of community-based nongovernmental organizations (NGOs), the social systems can be decomposed into various entities including household networks, public agency networks, and nonprofit organization networks, to study the intracity distributions of community social capital more closely (49). The common denominators for all the models in various granularities and scales are the importance of considering dynamic and complex interactions among heterogeneous entities and the availability of large-scale data for model calibration and validation.

Another important challenge that needs to be further addressed is to effectively connect the big data- and model-driven insights into the policy-making and decision-making process. The outputs need to be easy to understand and interpret and ultimately useful for policy makers. The awareness of the gaps between research methods and policy implementation has recently improved, mainly due to the frequently occurring disaster events including COVID-19, and there are various efforts in translating insights obtained from big data and quantitative models into information that can be digested easily by policy makers. It is important that communities prone to disasters have a strong voice in the decision-making process, which is a necessary condition to achieve equitable outcomes in building resilience.

Such data–policy pipelines can be implemented in the form of short diagnostic reports (50), interactive dashboards (51), data science toolkits (52), or pre- and postevent learning exchanges (53). In addition to such pipeline tools, effective frameworks for researchers and policy makers to share experiences, knowledge, and knowhow across different regions and stakeholders are needed to improve the uptake of data- and model-driven insights.

***Cross-Comparative Benchmarking and Validation of Models and Data.*** Despite the increasing availability of data, we still lack comprehensive validation of the proposed model using data from various disaster events and compound disasters. The data-driven dynamical complex systems modeling approach in the disaster resilience domain is nascent; therefore, there is not yet a standard modeling framework that is widely accepted to function well in various regional contexts and disaster events. For example, in the epidemiological domain, susceptible–infected–recovered (SIR) models and their variants have been analytically studied for many decades and are widely accepted as the de facto standard models in the domain (54). Therefore, when mobile phone location datasets became available in the early 2000s, integration of big data and dynamical models was seamlessly accomplished (55) and they are now widely used across the world to tackle the COVID-19 pandemic (56). Spurred by recent major disaster events and background stressors such as COVID-19, the use of big datasets for development is a very important tool for public policy (57, 58) for understanding not only single-event impacts and recovery but also compounding events such COVID-19 followed by a hurricane or a wild fire. Large tech firms and international agencies have also accelerated their engagement in utilizing big data sources for development projects (e.g., Development Data Partnership; https://datapartnership.org/). However, to link the outputs of the data-driven dynamical complex systems models with policy needs in a standardized manner, there needs to be sufficient benchmarking of both the methods/models and datasets. Using the significant availability and access to data from various disaster events across the world, developing a standardized framework and a collaborative effort in validating such dynamical models is one of the key challenges in disaster resilience research and policy.

To advance the efforts in cross-comparative benchmarking and validation of models, it is also crucial to continue collective efforts in understanding and overcoming the limitations of big data. Big data, despite their size and high granularity, are prone to biases in representation. For example, the sample populations in mobile phone location datasets are often biased toward specific sociodemographic and -economic segments of the population (59). Efforts to improve the data collection and preprocessing steps to quantify and overcome such biases are important to avoid policy recommendations that favor certain population groups over others. However, all data come with different biases. Although data gathered from surveys of households may be designed with careful representation of the households, they are often limited by small sample size, recall bias, and response bias (60).

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The COVID-19 crisis has pushed the democratization of big data through data-sharing schemes; however, access to data sources may be limited to specific groups of users, mainly due to privacy concerns. Alleviating the inequality in access to big data while protecting the users' privacy is another challenge that needs to be addressed.

## Conclusions

Improving the resilience of cities has never been more important given the rising risks of disasters due to rapid urbanization and climate change trends. The dynamic disaster resilience process is characterized by multiple factors, including antecedent conditions and system interdependencies, event characteristics, absorptive capacities, adaptive resilience, and the recovery trajectories. Big data now enable us to measure the recovery trajectories at an unprecedented high frequency, granularity, and scale. Data-driven complex systems modeling approaches allow us to further measure the intrinsic resilience characteristics of communities using such big-data–enabled observations. This approach brings a paradigm shift in modeling the disaster resilience process and its linkage with the recovery process, paving the way to answering important questions for policy applications via counterfactual analysis and simulations.

*Data Availability.* All study data are included in the main text.

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