Thinking Fast and Slow in Disaster Decision-making with Smart City Digital Twins

Many cities are vulnerable to disaster-related mortality and economic loss. Smart City Digital Twins can be used to facilitate disaster decision-making and influence policy, but first they must accurately capture, predict, and adapt to the city's dynamics, including the varying pace at which changes unfold.

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Cities are increasingly subject to stressors such as heat waves, hurricanes, wildfires, rising sea levels, tsunamis, windstorms, and epidemics. Close to 60% of cities with a population greater than 300,000 are facing high risk of exposure to cyclones, floods, droughts, earthquakes, landslides, and volcanic eruptions with a high degree of vulnerability to disaster-related mortality and economic losses [1]. Local governments, planners, and policy makers play a critical role in managing and reducing such risks, and strengthening cities' resilience and response capacity. To this end, cities are leveraging data, technological advancements, and computational capabilities to facilitate disaster decision-making. However, effective data-driven decision-making—whether it is during preparation or recovery, during moments of crisis, or in the midst of an ongoing disaster—requires a robust capacity for capturing the city's dynamics. This entails recurrently sensing and modeling the state of infrastructure, the human activities unfolding over and enabled by the infrastructure, and their complex interactions, thereby predicting the states of stability and change (i.e., evolution of urban systems). Although the widespread proliferation of sensor installations in cities and the availability of unprecedented levels of data about human-infrastructure interactions brings the promise of improved decision-making, our computational approaches in capturing, predicting, reacting, and adapting to changes in the state of our urban systems need to mirror the pace of change for that promise to be realized.

Fast and Slow Urban Dynamics

Change processes in urban human-infrastructure systems do not occur on a single timescale, but as a mix of slow incremental changes in the physical structure of cities (e.g., transport construction with an average lifetime of decades) with a range of fast fluctuations (e.g., daily mobility) influencing the way these changes unfold [2]. Similarly, control responses to these changing phenomena are only needed at certain cycles and are driven by the urgency of applicable decisions to be made. For example, managing highway throughputs, modeled for routine operations, demands a slower pace of decision-making than during emergency evacuations when throughput capacities are impacted by the emergency event (e.g., flooding during a hurricane).

As conceptually illustrated in Figure 1, fast and slow change processes in the real world are reacted to by fast and slow control responses. Data-driven disaster decision-making is analogous to Daniel Kahneman's Nobel Prize-winning research on human decision-making and the two—fast and slow—systems that support human decisions [3]. Kahneman's theory suggests that human cognition is governed by two systems: system 1, fast mode of thinking driven by intuition and heuristic processes, and system 2, slow, more analytical, mode of thinking. However, data-driven disaster decision-making is driven both by the decision maker's thinking process, and by the quality of the data-driven model in use in capturing fast and slow change processes in the real world. Therefore, it is crucial that our computational models evolve to account for fast and slow urban dynamics.

[insert Figure 1 approximately here]

When Change is Fast

Capturing and modeling the real world becomes particularly critical when the change processes are fast. In developing predictive models for slower change processes (e.g., climate prediction on the scale of years to decades), we tend to rely on slow retrospective data with lower levels of uncertainty. As the pace of change increases (e.g., flooding on the scale of minutes to hours), we are faced with higher levels of uncertainty coupled with curtailed response times. In other words, when change is fast (e.g., in the event of an earthquake), rapid response relies on the quality of fast decision-making. This is informed by the speed of capturing and predicting states of change in the real world through real-time and predicted data, as we can no longer only rely on retrospective data. Timely predictions of weather variables (that is, cloud coverage, precipitation, snow, wind speed, temperature, humidity, visibility loss, lighting, and so forth), for example, can enable short-term weather—especially severe weather—predictions. Predictions on the scale of minutes and hours are essential in informing early warning systems, enabling rapid emergency response, and initiating timely communication with communities. In 2020 alone, 60,714 such events in the US resulted in 585 deaths and 1,708 injuries [4]. Such predictions can inform decisions on weather related accidents and could result in fast decisions that save more lives.

Smart City Digital Twins

A promising data-informed computational approach to modeling and predicting a range of phenomena in urban areas is the emergence of Smart City Digital Twins (SCDTs) [5]. SCDTs are "living digital replicas of a city that are continuously updated with real-time data and analytics on interactions between humans, infrastructure, and technology" [6] that can offer more holistic views of the changes that take place in a city. They couple real and simulated versions of city infrastructure systems to track states of spatiotemporal flux and create synergistic feedback loops between the two systems, offering the promise of a real-time decision-making support system for smart cities. As it evolves in parallel with the real system, a SCDT enables hyperlocal decision-making through monitoring, assessment, and "*what if*" scenario prediction and adaptation across urban systems [5, 7]. However, such capacity requires the digital twin to be progressively cognizant of the pace and magnitude of change processes across urban human-infrastructure systems at varying timescales. Planners, policy makers, and government officials are not only faced with a dyadic fast- and slow-decision-making, but also with a range of in-between layers of transitional states across all phases of the emergency management cycle (i.e., mitigation, preparedness, response, recovery [8]). While planners may be well prepared to make decisions on slow changing phenomena (related to preparedness and devising mitigation strategies), control decisions made during fast changing response times can very well generate new feedback loops of human-infrastructure interactions that would challenge the reliability of previous decisions made. Once the pace of decision-making goes beyond the threshold of urgency and the influencing factors become dynamic, a SCDT needs to be able to adapt and autonomously capture and predict across a dynamic range of changing phenomenon, which will depend on whether the conditions require preparing for, reacting to, or recovering from a disaster event.

Model Synthesis and Nowcasting

Synthesizing disaster dynamics across multiple timescales in SCDT decision-making models is critical in providing timely responses to various disaster control measures such as fluctuating demand for infrastructure services, allocation of assets, and managing risks. Synchronization of a SCDT, ideally done in real-time, crucially relies on the availability of uninterrupted data from the real system. Heterogeneous urban data that progressively feed the SCDT are obtained at mixed (fast and slow) frequencies, often with substantial latencies, which complicate the data fusion process. Dynamic association of SCDTs with the city at both levels of data fusion and predictive model generation, while incorporating all the endogenous and exogenous variables across fast and slow timescales, is complex. Current understanding of the research community on how digital twins should best integrate heterogeneous data generated at mixed frequencies to model city evolutionary dynamics is limited. In order for the modeling efforts to be based on a more complete understanding of urban dynamics across mixed frequencies of changing phenomena, and driven by the desired (fast) pace of decision-making, we must advance our understanding of the multi-timescale nature of digital twin dynamic modeling.

Among dynamic models accounting for multiple timescales, a number of studies have shown that mixed frequency nowcasting models [9]–[12] are capable of handling irregularities of heterogeneous data (i.e., mixed frequencies and latencies) in real-time and recursively updating predictions. Nowcasting, increasingly used in meteorology, economics, and healthcare, refers to an objective, near-term (often ranging from +0–6-hrs) estimate of current states, or short-term forecasting. It relies heavily on the availability of rapidly updated, high-resolution observations. However, current nowcasting models have limited representation of physical processes and the object of interest is often low frequency variables such as quarterly gross domestic product (GDP) growth. We lack scientific research investigating the applicability and scalability of nowcasting approaches in developing integrated predictive models of SCDTs for dynamic disaster decision-making across both fast and slow timescales.

Vector auto regressive (VAR) models [13], for example, are widely used in macroeconomics to jointly model the dynamics of economic variables. Despite the dependency of each variable on past patterns of all other variables, patterns of correlation of the forecast errors in these models remain unconstrained. Such overparameterization becomes problematic in the already high dimensional setting of SCDTs, with both static and dynamic variables. Bayesian VARs (BVARs), incorporate a naïve prior model that assumes random-walk evolution for all variables. However, the challenge of making inferences on the model's parameters in the face of data irregularities (i.e., missing data, mixed frequency, and so forth) when nowcasting with large BVAR models remains.

Dynamic Factor Models (DFMs) [11] assume that observations of different variables in time are driven by a few unobserved dynamic factors, and features specific to each variable are captured by errors. These models handle the mixed-frequency data by initiating the model at the highest available data frequency and treating the lower frequency data as a filtered version of latent high-frequency data that are missing at certain intervals using likelihood-based methods and Kalman filtering techniques [11]. More complex models integrated with Machine Learning (ML) algorithms are particularly suitable for improving the DFM by handling data with a larger number of possible regressions [14], although these models are more effective for slower timescale (e.g., seasonal) predictions. In capturing disaster dynamics at a city scale, these models need to both scale to encompass the increasing dimensionality and to control for exogenous variations along with their long vs. shortlived effects. High dimensionality is often addressed by model approximation, which may compromise the ability to capture interdependencies of human-infrastructure interactions.

More recently, researchers have established promising mathematical foundations for digital twin modeling and coupling dynamical systems based on probabilistic graphical models integrated within data-driven analysis and decision-making feedback loops [15]. However, in order to achieve scalability for SCDTs, we are still challenged by the need for improved parameterization inclusive of appropriate exogenous controls, reduced order modeling, and model assumptions to be relaxed.

Concluding Remarks

Change processes across urban human-infrastructure systems occur at not a single, but a range of temporal scales and we are faced with the challenging task of modeling a range of dynamic associations between SCDTs and the real city infrastructure. Building on existing models that can, with limitations, capture irregularities of scale and mixed frequency data (e.g., BVAR/DFM models), future research on digital twin modeling should advance in the direction of multi-timescale prediction as a critical next step in supporting dynamic disaster decision-making. The bottleneck in this direction is encompassing increasing dimensionality while capturing mixed frequency data and controlling for exogenous controls with varying temporal effects. Investigating computational methods by which digital twins can best integrate heterogeneous data generated at mixed frequencies to model city evolutionary dynamics is central to this effort. Inevitably, dynamic modeling of SCDTs also escalates into the spatial dimension. Identifying the most relevant spatial scale and aggregation by which disaster dynamics and real world change processing need to be captured is yet another poorly explored area of research. Future research should expand computational modeling efforts in all three dimensions of time, space, and frequency, investigating ways to control for both endogenous and exogenous change processes in urban systems. Understanding the multi-spatiotemporal scale nature of SCDT dynamic modeling is a first step towards providing timely responses to various control measures in urban disaster and risk management.

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Author Contributions

N.M. and J.T. conceived and designed the research, wrote the first draft, edited the manuscript, contributed to revisions, and approved the manuscript.

Competing Interests

The authors declare no competing interests.

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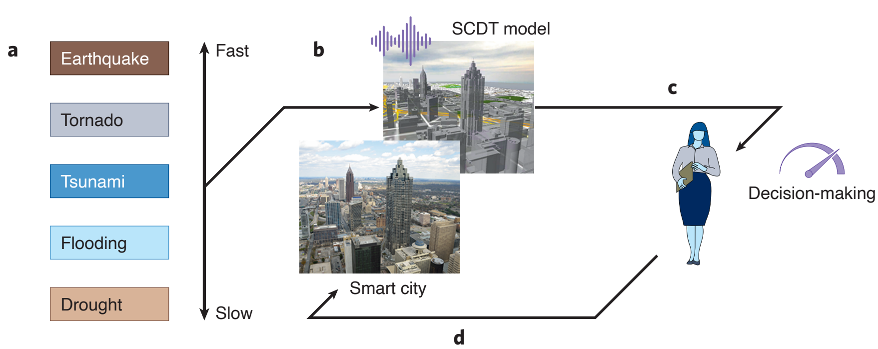
Figure Captions

Figure 1. Fast and slow disaster decision-making dynamics.

a, Fast (e.g., earthquake, tsunami) and slow (hurricane, wildfire) onset disaster events result in change processes in real cities that vary in terms of the pace and duration of change. **b**, Heterogeneous data needs to be captured at mixed-frequency and integrated into Smart City Digital Twin (SCDT) models in real-time at the corresponding frequencies that change processes are taking place. Both fast and slow modes are integrated into the same SCDT model, which is progressively updated in parallel with changes in the real world. **c**, A SCDT informs decision-makers who must use a combination of fast and slow thinking to adaptively devise interventions at various levels of urgency. **d**, Decision-makers generate time critical decisions that impact the real environment and the cycle continues as new interventions—and ultimately new policies/strategies—generate new, iterative change processes in the real world.


a
Earthquake
Tornado
Tsunami
Flooding
Drought
Fast
Slow
b
SCDT model
Smart city
c
Decision-making
d