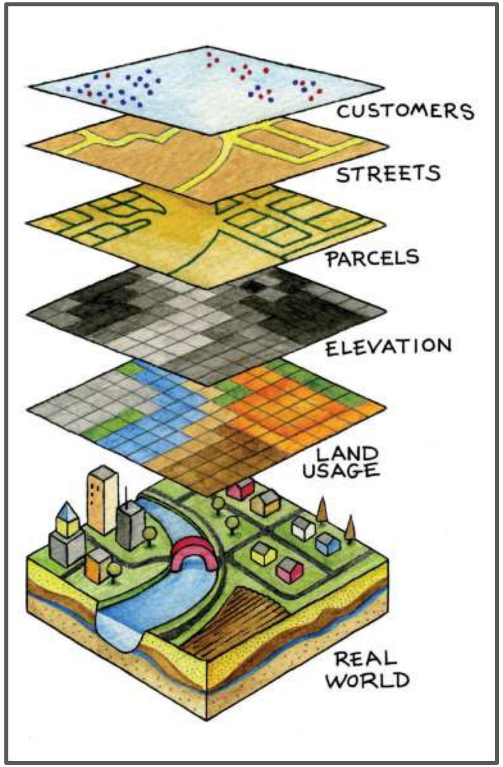
HumNet Lab

UC Berkeley USA – Dec 2021

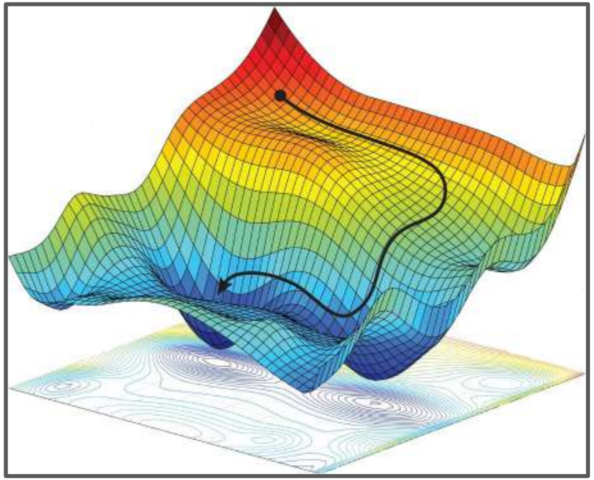
An interdisciplinary data-science approach to managing natural hazards risk

MARTA C. GONZALEZ
CRISTOBAL PAIS
MINHO KIM
JOHN RADKE
UNIVERSITY OF CALIFORNIA, BERKELEY

High-level Flow diagram

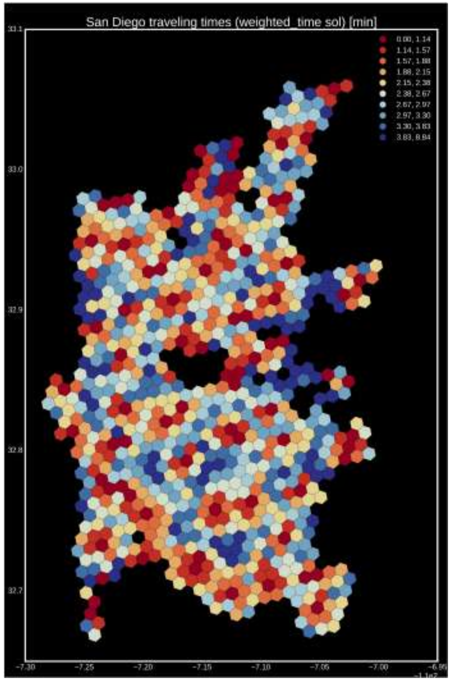


Data layers



Optimization model

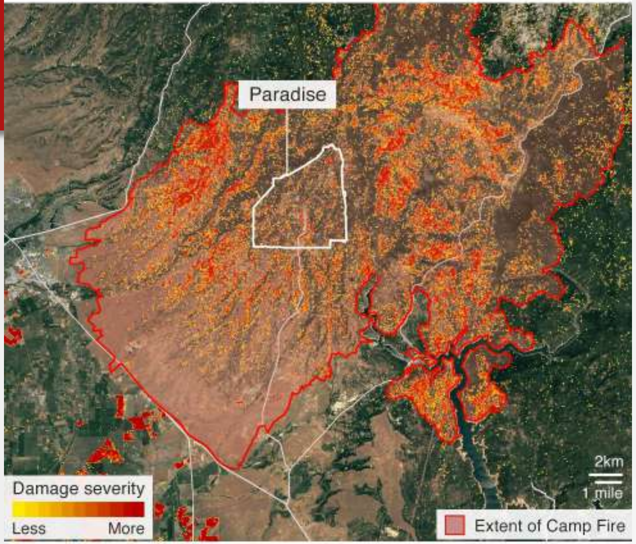
- Decisions
- Constraints
- Objective



Outputs & analysis

Fire Hazards

Camp Fire: Damage assessment



Source: NASA Earth Science Disasters Program

Oakland firestorm of 1991

3,280 structures; 6 km^2

Losses near 3 billion (in 2020 $s)

October 19–23, 1991;

Caused by an incompletely extinguished grass fire

Camps Fire (Paradise), 2018,

18, 804 structures ; 621 km^2, October 19–23, 1991; caused by a

Costs: $16.65 billion

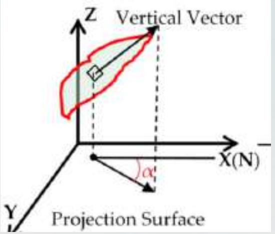
November 8 – November 25, 2018

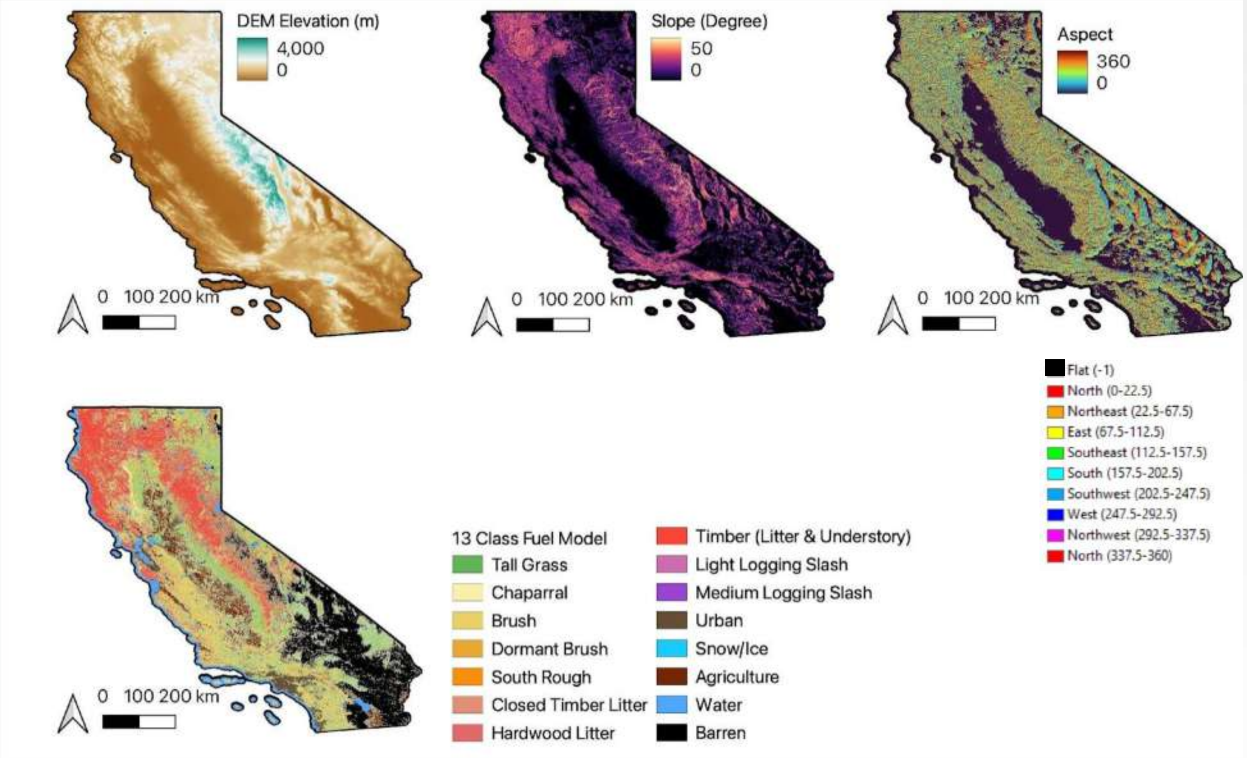
Caused by PG&E power line failures during high winds .Drought was a factor: Paradise, which typically sees **5" inches of autumn rain by November 12, had only received 1/7" by that date in 2018**

Input Layers

Data: Fire Behavior Model by FlamMap

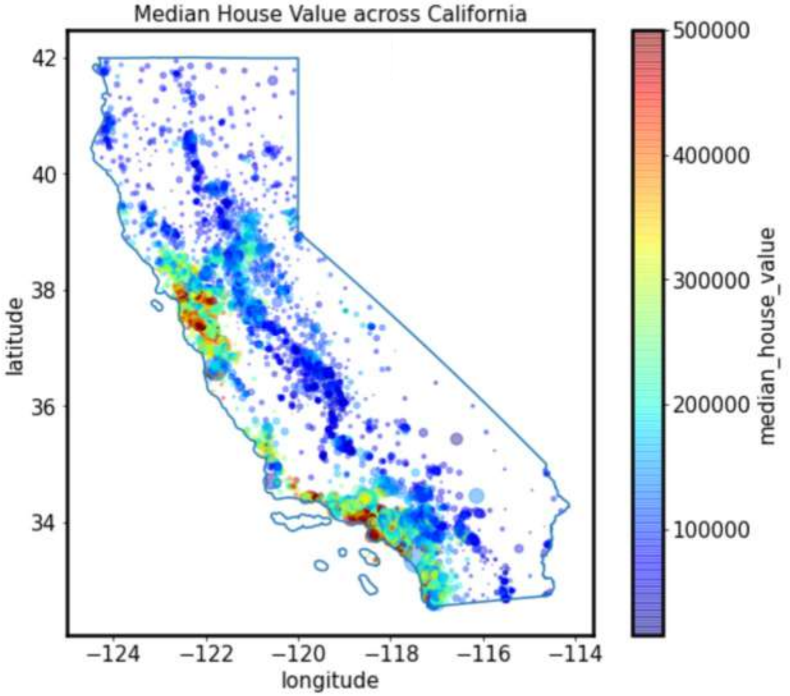
Driver	**Data Layer**
Topography	Elevation
	Slope
	Aspect
Vegetation	Fuel Model
	Canopy Cover
	Canopy Base Height
	Canopy Bulk Density
	Canopy Stand Height
Weather	Precipitation, temperature, relative density, wind speed, wind direction



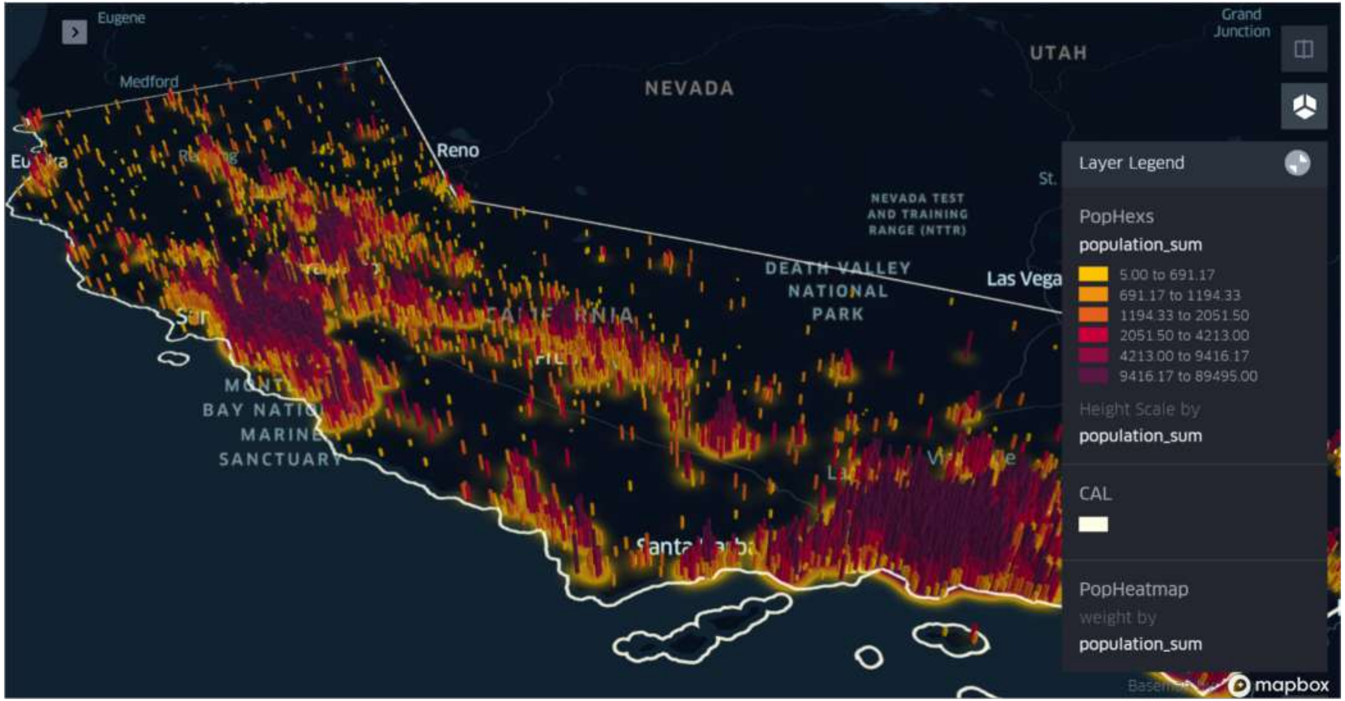


Data: Median house values

- **Dataset**: Median house value across California 2020 (source: Zillow).
- **Location:** Multiple sample points from zip level analysis.
- **Total area covered:** State level.



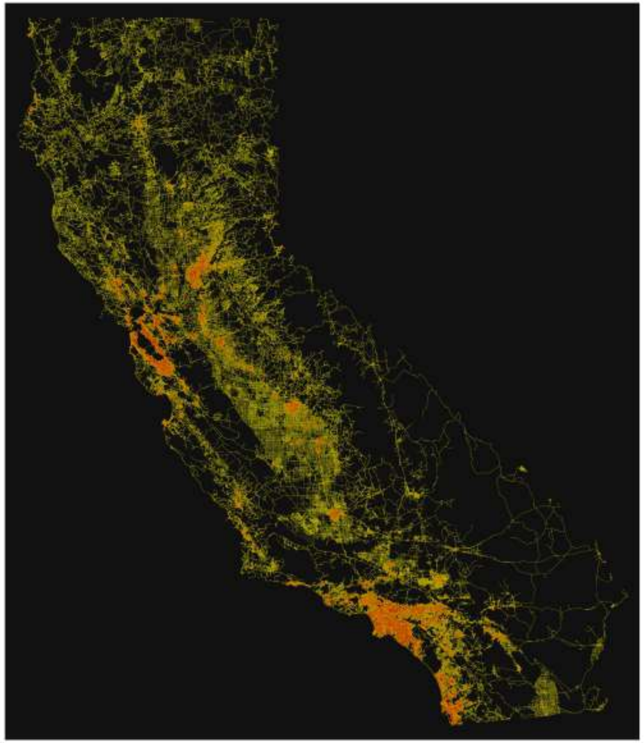
Data: Population



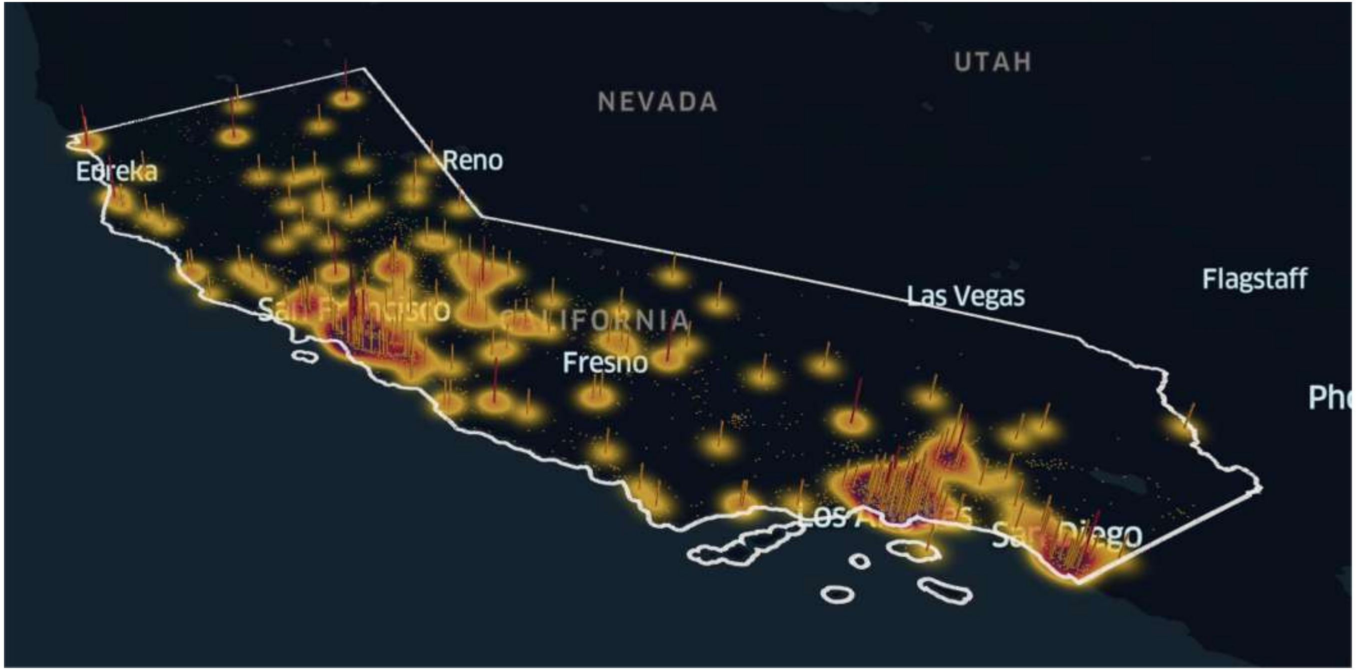
- **Dataset**: Population California (source: Census).
- **Total area covered:** State level. Granularity at a block level.

Data: Street network and expected travel times

- **Dataset**: State level road network. Total of **2,456,671 nodes** (including intersections and dead ends) and **6,039,371 edges**.
- **Traveling times:** *OpenStreetMap* and publicly available traveling times from ride sharing companies.
- **Total area covered:** State level.



Data: Wildfire and related



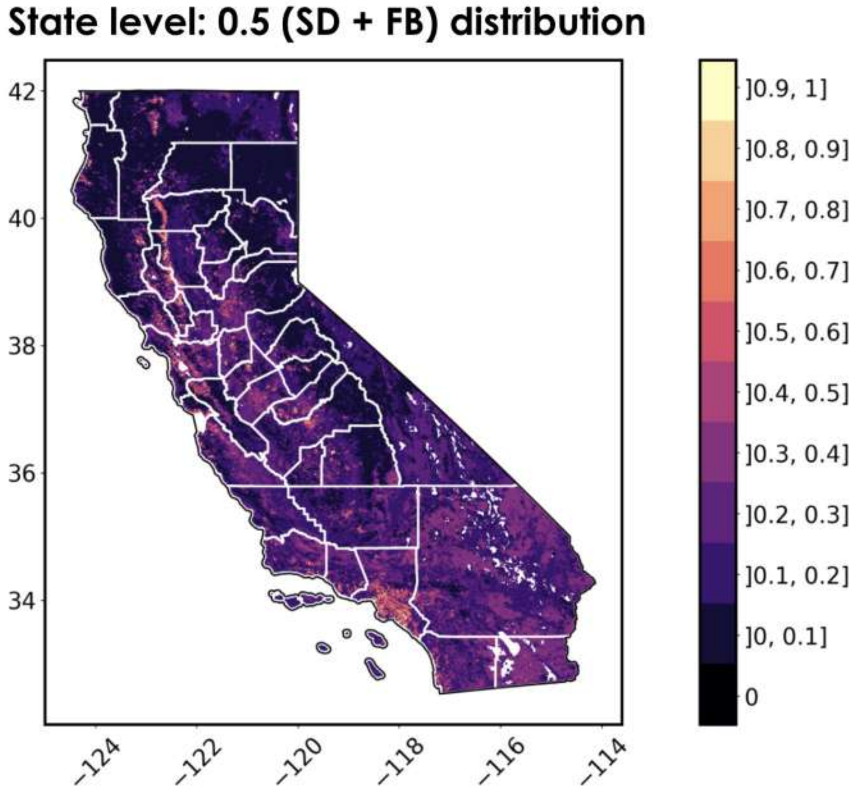
Location of fire stations (3150) across the state.

CALFIRE: https://wifire-data.sdsc.edu/es_AR/dataset/cal-fire-facilities-for-wildland-fire-protection
Homeland Infrastructure Foundation-Level Data (HIFLD): https://hifld-geoplatform.opendata.arcgis.com/

Tessellation: Resolution and aggregation patterns

- We use **h3 library** from Uber
- **Dynamic and adaptable** tessellation depending on the data resolution
- Effective for **statistic** and comparison: the distance between the centroids of the neighbors is always the same (in contrasts, e.g., to squares, triangles, and other schemes).

RI: Risk index definition


State level: 0.5 (SD + FB) distribution

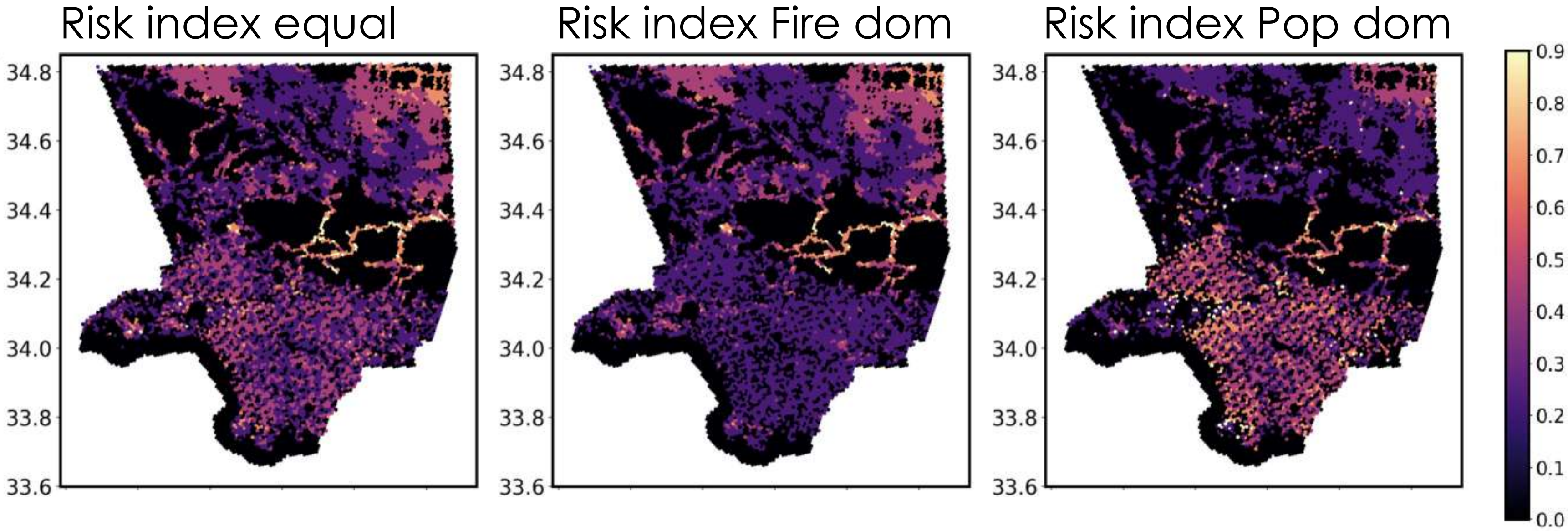
$$RI = 0.5 \times (FB + SD) \times STTFS$$

$$\mathrm{RI} \in [0, 1]$$

FB: Fire behavior depends on the Rate of Spread
and Fire intensity

SD: Takes as input Population, Median house values

STTFS: Shortest travel time from Fire Station



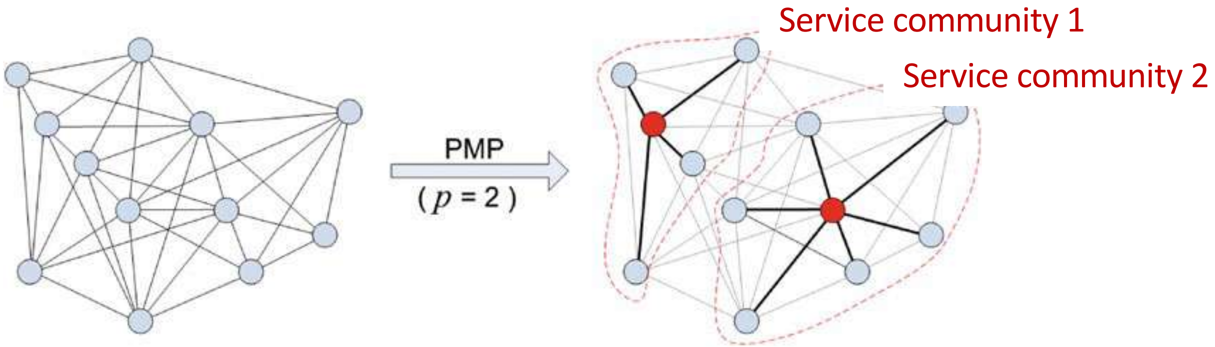
Risk index equal

Risk index Fire dom

Risk index Pop dom

Optimal distribution of facility

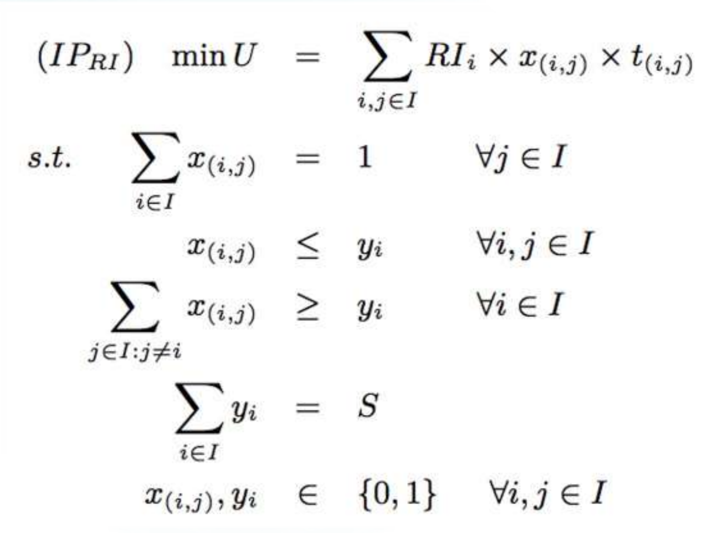
- Given a city, if we know the distribution of population and road network, what’s the optimal distribution to deploy Fire station facilities?
- Problem statement:
  - Minimize the total travel time of the Fire station capabilites.
  - N blocks in a city with population.
  - k of N blocks are assigned with Fire station capabilities
  - People choose facility per the free flow travel time from their residential block to facility block.



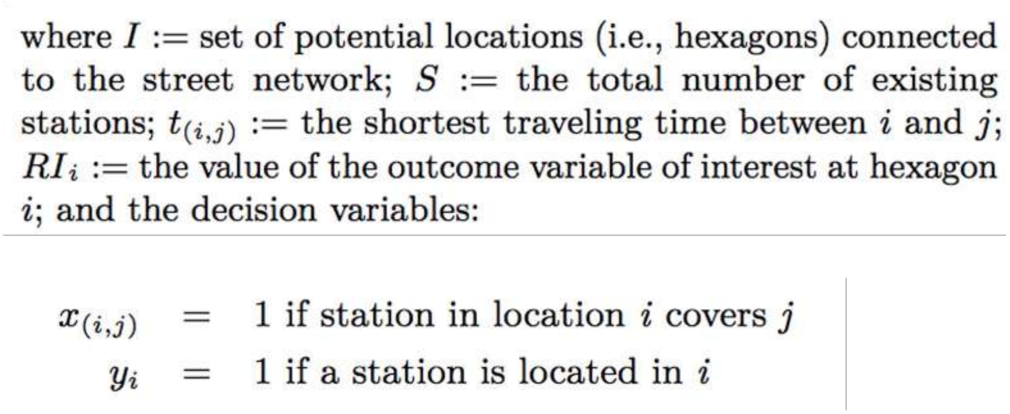
Optimization model

Objective functions

Minimize maximum traveling times from fire stations to nodes/hexs centroids; taking into account risk index given by demographics and fire behavior



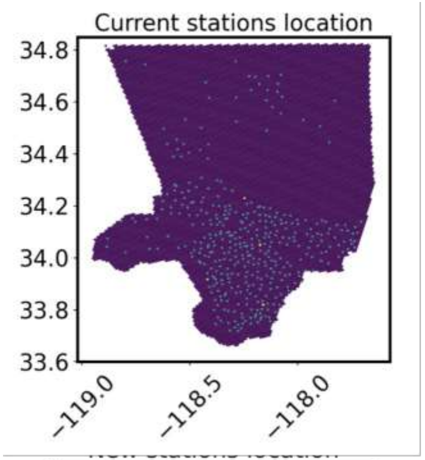
$$
\begin{aligned}
(IP_{RI}) \quad \min U &= \sum_{i,j \in I} RI_i \times x_{(i,j)} \times t_{(i,j)} \\
\text{s.t.} \quad \sum_{i \in I} x_{(i,j)} &= 1 \qquad \forall j \in I \\
x_{(i,j)} &\leq y_i \qquad \forall i,j \in I \\
\sum_{j \in I : j \neq i} x_{(i,j)} &\geq y_i \qquad \forall i \in I \\
\sum_{i \in I} y_i &= S \\
x_{(i,j)}, y_i &\in \{0,1\} \qquad \forall i,j \in I
\end{aligned}
$$

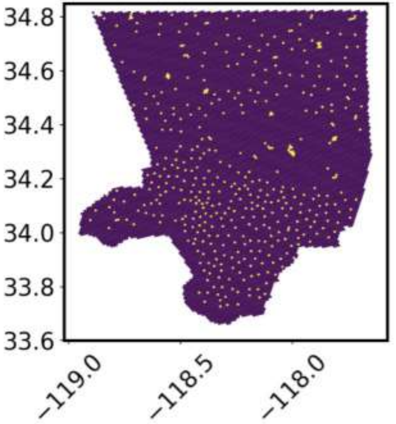


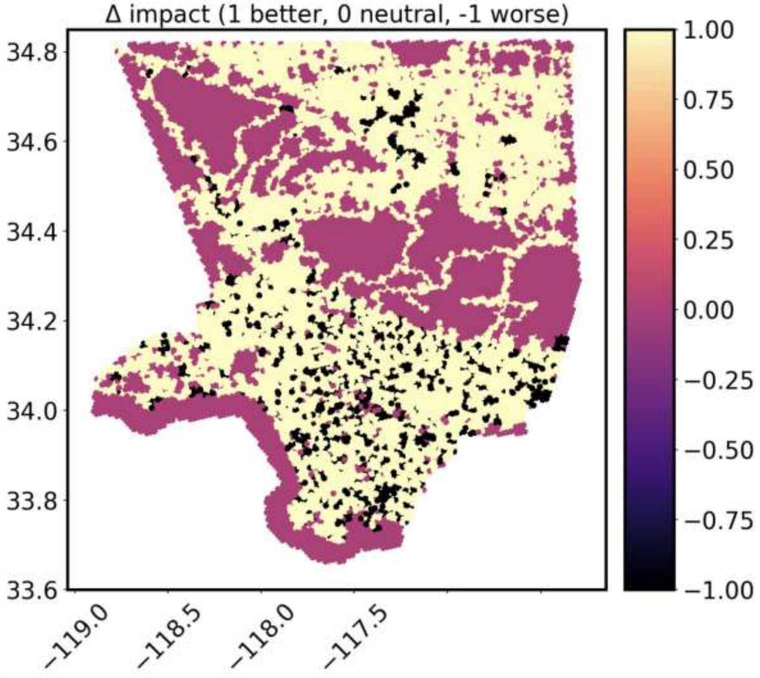
where I := set of potential locations (i.e., hexagons) connected to the street network; S := the total number of existing stations; $t_{(i,j)}$:= the shortest traveling time between i and j; RI_i := the value of the outcome variable of interest at hexagon i; and the decision variables:

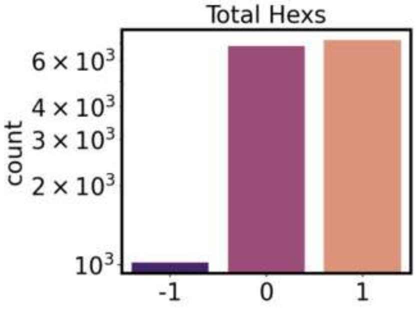
$$
\begin{aligned}
x_{(i,j)} &= 1 \text{ if station in location } i \text{ covers } j \\
y_i &= 1 \text{ if a station is located in } i
\end{aligned}
$$

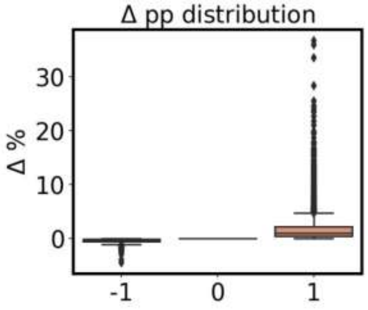
Example: LA County optimization





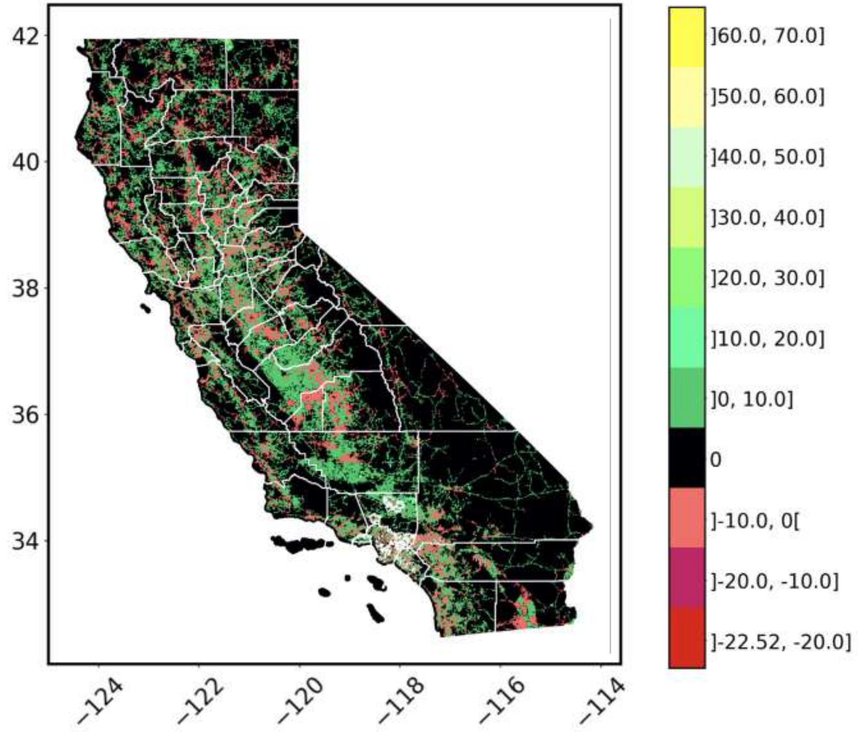




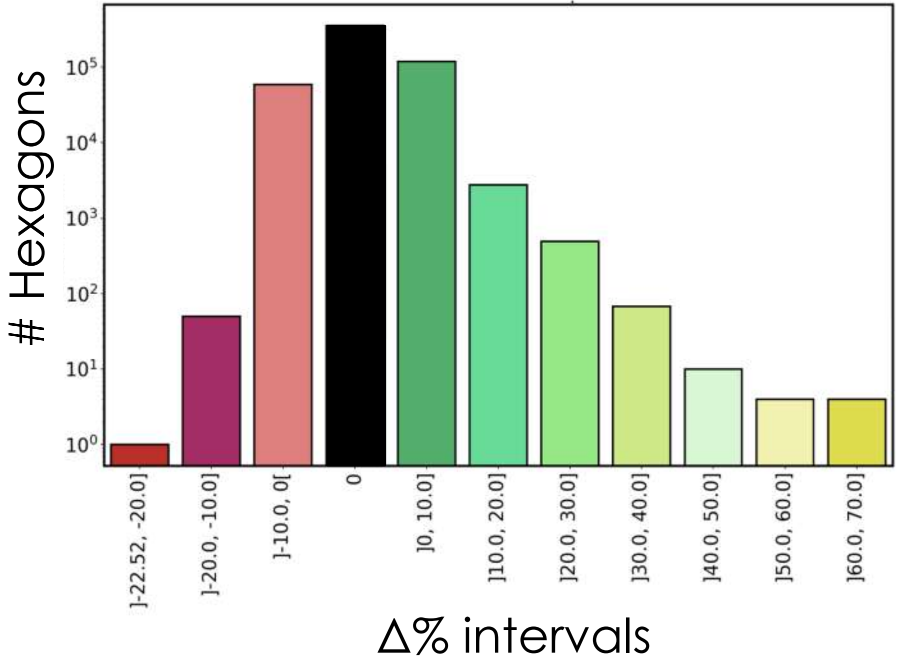


California: Optimizing RI

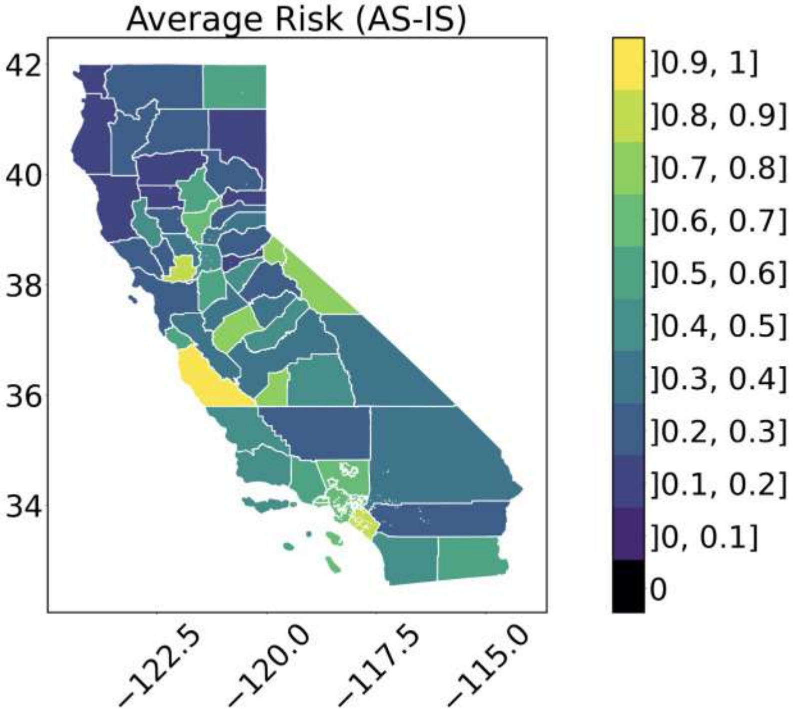
Δ improvement % points (+ is better)



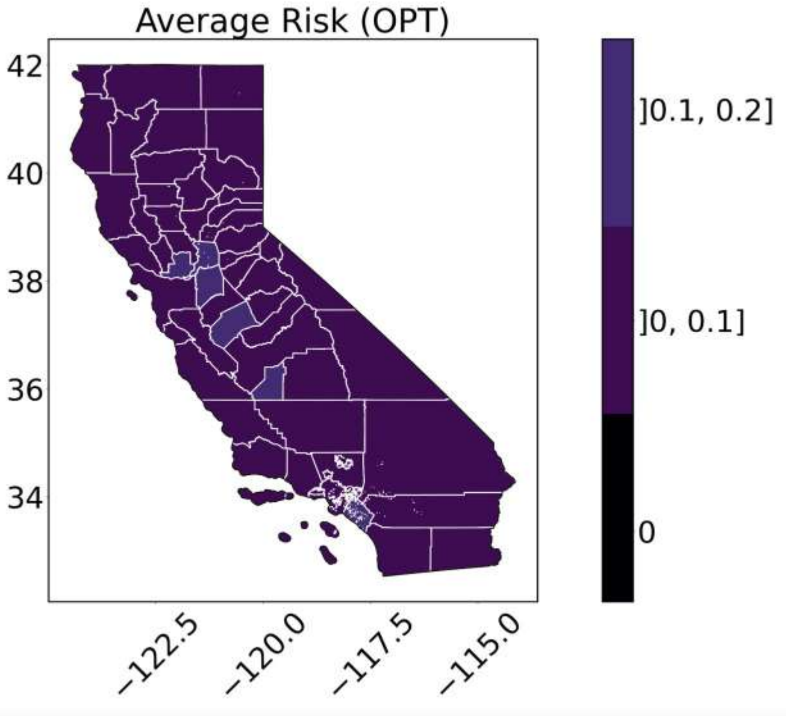
Δ improvement % distribution



California: CBSA Level RI

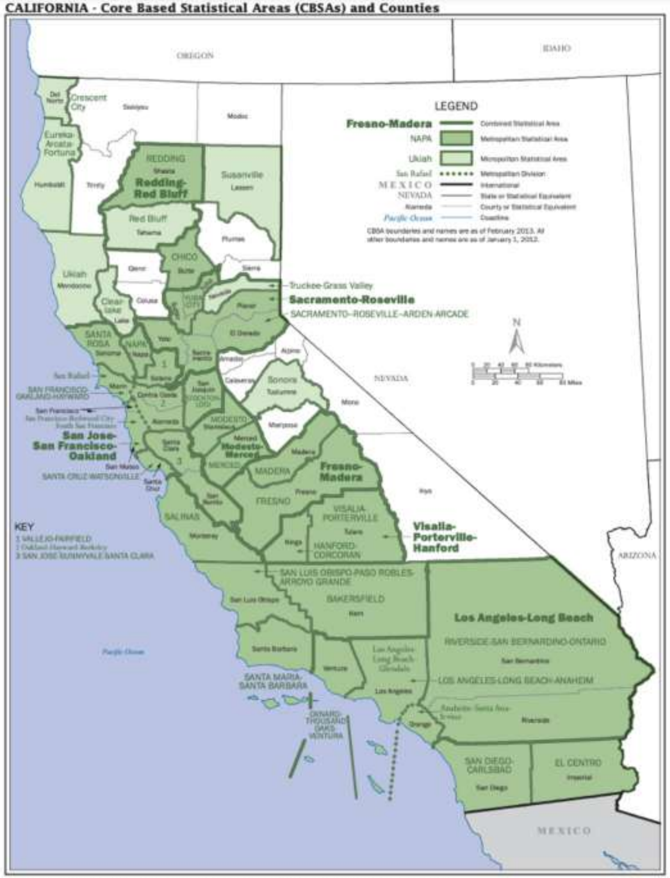


OPT

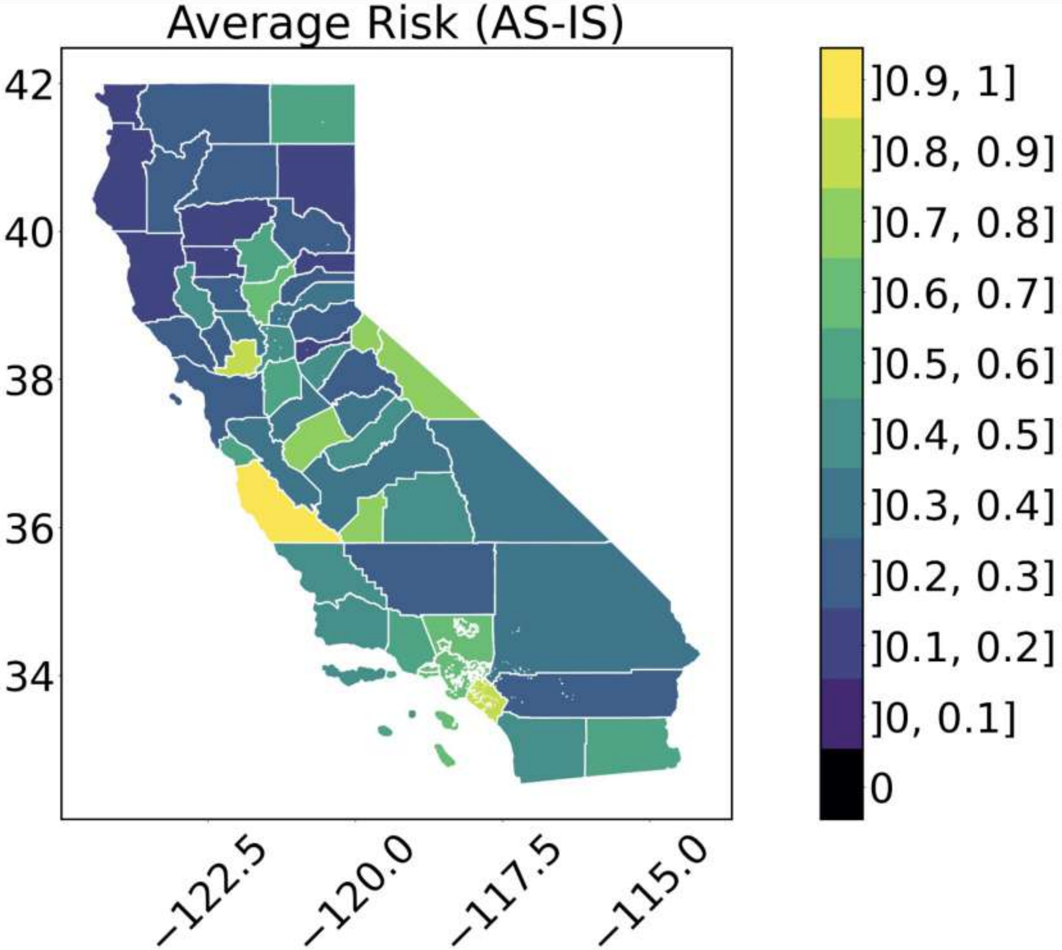


A **core-based statistical area** (**CBSA**) is a U.S. geographic area defined by the Office of Management and Budget (OMB) that consists of one or more counties (or equivalents) anchored by an urban center of at least 10,000 people plus adjacent counties that are socioeconomically tied to the urban center by <u>commuting</u>

CALIFORNIA - Core Based Statistical Areas (CBSAs) and Counties



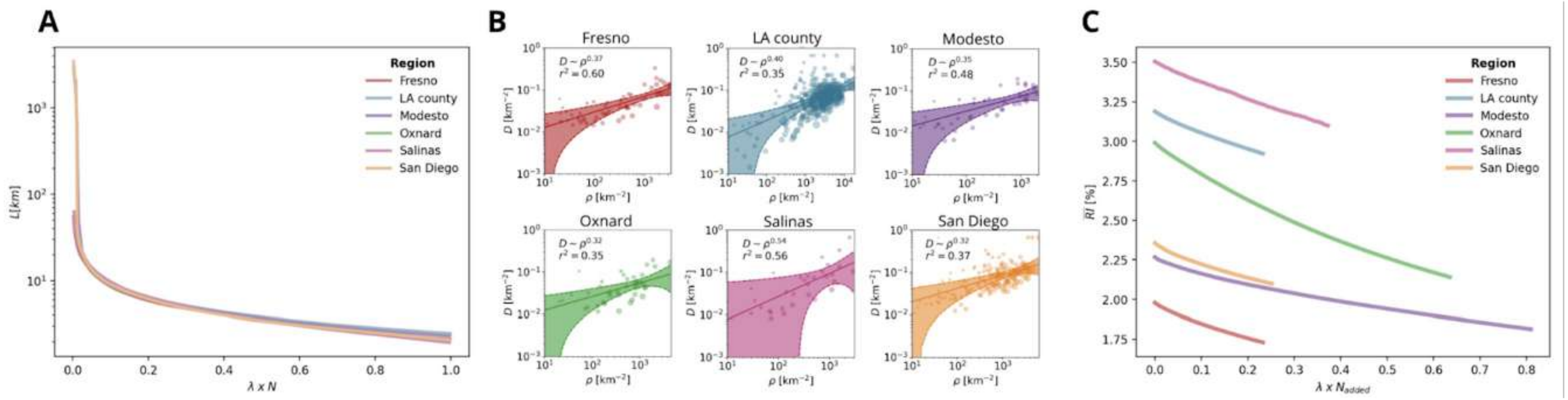
U.S. DEPARTMENT OF COMMERCE Economics and Statistics Administration U.S. Census Bureau



Average Risk (AS-IS)

What can we generalize about an interdisciplinary data-science approach to managing natural hazards risk?

Optimal deployment of Fire station Facilities



Average distance L
vs. number of facilities

$$\lambda = 1.833/N_{occ}$$

Fire station density versus population density in the optimal scenario.

Decrease in Risk Index % by adding facilities

N_{occ}: number of blocks with population above 500 (urban area)

N: number of facilities

D: Facility Density

ρ: Population Density

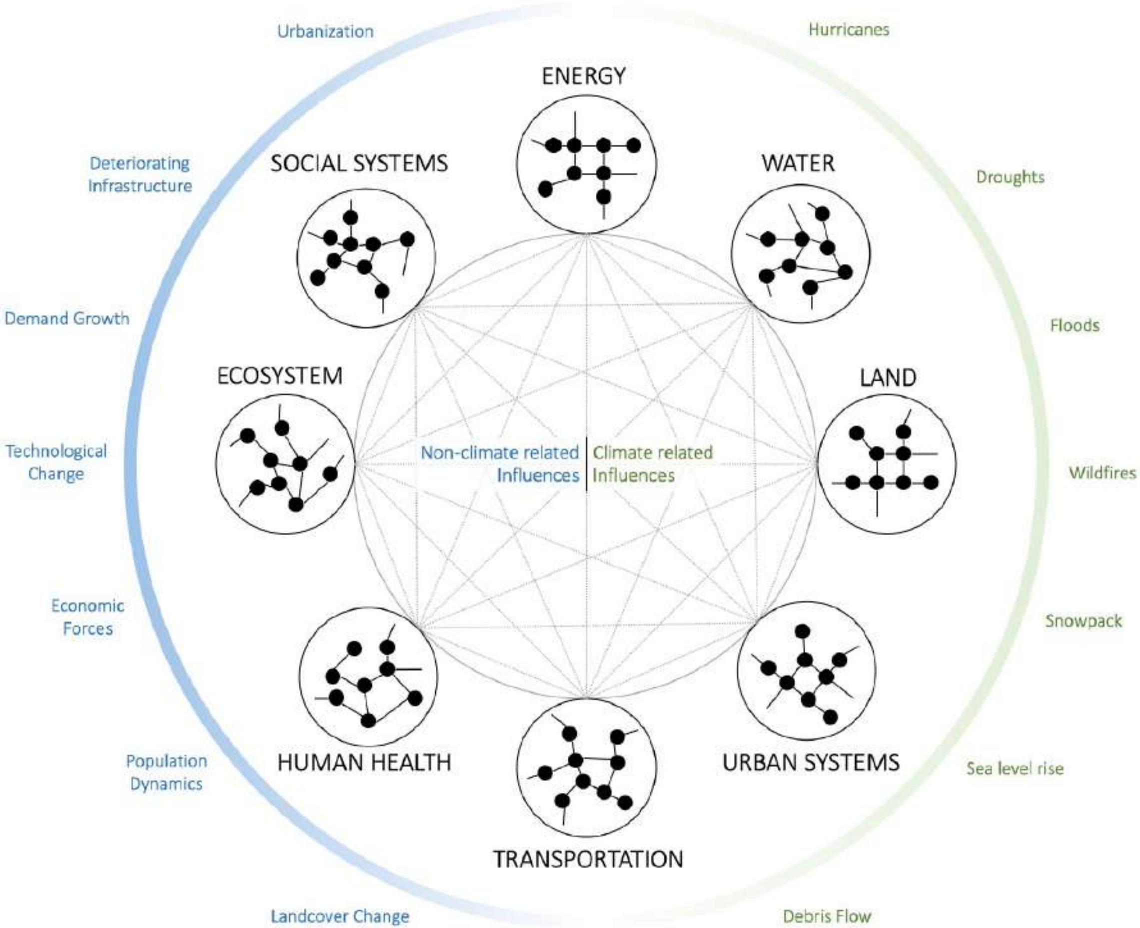
Deconstructing laws of accessibility and facility distribution in cities
Y Xu, LE Olmos, S Abbar, MC González **Science advances** (2020)

Summary

Environmental and Decision Sciences allowed us to target vulnerable locations at state level

When defining a compound risk index that includes environmental behavior the universalities of optimal distribution of facilities disappear.

It is a must to combine disciplines in risk mitigation strategies


Urbanization
Hurricanes
ENERGY
Deteriorating Infrastructure
SOCIAL SYSTEMS
WATER
Droughts
Demand Growth
Floods
ECOSYSTEM
LAND
Technological Change
Non-climate related Influences
Climate related Influences
Wildfires
Economic Forces
Snowpack
HUMAN HEALTH
URBAN SYSTEMS
Population Dynamics
Sea level rise
TRANSPORTATION
Landcover Change
Debris Flow

Towards Resilient Critical Infrastructures: Understanding the Impact of Coastal Flooding on the Fuel Transportation Network in the San Francisco Bay

Y He, S Lindbergh, Y Ju, M Gonzalez, J Radke

ISPRS International Journal of Geo-Information (2021)

Research Question

How will **coastal flooding** impact **fuel transportation networks** under future **climate change** scenarios?

STEP 01

- The definition of **fuel transportation networks**
- Build a **network model** to represent the network
- **Network properties** and characteristics

STEP 02

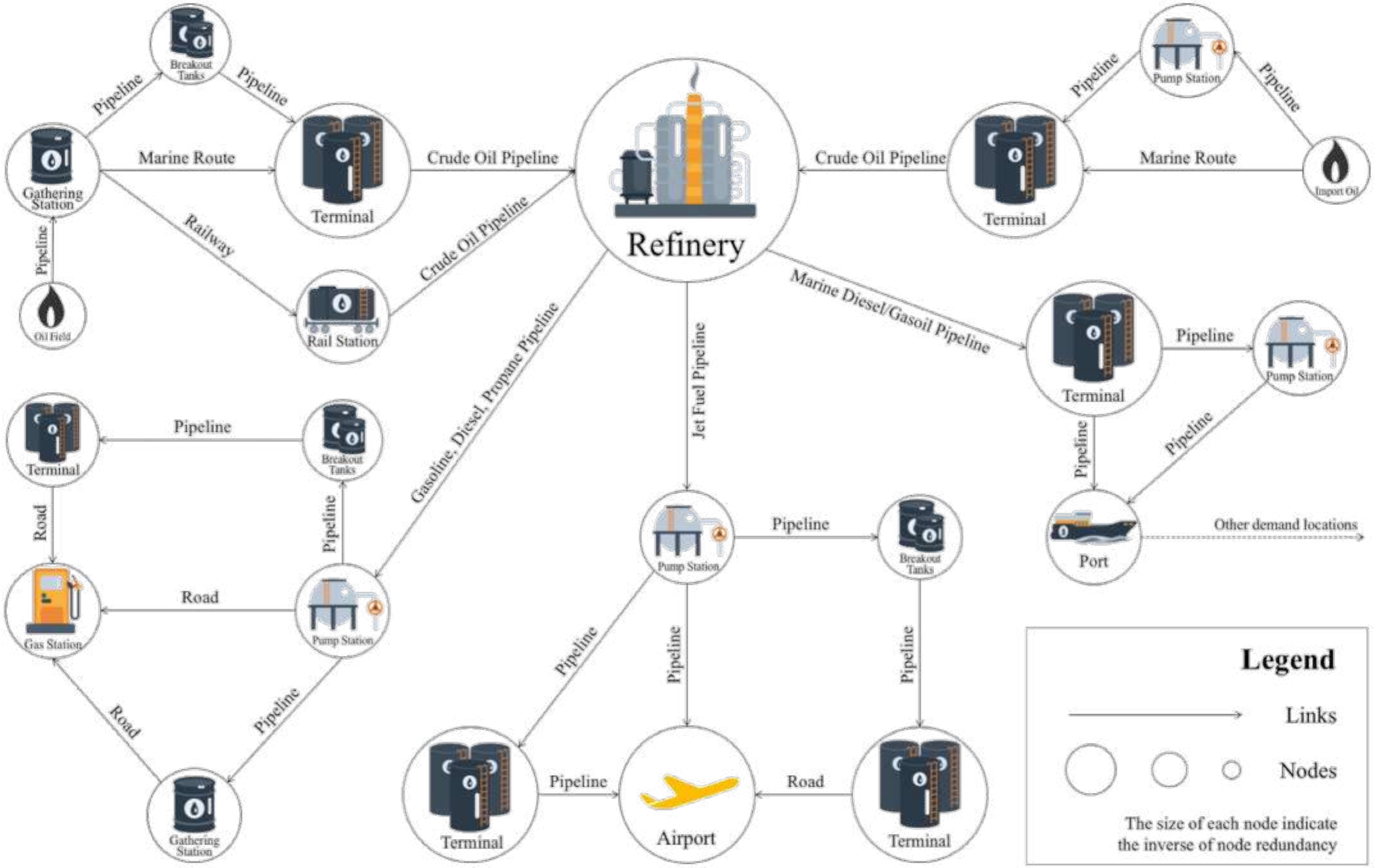
- The definition of **coastal flooding**
- **Scenarios** of coastal flooding under future **climate change** (GCM, RCP, SLR percentiles, time horizons)

STEP 03

- **Regional impact** analysis of network properties
- **Local impact** analysis focusing on cascading effects and routing simulations

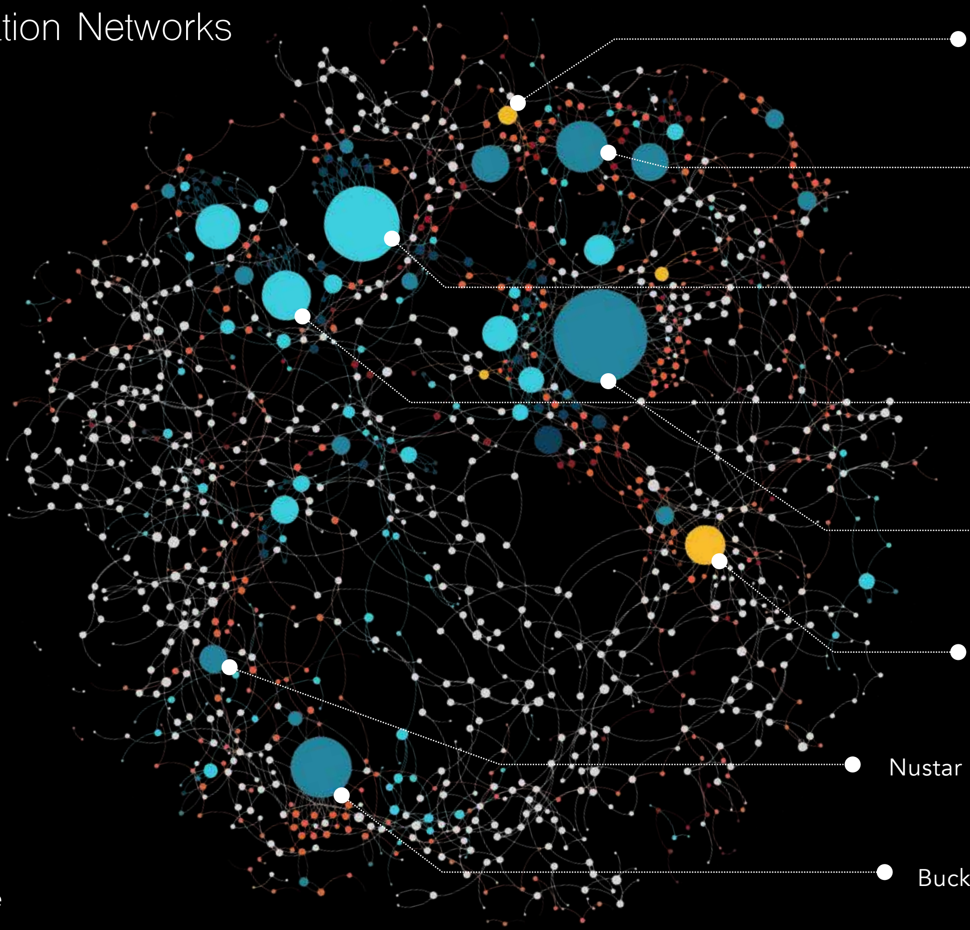
| STEP 01 |

Fuel Transportation Networks



| STEP 01 |

Fuel Transportation Networks



Shell Martinez Refinery

Kinder Morgan
Concord Terminal

Port of Richmond

Port of Oakland

BNSF Richmond
Rail Terminal

Valero Benicia Refinery

Nustar Energy Crockett Terminal

Buckeye Sacramento Terminal

Legend

- ● Terminal
- ● Refinery
- ● Port
- ○ Airport
- ● Product Pipeline
- ● Rail
- ● Marine Route
- ● Crude Oil Pipeline

| STEP 02 |

120 Coastal Flooding Scenarios


Kinder Morgan Pipelines

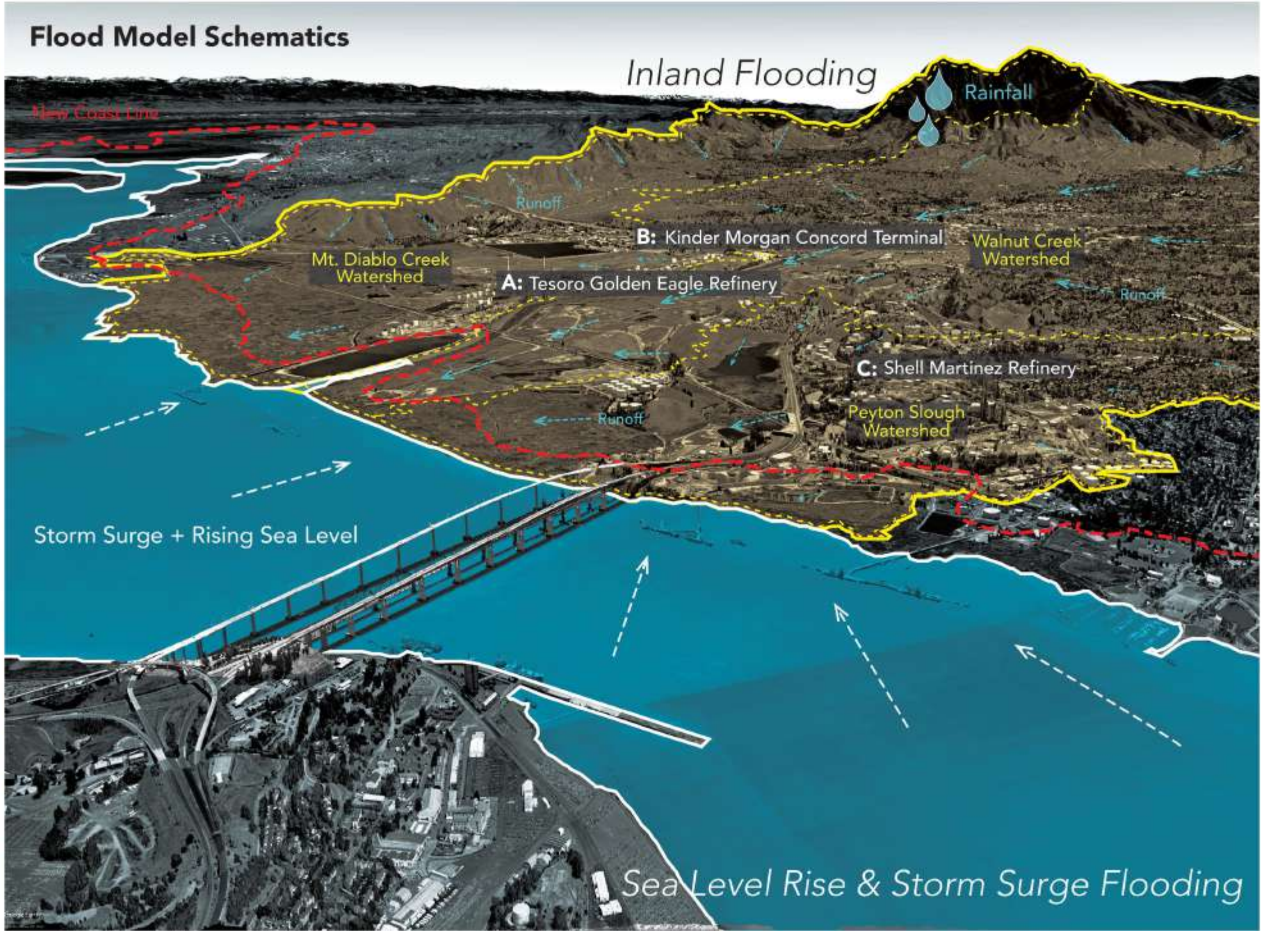

Union Pavcific (UP) Railway & Kinder Morgan Pipelines


UP & Burlington Northern Santa Fe (BNSF) Railway


Kinder Morgan Pipelines

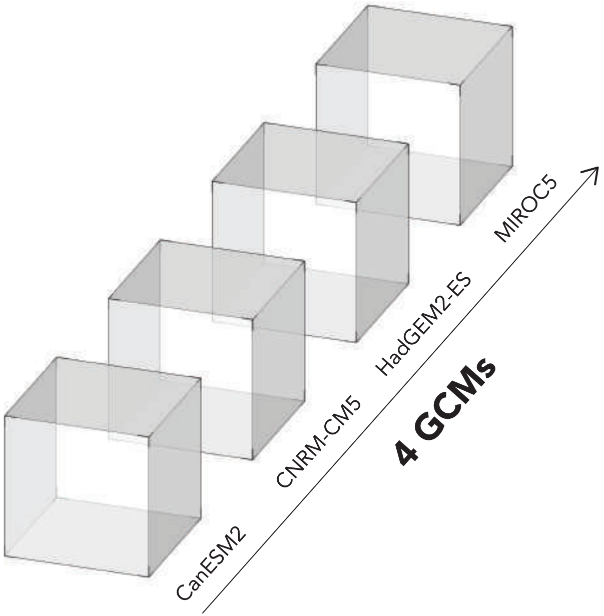

Tanker Vessels

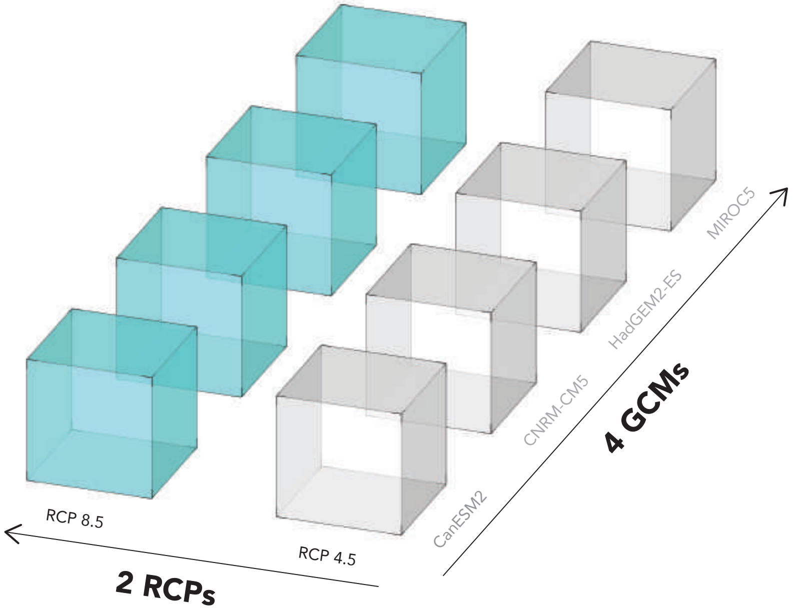

Kinder Morgan Pipeline Pump Station



| STEP 02 |

120 Coastal Flooding Scenarios



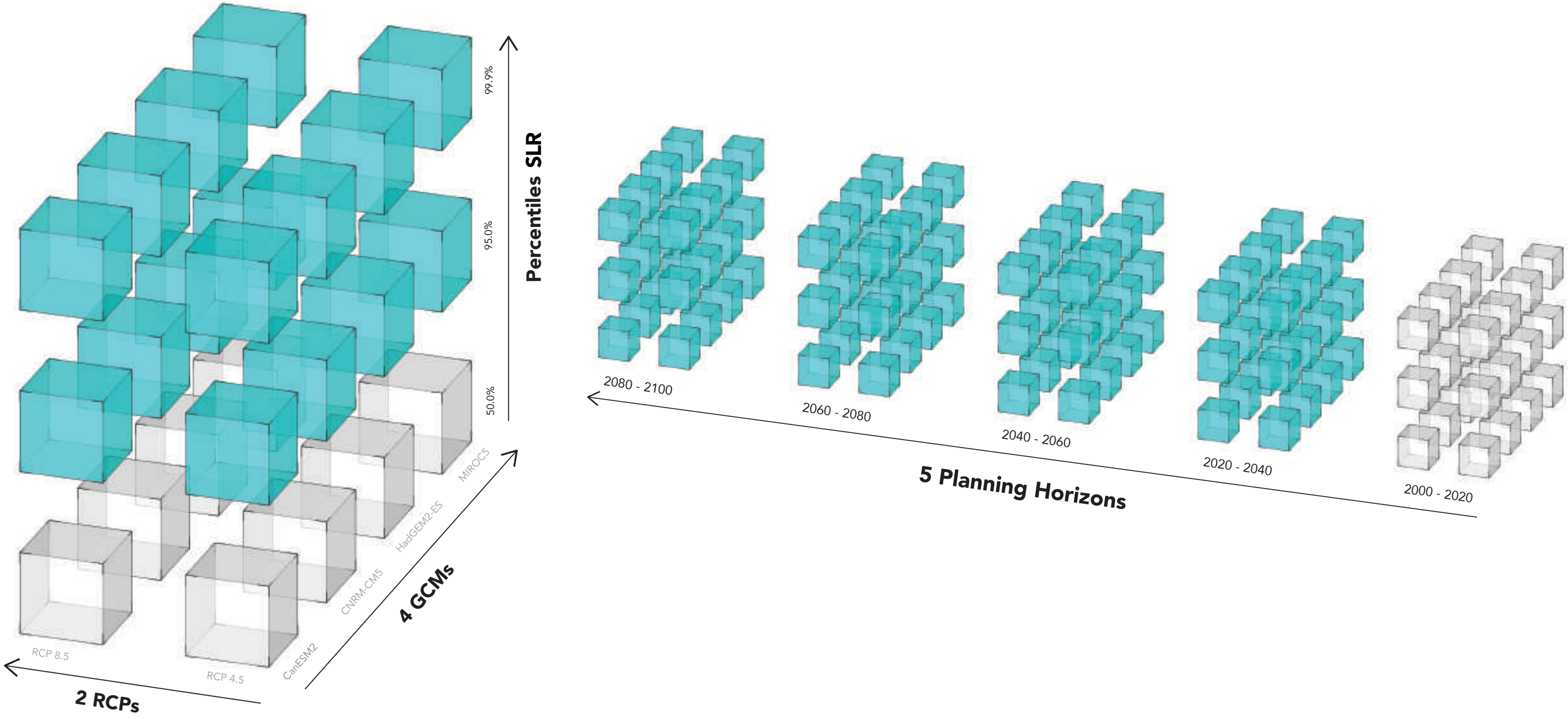


General Circulation Models (GCMs) represent physical processes in the atmosphere, ocean, cryosphere and land surface, are the most advanced tools currently available for simulating the response of the global climate system to increasing greenhouse gas concentrations

Representative Concentration Pathways (RCPs) are four greenhouse gas concentration (not emissions) trajectories adopted by the IPCC for its fifth Assessment Report (AR5) in 2014.

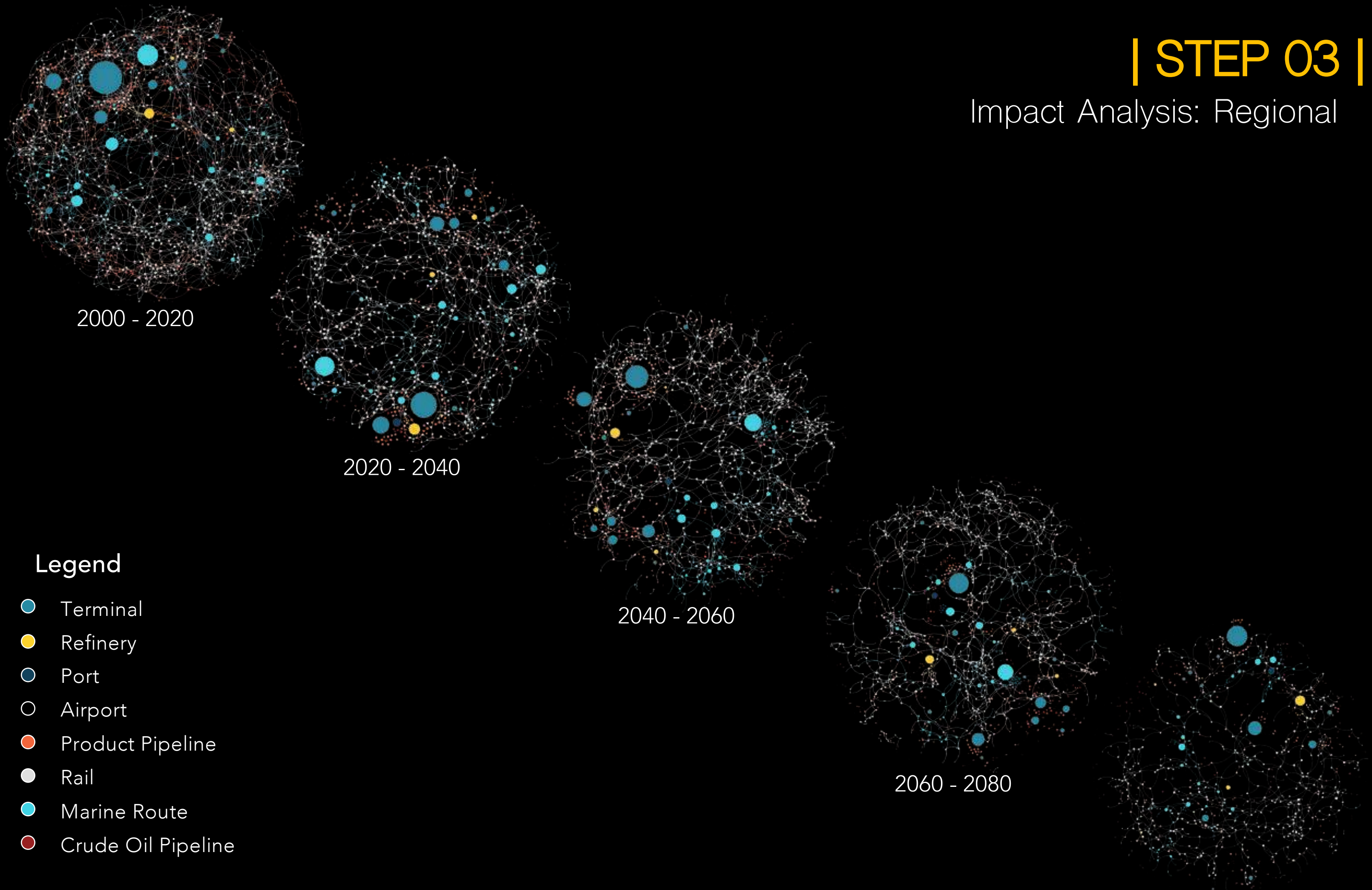
| STEP 02 |

120 Coastal Flooding Scenarios



| STEP 03 |

Impact Analysis: Regional



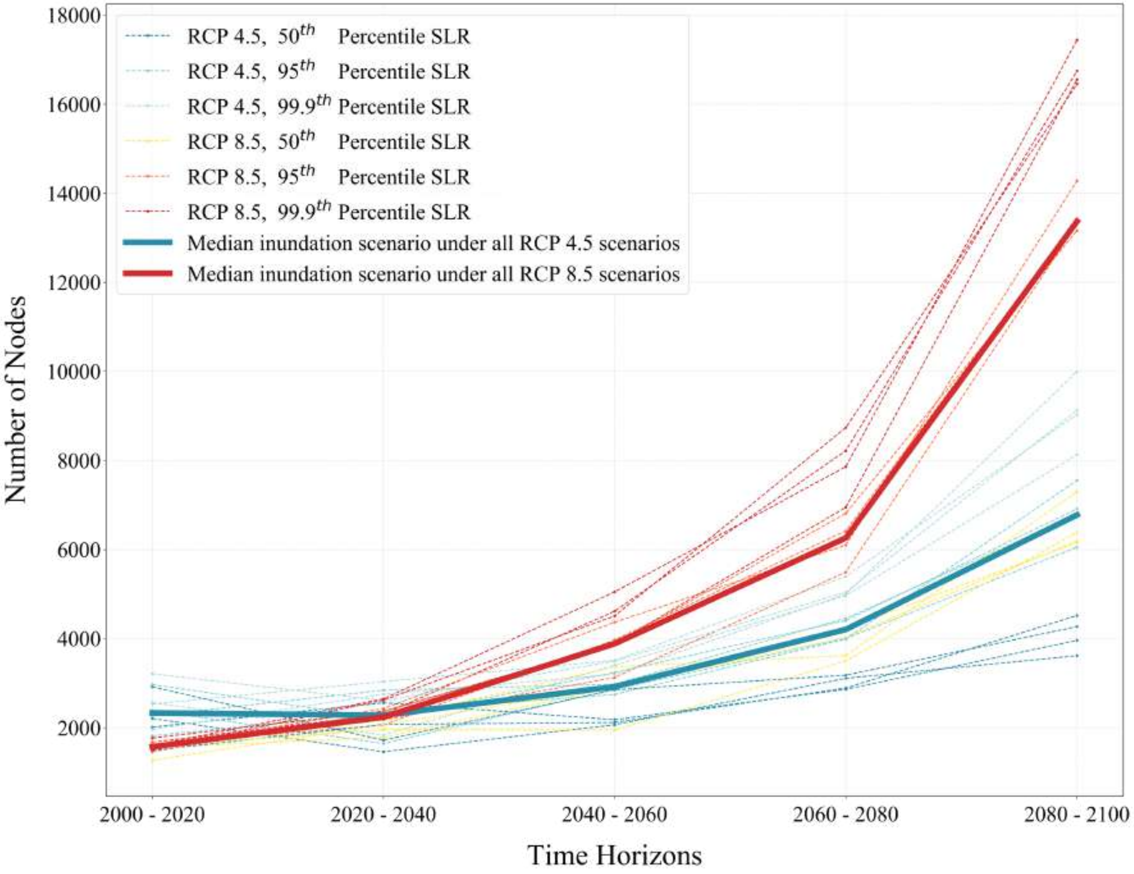
Legend

- ● Terminal
- ● Refinery
- ● Port
- ○ Airport
- ● Product Pipeline
- ● Rail
- ● Marine Route
- ● Crude Oil Pipeline

Note: for each time period, the flooding scenario with RCP 4.5, MICRO5 GCM and 95th percentile SLR is selected

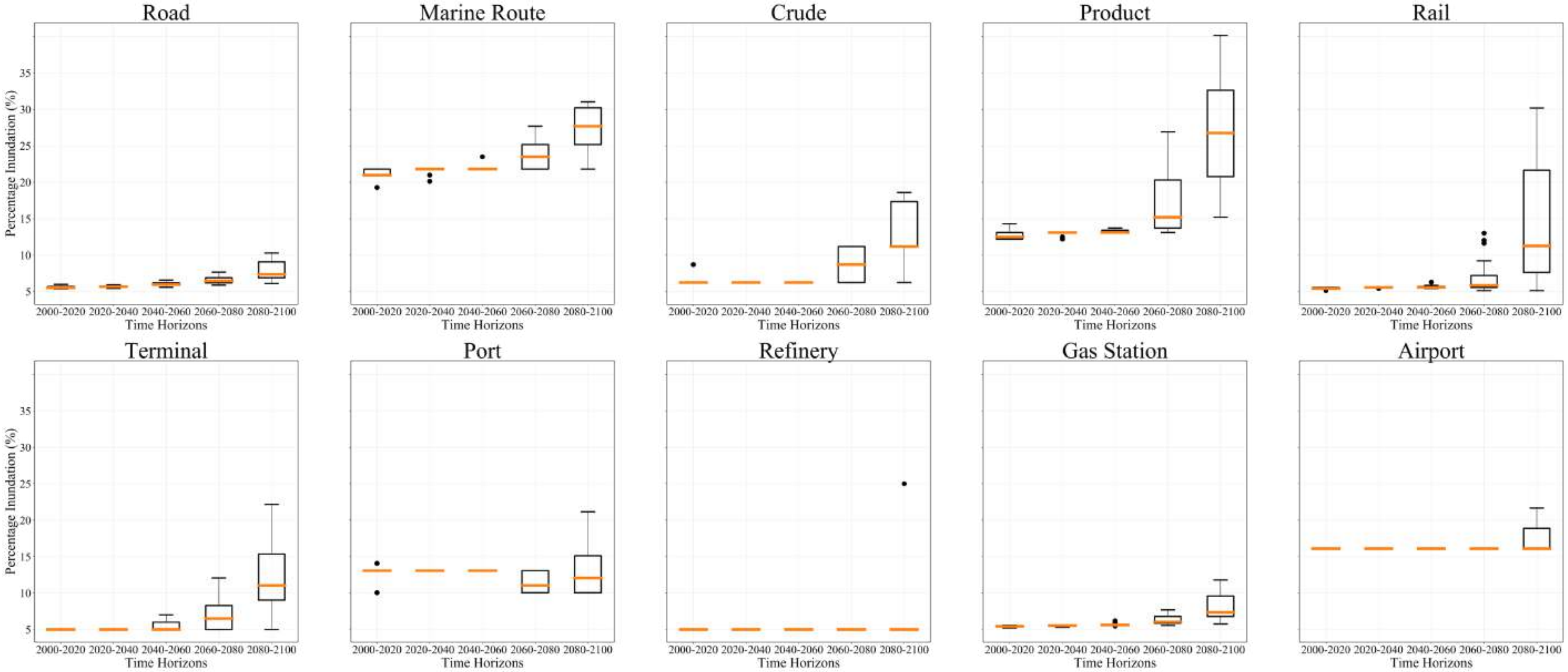
| STEP 03 |

Impact Analysis: Regional



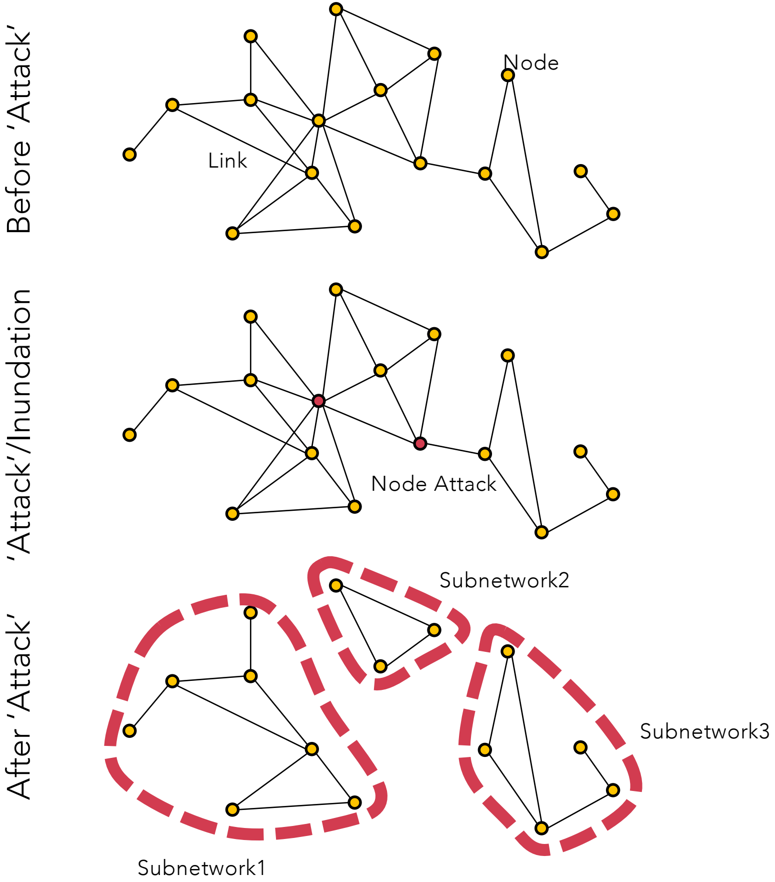
| STEP 03 |

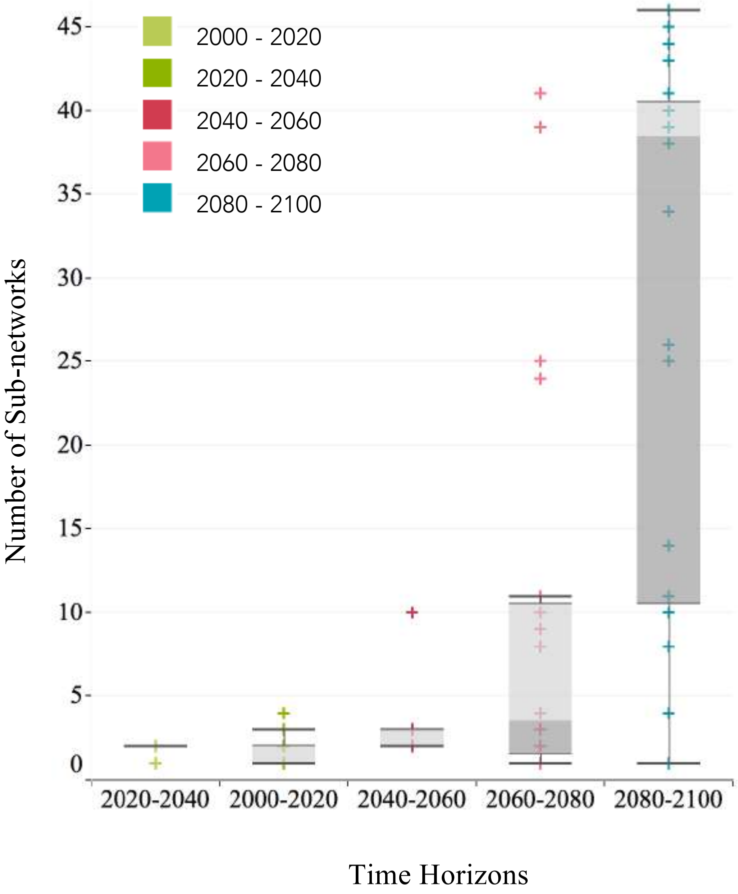
Impact Analysis: Regional



| STEP 03 |

Impact Analysis: Regional





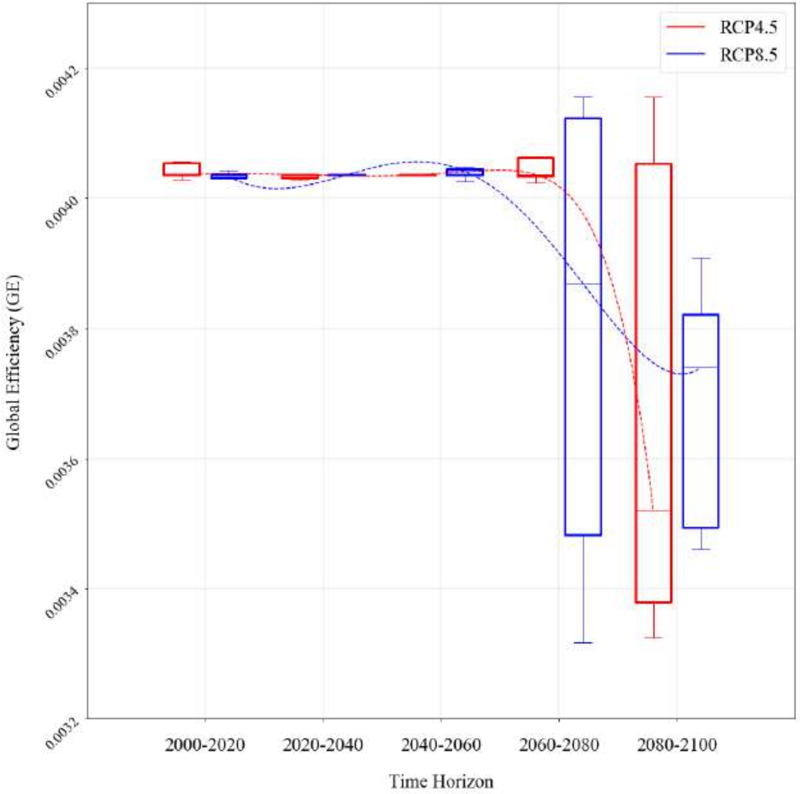
| STEP 03 |

Impact Analysis: Regional

$$GE = \frac{1}{N(N-1)} \sum_{s \neq t}^{n} \frac{1}{Z_{st}}$$

Latora and Machori proposed Global Efficiency (GE) as a measure of the exchange of information within a network.

Osei-Asamoah et al. explained that GE quantifies how flow is exchanged between nodes in a transportation network.



- Z_{st} is the length of the shortest path between node s and node t
- N is the total number of nodes in the network
- The GE value is normalized by dividing by the GE of an ideal network where all node pairs are connected

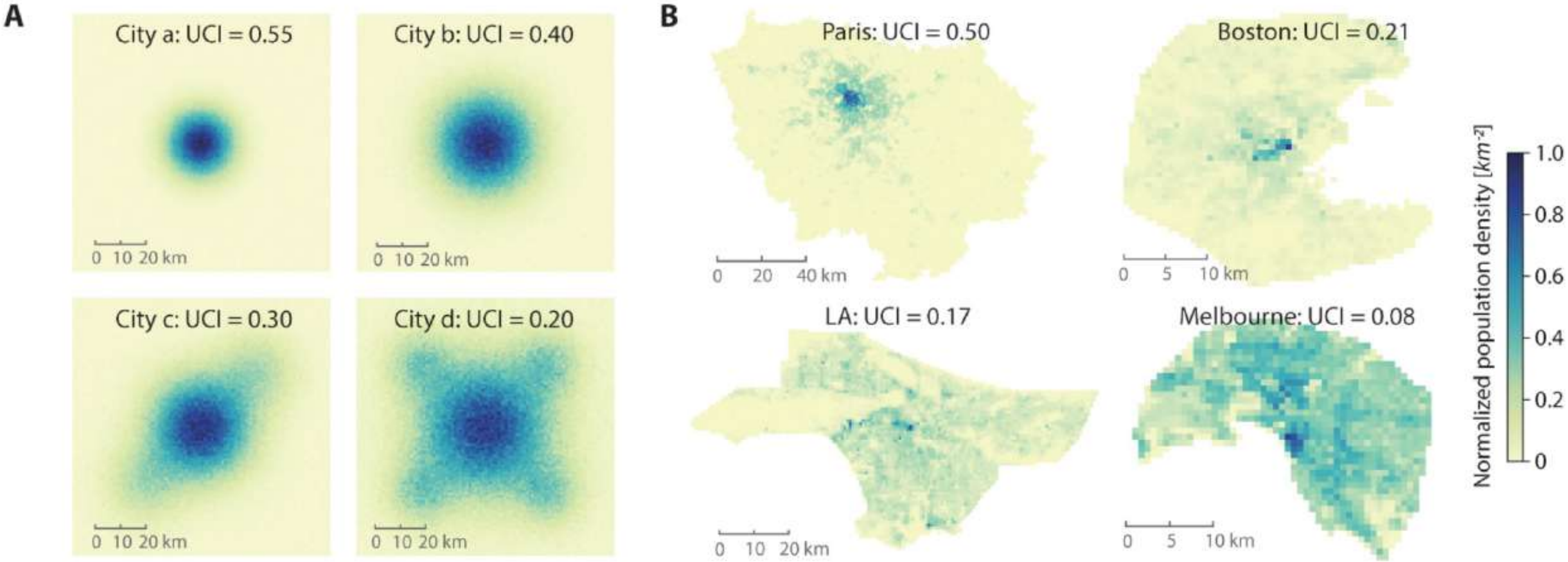
Conclusions

- The direct impact of coastal flooding on fuel transportation networks increases overtime across different climate scenarios. The impact under RCP 8.5 scenarios is larger than RCP 4.5 scenarios.

- The multimodal network is likely to become fragmented towards the end of century, breaking down into smaller sub-networks. The efficiency within the network will decrease as well.

- When considering cascading effects within the network, the real impact of coastal flooding will be larger. Some smaller hubs within the network could cause a bigger ripple effect than some of the biggest hubs.

Deconstructing laws of accessibility and facility distribution in citiesY Xu, LE Olmos, S Abbar, MC González **Science advances** 6 (37), eabb4112 (2020)



We introduce 17 toy cities with different UCI (Ref. Pereira 2013), and another six real-word cities (Paris, Barcelona, London, Dublin, Mexico City, and Melbourne).

Source: R. H. M. Pereira, V. Nadalin, L. Monasterio, P. H. Albuquerque, Urban centrality: A simple index. *Geogr. Anal.* **45**, 77–89 (2013).

Deconstructing laws of facility distribution in cities

City-customized function

$$L(N) = l_{min} \cdot (1 - e^{-\alpha N}) + A \cdot N^{-\lambda} \cdot e^{-\alpha N} \quad ,$$

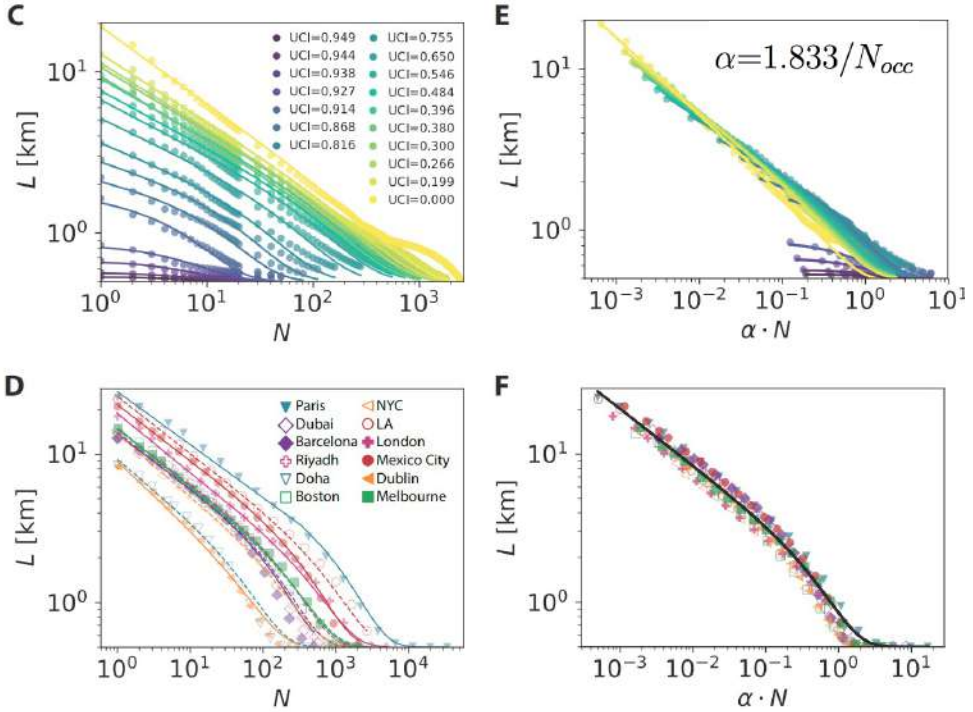
Universal function

$$L(N) = l_{min} \cdot (1 - e^{-\alpha N}) + 1.4443 \cdot (\alpha N)^{-\bar{\lambda}} \cdot e^{-\alpha N} \quad ,$$

We find collapse of the L among diverse cities by rescaling N with the urban area N_{occ}.

The collapse may give us insights on the universal laws for facility planning in diverse cities. $\bar{\lambda} = 0.382$ $l_{min}=0.5\ \text{km},$

E and **F** show $L(D_{occ})$ $D_{occ} = \dfrac{N}{N_{occ}}$



N_{occ}: number of blocks with population above 500 (urban area)

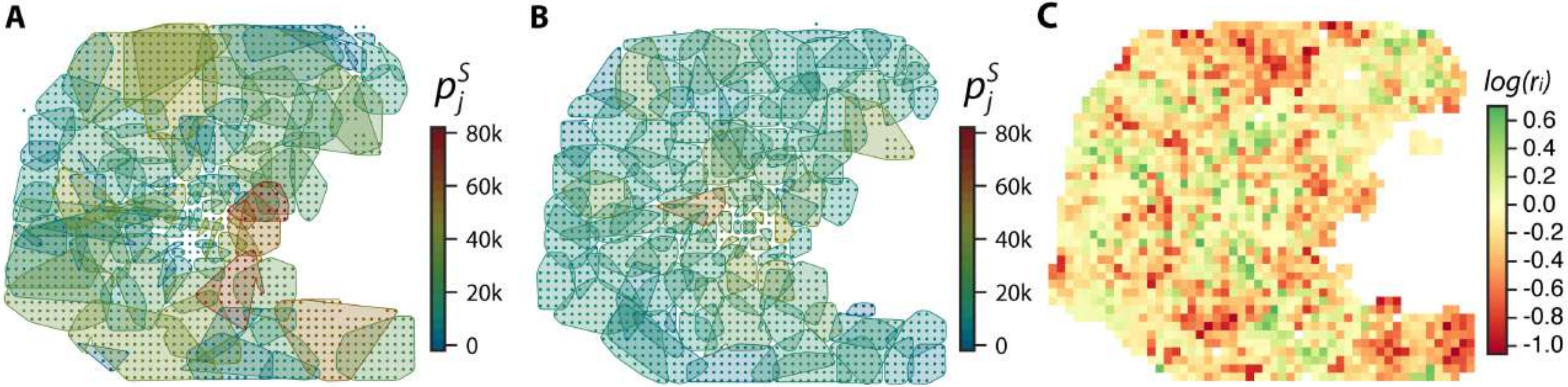
N: number of facilities

Example: Actual vs Optimal Distribution

Gain index of block : $r_i = \frac{Travel\ distance\ to\ facility\ in\ optimal\ scenario}{Travel\ distance\ to\ facility\ in\ actual\ scenario}$

$r_i > 1: benefit\ from\ planning$

$r_i < 1: affected\ by\ planning$



A: Service communities and population in the actual scenario
B: Service communities and population in the optimal scenario
C: Gain index of each block