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Resilience of Mobility-Infrastructure Networks

Model and Data-Driven Investigations in the Greater Los Angeles Area

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Motivation:

Increasing Exposure to Disasters

- **COST** of disasters have exceeded $2.5 trillion in the 21st century—a figure that is at least 50 percent higher than previous estimates [1].

- **FACTORS** such as urban inequality, increasing hazard exposure, rapid urbanization and the overconsumption of energy and natural capital are causing unprecedented risks to urban communities.
- **FUTURE** of increase in frequency and severity of extreme weather events, threats of terrorism, and the risk due to existing earthquake active faults near urban areas, cities will be facing an increasingly complex resilience challenge.

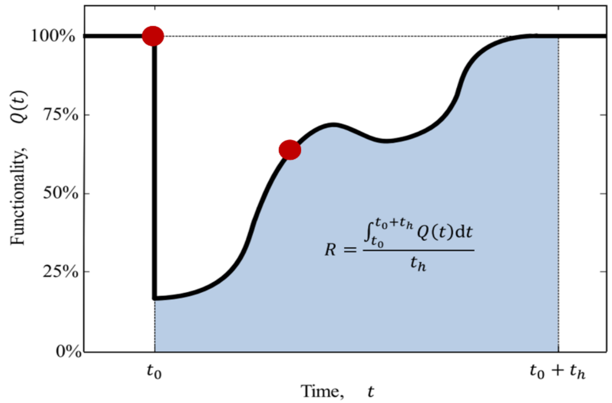
Hurricane Katrina, 2005

CA Wildfires, 2018

Motivation:

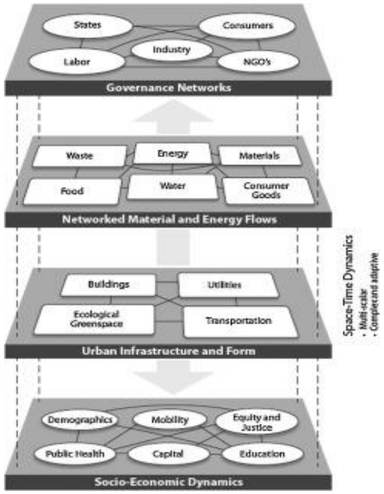
Taking on the Urban Resilience Challenge

- **URBAN RESILIENCE** refers to the ability of an urban system –and all its constituent socio-ecological and socio-technical networks across temporal and spatial scales– to **maintain** or **rapidly return to desired functions** in the face of a disturbance, to adapt to change, and to quickly transform systems that limit current or future adaptive capacity [2].



- **URBAN SYSTEM** is characterized by its governance networks, networked material and energy flows, urban infrastructure and form, and socio-economic dynamics [2].

- Among all, **civil infrastructure systems (lifelines)** constitute the foundation that supports the lives, interactions, and dynamics of urban dwellers.



Figures from [2] and [10].

Motivation:

Mobility in the Shade of Disasters

- It is argued that transportation is the most significant lifeline: **disturbance to transportation imposes extra burden on the other lifelines** [3].
- Mobility of people and goods is an immediate functional need in the immediate aftermath of and the recovery from disasters.
- Rapid recovery from transportation disturbances is one of the principal enablers of disaster resilience.

Hurricane Harvey, 2017

Motivation:

Poor Infrastructure Conditions Jeopardizing Mobility

- Most recent ASCE report grades nation's roads and bridges at **D and C+,** respectively [4].

- The poor condition of the United States' transportation infrastructure weakens the ability to support human mobility under the influence of disasters.

- Alarming situation for **metropolitan areas in seismically active regions**, as the implications of disruption to transportation infrastructure can far exceed the cost to repair or replace its constituents.

A sinkhole on West Boulevard in 2017

Motivation:

Models and Data are Increasingly Available

- Scalable urban mobility data are increasingly available from both conventional and novel sources. These data include commuting data from Census Transportation Planning Products (CTPP), mobility data from social media and smart phones, etc. [5-7]

- Modeling technology has advanced and many MPOs develop and maintain large scale travel demand models (e.g., SCAG RTDM).

Background:

Topology-Based vs System-Based Approaches in Transportation Vulnerability and Resilience Research

Topology-Based

- ✓ Graph-theoretical representation
- ✓ Practical, not data hungry
- ✓ Abstract thinking

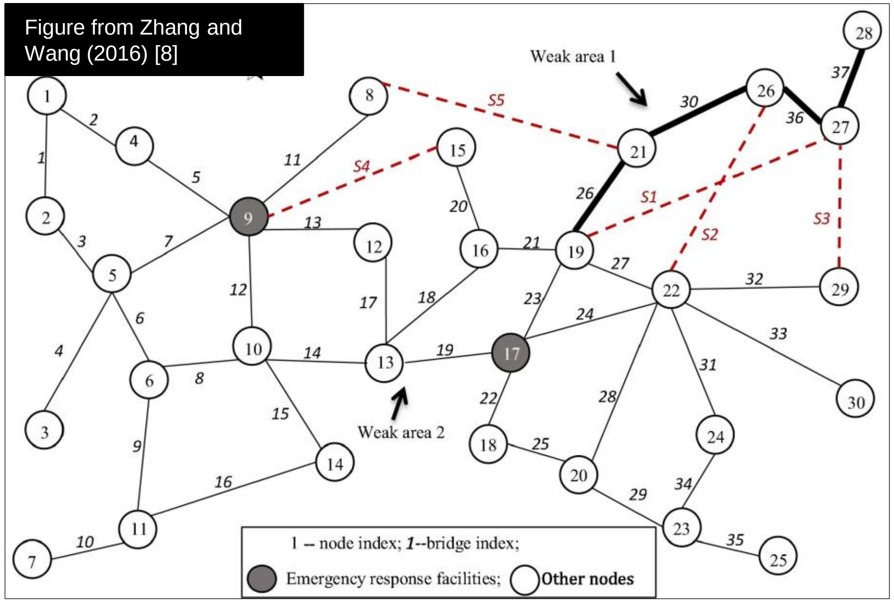
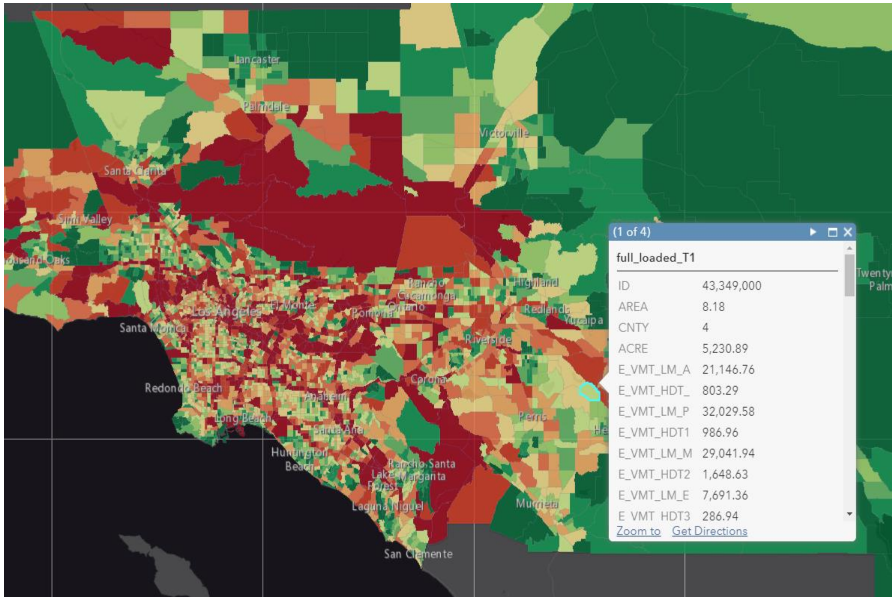


Figure from Zhang and Wang (2016) [8]

System-Based

- ✓ Models demand and supply
- ✓ Extensive data/modeling reqs.
- ✓ Concrete thinking



Background:

Network Analysis for System-Based Transportation Resilience

Lack of comprehensive resilience assessments that utilize **explicit** and **holistic** network models of large metropolitan areas.

- Historically due to limitation of tools and computational power.
- Results in an over-simplified abstraction of physical transportation networks when they could explicitly be modeled.
- Does not allow realistic hazard simulations to be incorporated into the analyses.

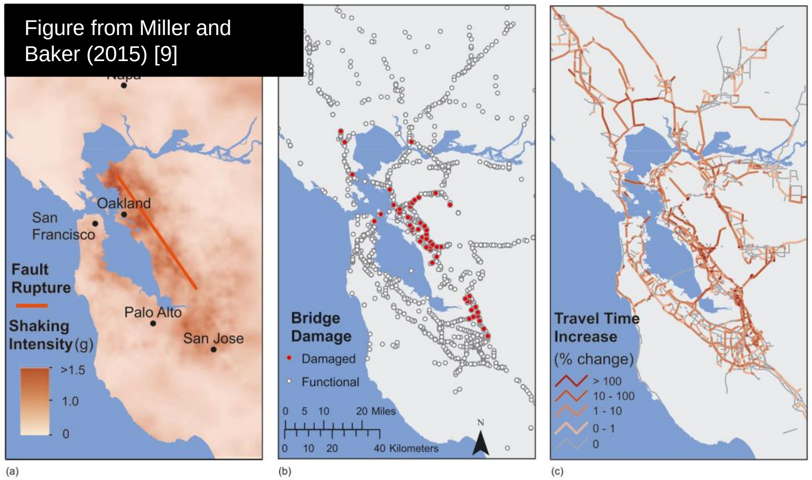
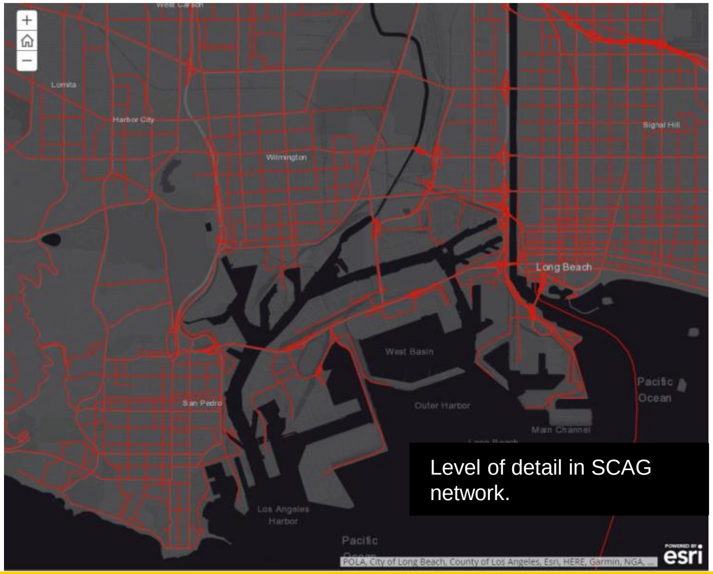


Figure 2. Illustration of the risk framework for one earthquake scenario including: (a) one-second spectral acceleration (ground-motion intensity) map with earthquake rupture, (b) bridge (component) damage map, and (c) travel time increase (network performance measure) values.

vs.



Background:

Hazard Analysis for Transportation Resilience

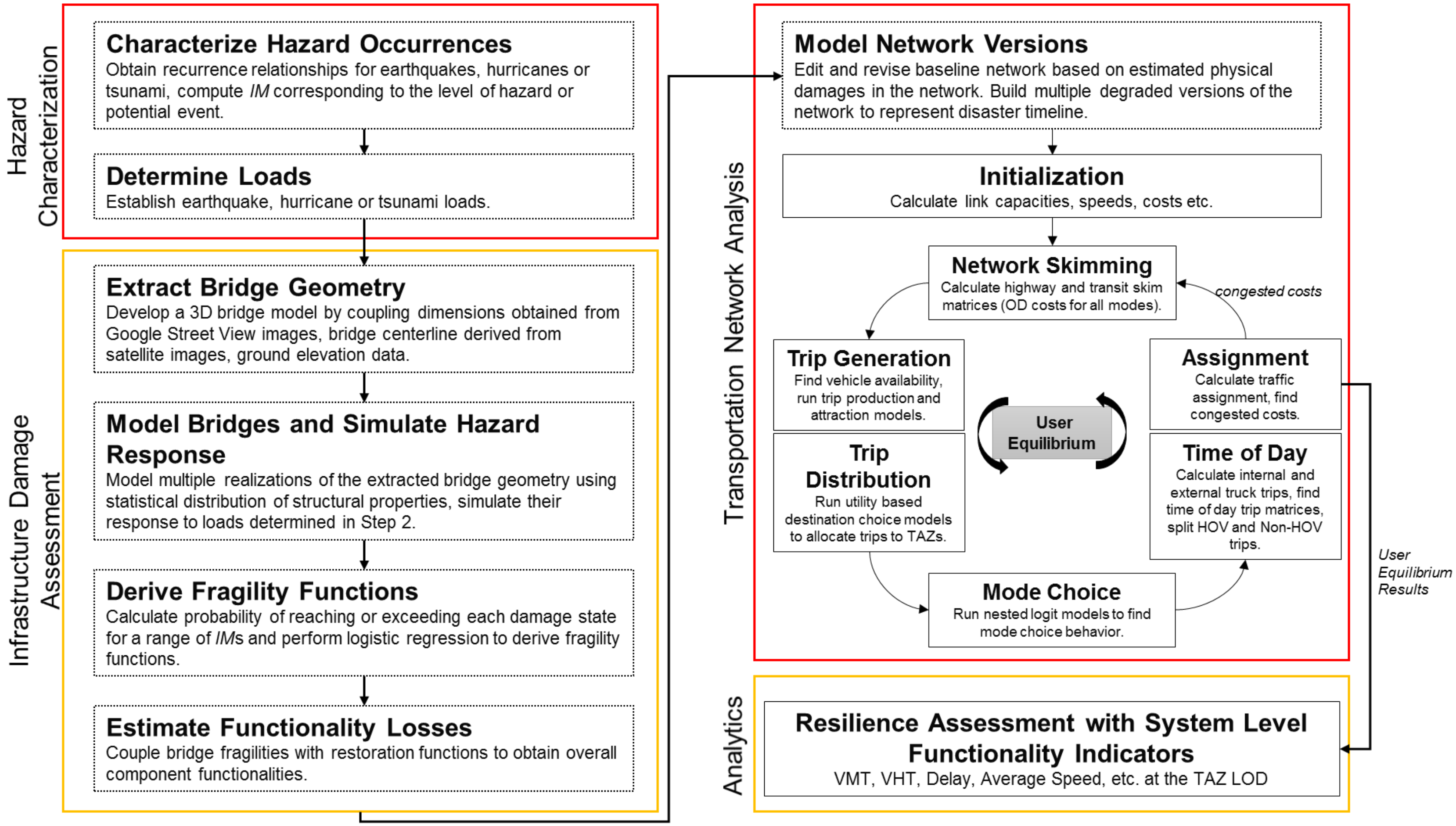
- Sophisticated analyses of the hazard itself are rarely included.
- Researchers traditionally resort to simple **what-if scenarios** or **coarse binning procedures** for quantifying physical damages.
- Many structure-specific and site-specific details are disregarded.

Bridge Inventory around Ports of LA/LB.

Bridge closures on day 7 after scenario EQ.

Objective and Methodology

Comprehensive and Actionable Assessment of Transportation Resilience in Metropolitan Areas



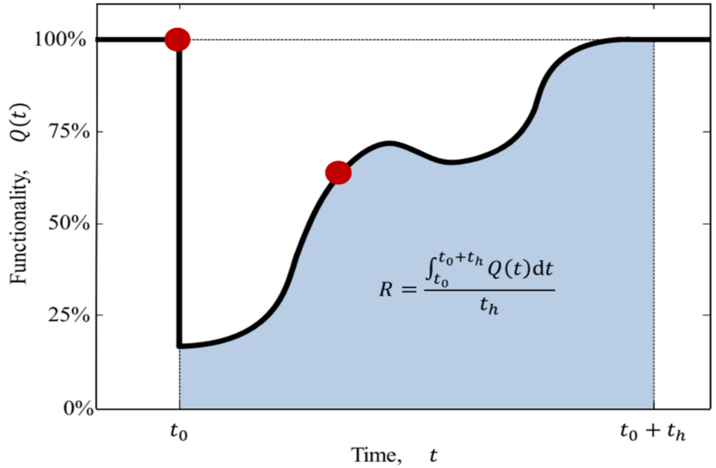
Methodology

Network Resilience

- $$R = \frac{1}{h}\int_{t}^{t+h} Q(t)dt$$

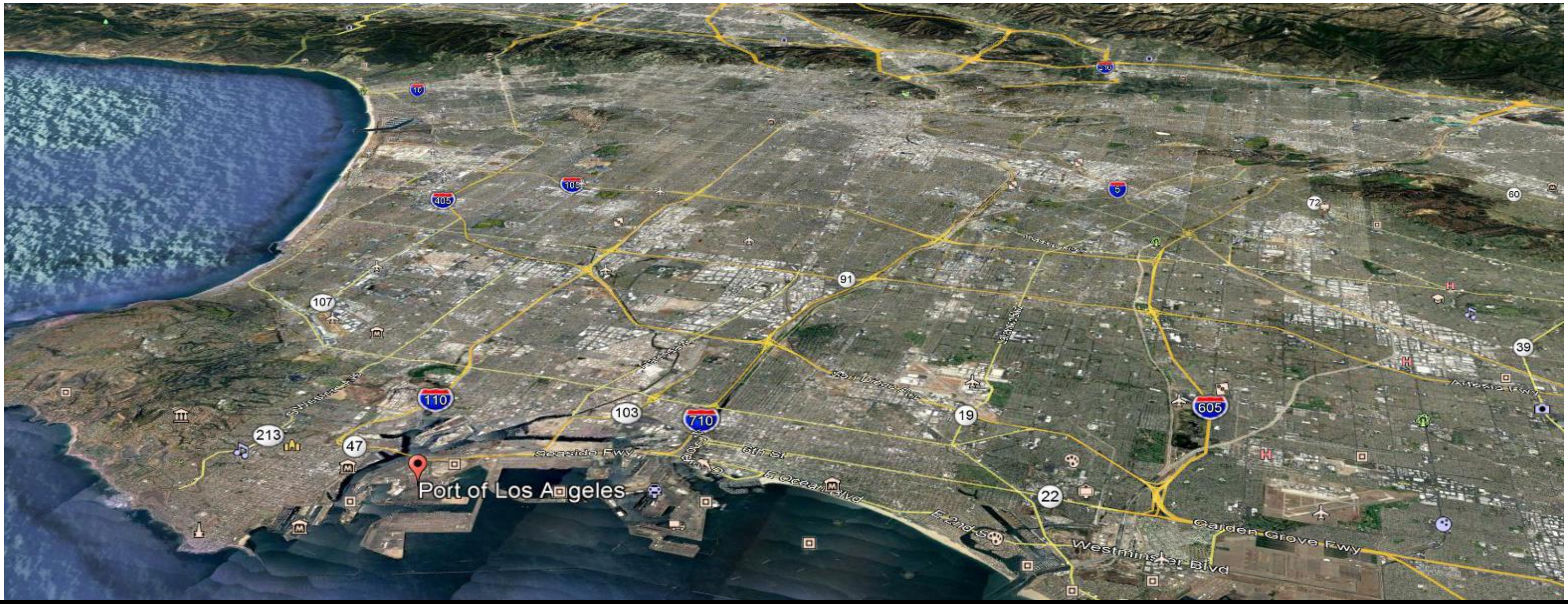
  where t is the instant in which the disruption occurs and h is the investigated time horizon and Q(t) is an indicator of functionality.

- For transportation networks, several functionality indicators have been proposed in the literature with system total travel time (Vehicle Hours Traveled: VHT) and total travel distance (Vehicle Miles Traveled: VMT) being common to most system-based indicators [10].



Case Study: 7.3M Earthquake in Palos Verdes

Title: Granular Simulation of Bridge Closures due to a Southern California Scenario Earthquake and its Effects on the Disruption and Recovery of Freight Traffic to and from Ports of Los Angeles and Long Beach, *Proceedings of the ASCE International Conference on Sustainable Infrastructure 2019*.



- Ports of Los Angeles and Long Beach are largest container terminals in the US (>15 million TEUs, 40% of imports and 25% of exports).
- Disaggregated probabilistic seismic hazard (PSH) results for a return period of 975 years.
- Governing seismic hazard is identified as the Mw 7.3 earthquake caused by a rupture of the Palos Verdes connected fault system
- 95 bridges modeled with the image-based methodology, rest of SCAG inventory complemented from HAZUS.

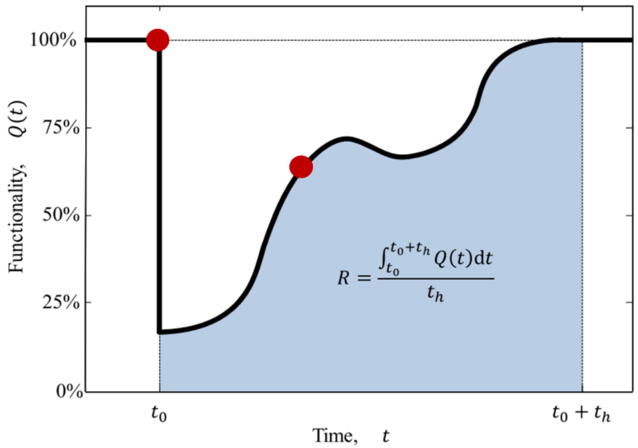
Case Study: 7.3M Earthquake in Palos Verdes

- 55 bridges were below 75% functionality and deemed closed on day 30.
- These closures were modeled on TransCAD by revising the SCAG network.

Case Study: 7.3M Earthquake in Palos Verdes

- Expectedly, network functionality indicators such as TTT (total travel time traveled), TTD (total travel distance covered) and delay were shown to indicate higher congestion levels as well as increasing travel costs.
- Authors also published a publicly available ArcGIS ‘story map’ visualizing data on bridge closures, impacts on container truck traffic, etc. at a high spatial resolution, results aggregated to 4,192 TAZs https://arcg.is/1GTvLX0.

Traffic Direction	Functionality Indicator	Baseline	Day 30	% Increase
From Ports to all TAZs	TTT (1000 mins)	267.52	340.31	**27.21**
	TTD (1000 miles)	211.04	225.90	**7.04**
From all TAZs to Ports	TTT (1000 mins)	287.27	347.85	**21.09**
	TTD (1000 miles)	223.01	230.52	**3.37**



Understanding the Demand Side

- **Fixed demand assumption** where uncertainty and travel time unreliability are factors that affect travel behavior.

- Travel behavior after catastrophic events is still not well understood. Empirical data on such events have only become available recently with the help novel data sources and methods to utilize them.

- Still, waiting for an EQ to collect data is not a viable option!

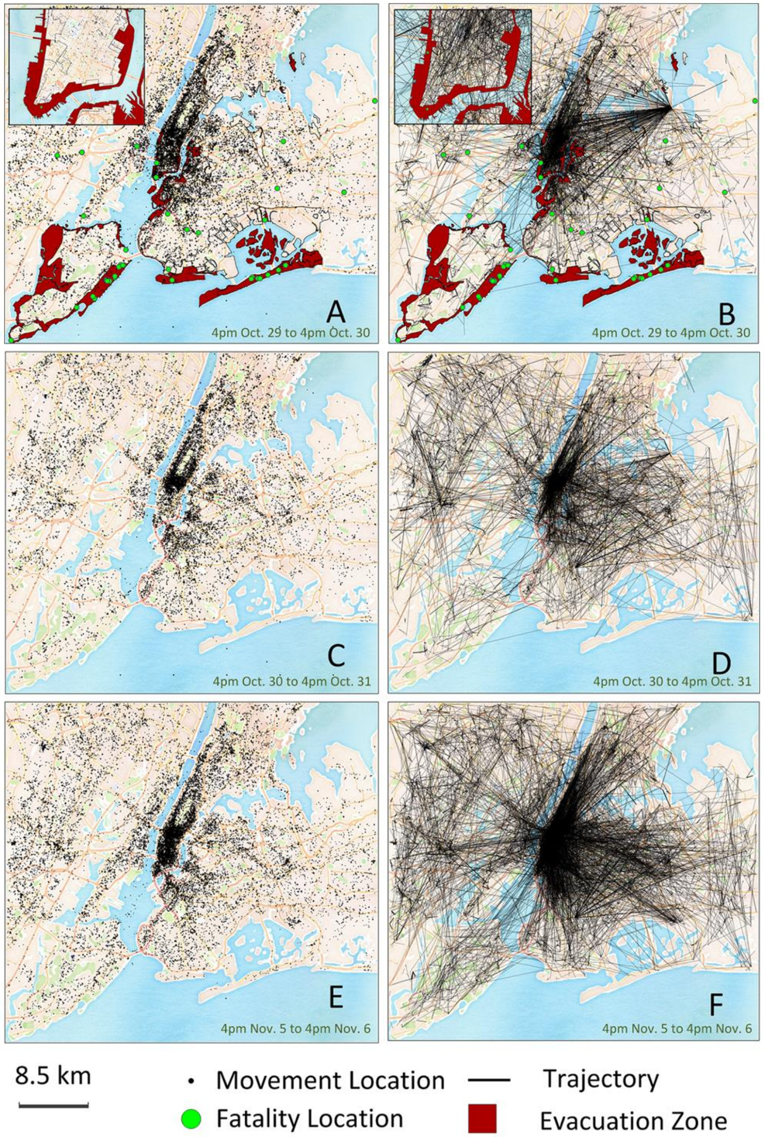
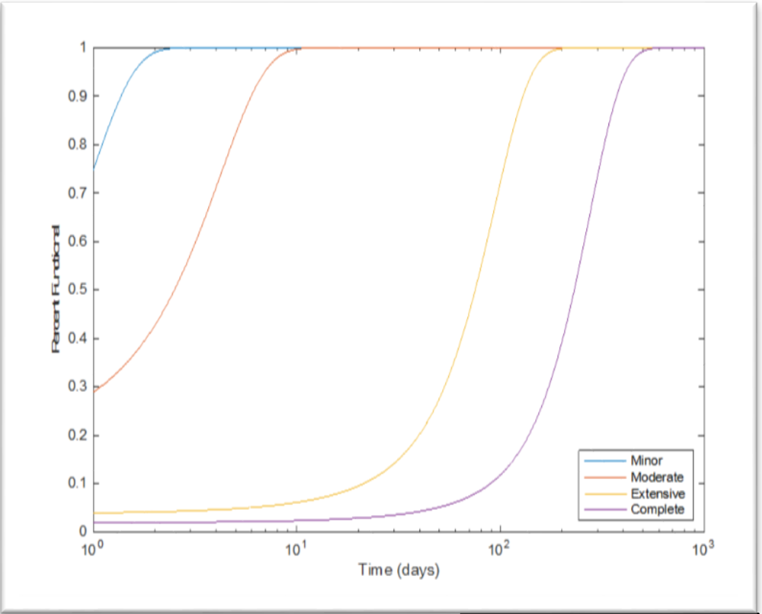


Figure from Wang and Taylor (2014).

Mobility before, during and after Hurricane Sandy in 2012.

Understanding Recovery and Adaptation

- Literature on infrastructure component restoration functions is limited.
- Virtually no data on recovery capacity and closure policies.
- Simplifications made in defining bridge closures may affect the accuracy of the obtained results.
- Adaptation options need to be investigated.
  - What are the critical corridors given disaster scenario?
  - How to find optimal repair and recovery strategies?
- Environmental impacts of surging travel time and distances need to be studied.

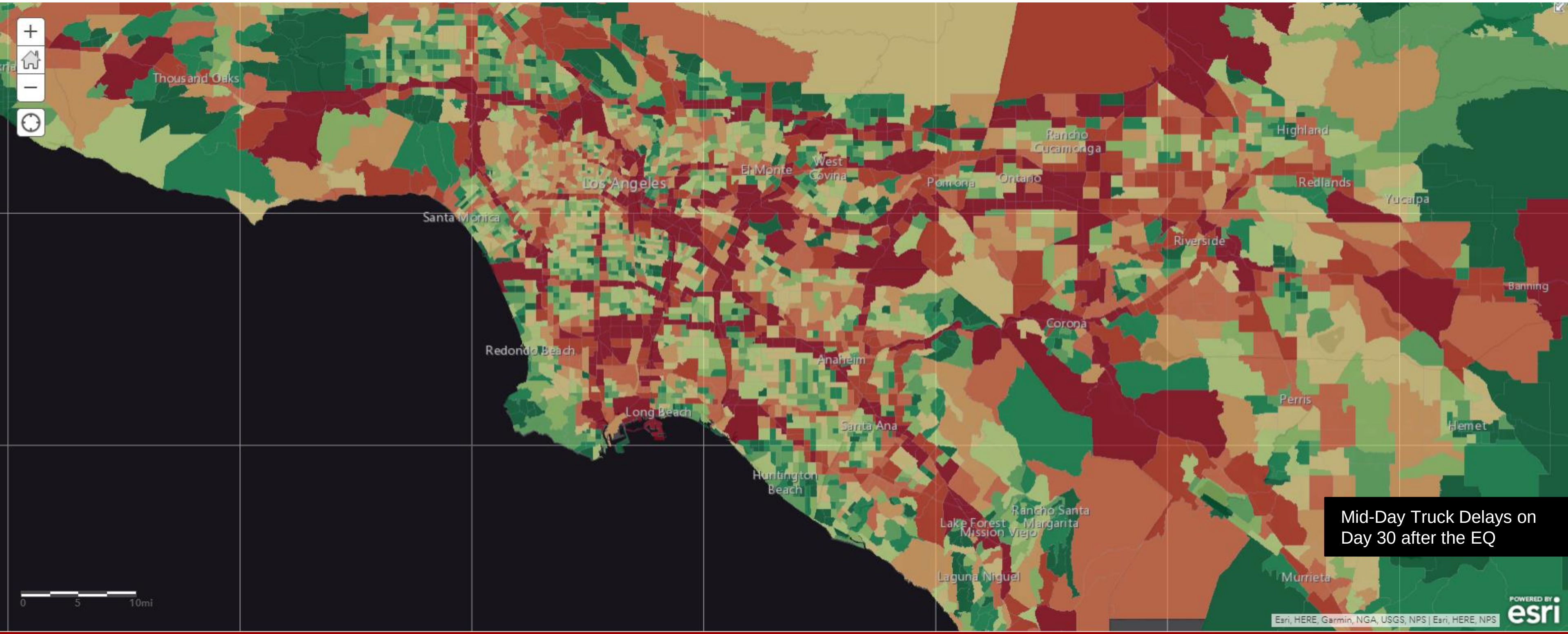


ATC-13 Bridge Restoration Curves

Conclusions

Granular assessments incorporating hazard, inventory and network modeling approaches show promise

- Methodology combining (1) hazard loss assessment through novel image-based inventory modeling coupled with traditional approaches and (2) system-based transportation network resilience assessment realized with a large-scale travel demand model of a metropolitan area.



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