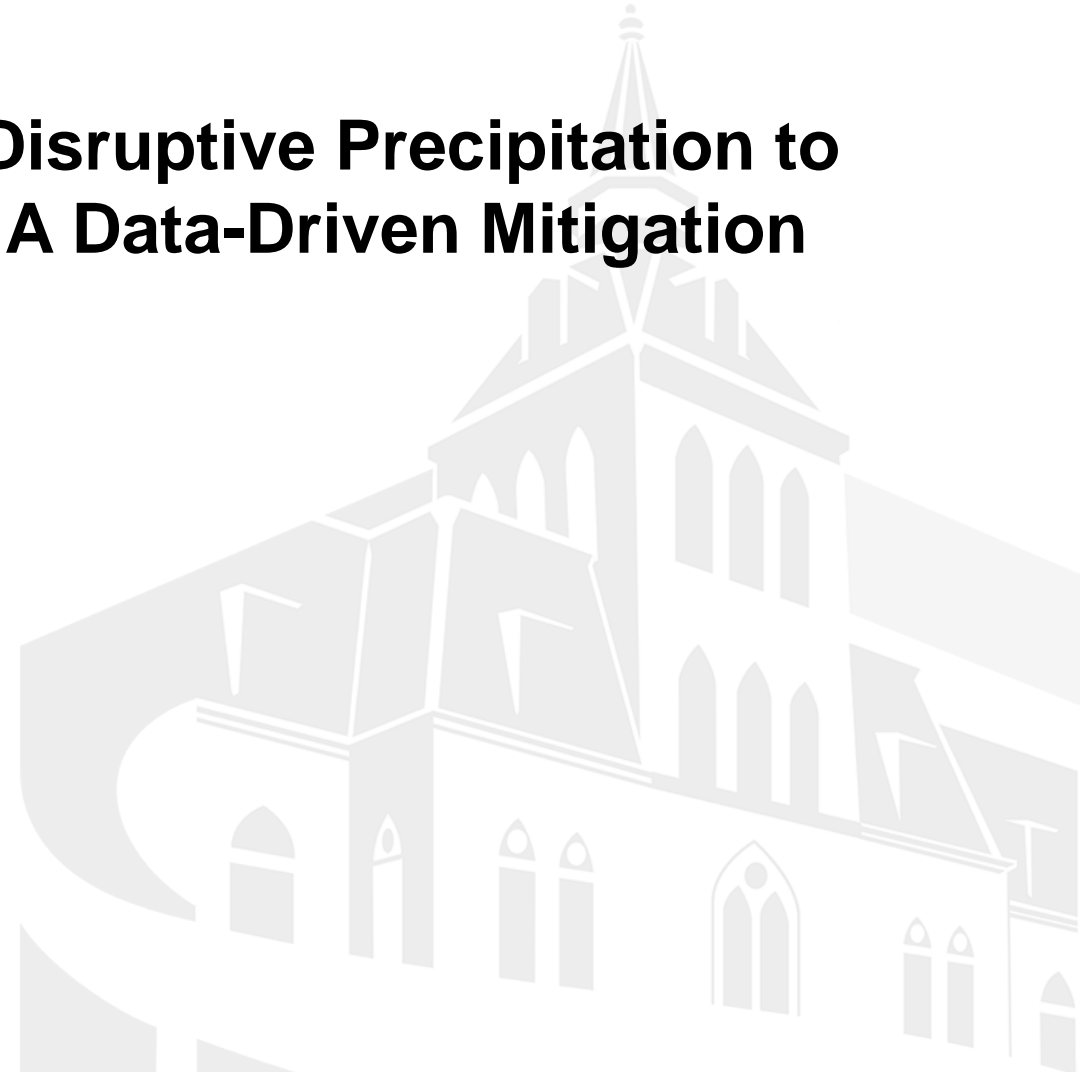




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Quantifying Impacts of Disruptive Precipitation to Surface Transportation: A Data-Driven Mitigation Approach

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Motivation

What is the problem?

Flooding during hurricane Sandy in 2012 ¹ (left), and in 2018 (right). ²



¹ <http://www.yimiton.com/2012/10/hurricane-sandy-images-of-flooding-in.html>

² <http://hmag.com/hoboken-finally-moves-fix-chronic-costly-flooding-9th-madison/>



Research gaps

What are we adding to the literature?

The transportation vulnerability literature lacks a multidisciplinary approach to transportation flood mitigation.

- Few studies investigate the impacts of flood events on mobility and accessibility (Suarez et al. 2005, Yin et al. 2015, Pyatkova et al. 2019). The literature is especially absent with respect to more frequent events, such as rainfall-induced flooding.
- No studies incorporate the elements leading to flood vulnerability (e.g., network configuration, underlying terrain and drainage, drivers, etc).

Suarez P, Anderson W, Mahal V, Lakshmanan TR. Impacts of flooding and climate change on urban transportation: a systemwide performance assessment of the Boston Metro Area. 2005

Yin J, Yu D, Yin Z, Liu M, He Q. Evaluating the impact and risk of pluvial flash flood on intra-urban road network: a case study in the city center of Shanghai, China. 2016

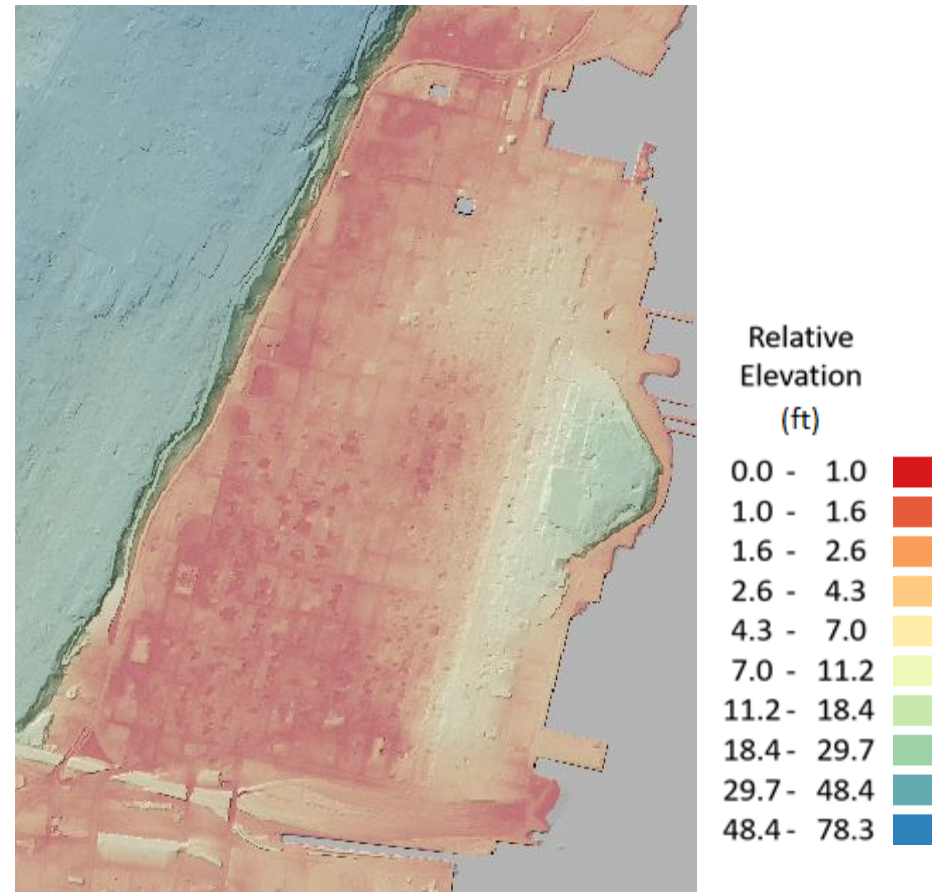
Pyatkova K, Chen AS, Butler D, Vojinović Z, Djordjević S. Assessing the knock-on effects of flooding on road transportation. 2019

Research gaps

Investigating more frequent events
(e.g., 5-year storms)



Using a multidisciplinary approach
To transportation flood vulnerability





Objective and metrics

How to measure transportation performance loss?

- Mobility metrics:
 - Vehicle Miles Traveled (VMT): Total miles collectively driven to fulfill transportation needs.
 - Vehicle Hours Traveled (VHT): Total hours collectively spent to fulfill transportation needs.
 - Both metrics will be normalized by the number of trips completed for comparison.
- Accessibility metrics:
 - Trips completed (TC): Percentage of trips demanded that were effectively completed.

Work published in: Bucar, Raif CB, and Yeganeh M. Hayeri. "Quantitative assessment of the impacts of disruptive precipitation on surface transportation." *Reliability Engineering & System Safety* 203 (2020): 107105.

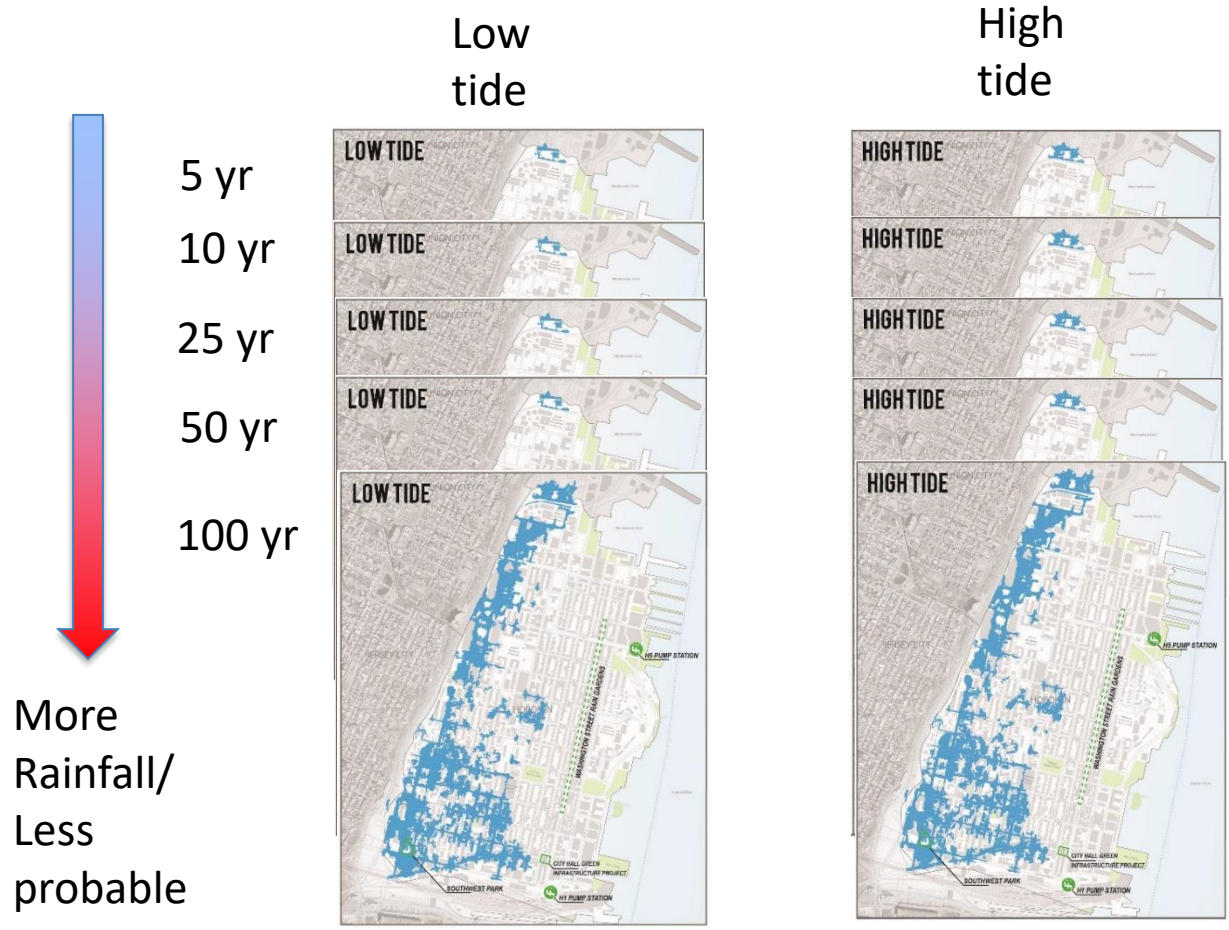
Methods

How to evaluate mobility and accessibility metrics?



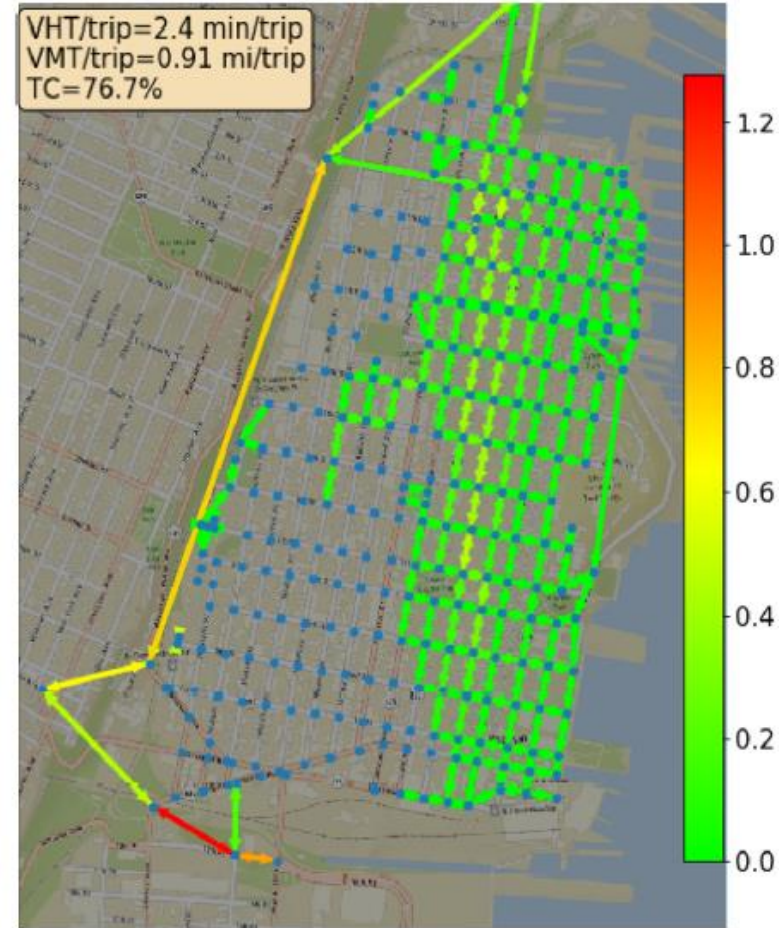
Methods

How to evaluate mobility and accessibility metrics?



Methods

How to evaluate mobility and accessibility metrics?



VHT: Vehicles Hours Traveled

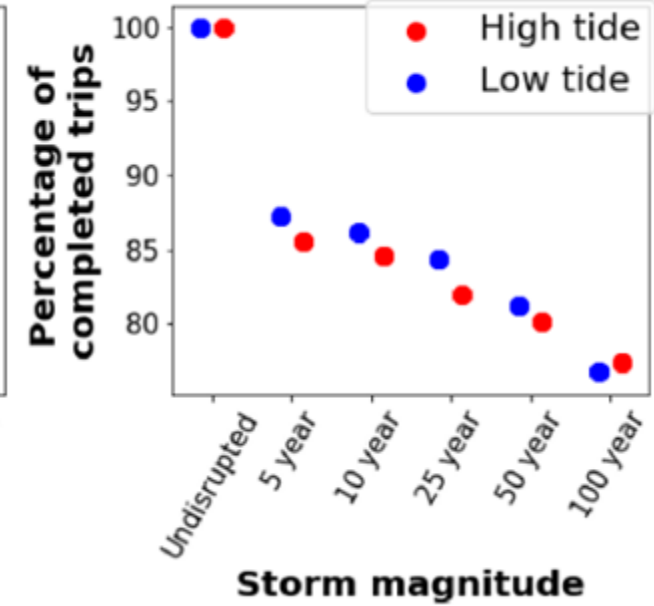
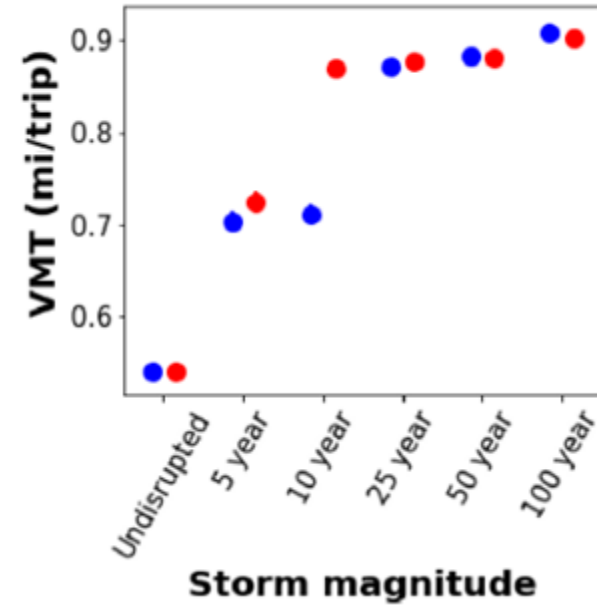
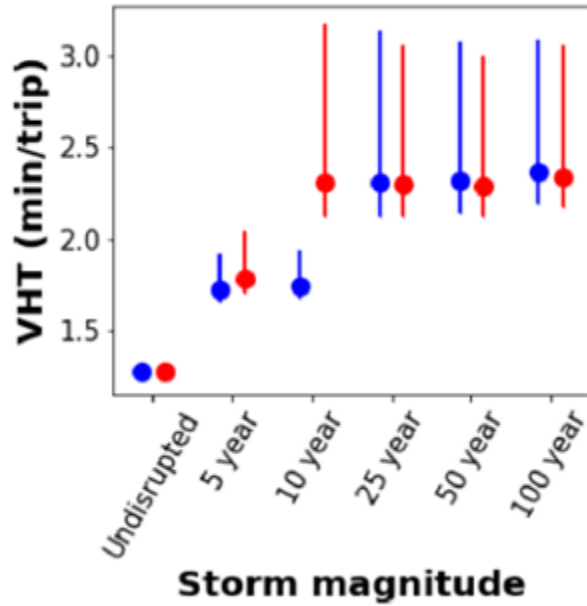
VMT: Vehicles Miles Traveled

TC: Trips Completed



Results

Compare mobility and accessibility metrics for different levels of disruption



VHT: Vehicles Hours Traveled

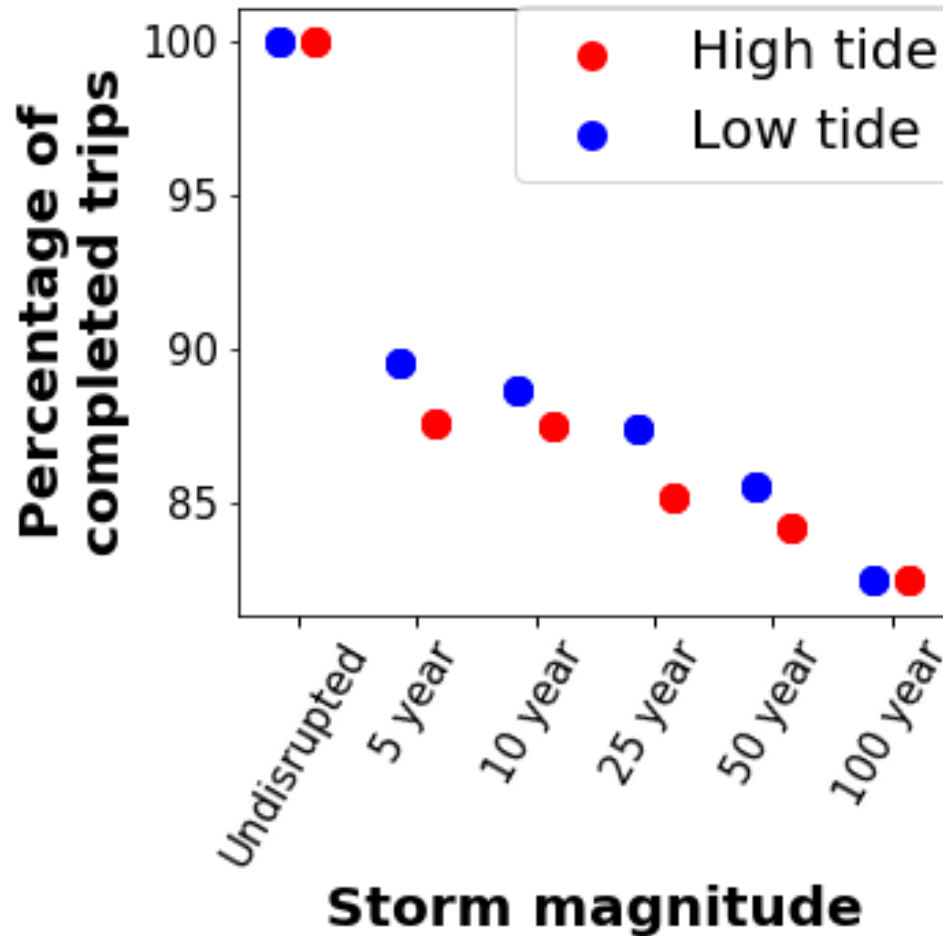
VMT: Vehicles Miles Traveled

TC: Trips Completed



Discussion

Why TC decreases continually?



VHT: Vehicles Hours Traveled

VMT: Vehicles Miles Traveled

TC: Trips Completed



Discussion

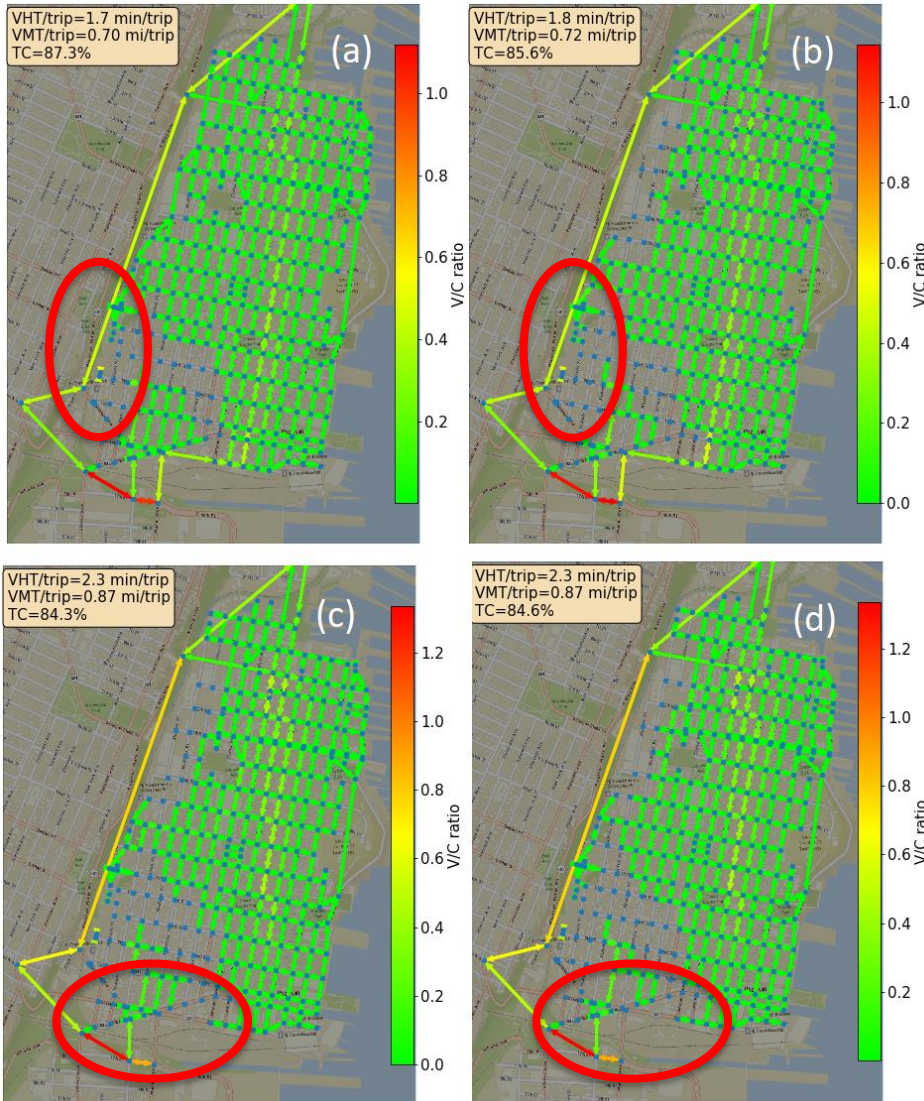
Why TC decreases continually?

TC and flood area extent have significant correlation, indicating that reducing the flooded area improves accessibility

	Low tide		High tide	
Storm scenario	Area flooded (acres)	Trips completed	Area flooded (acres)	Trips completed
No storm	0	100%	0	100%
5-year storm	25.5	89.6%	48.4	87.7%
10-year storm	35.5	88.7%	59.7	87.8%
25-year storm	64.5	87.4%	95.9	85.2%
50-year storm	95.1	85.6%	122.1	84.2%
100-year storm	147.5	82.5%	148.6	82.5%
Pearson's correlation coefficient			-0.869	

Discussion

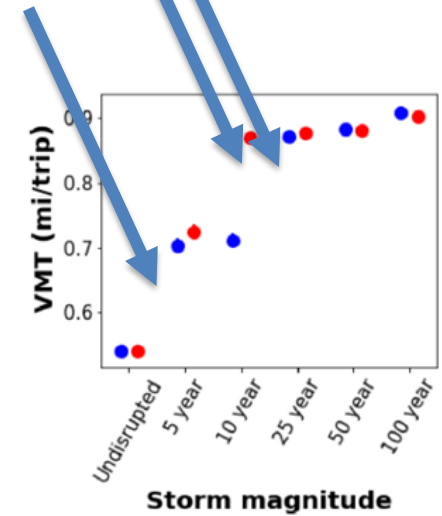
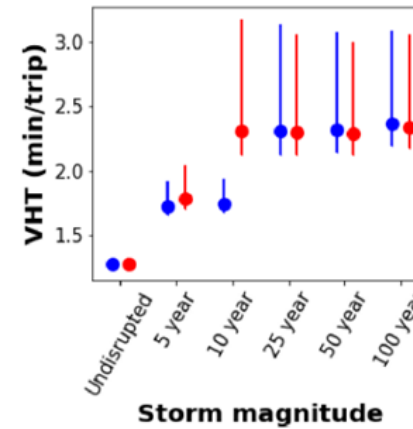
Why VHT and VMT increase in steps?



Losing access to city exits significantly hindered mobility. Access to city exits must be guaranteed to safeguard mobility.

1st step:
Loss of SW
city exit

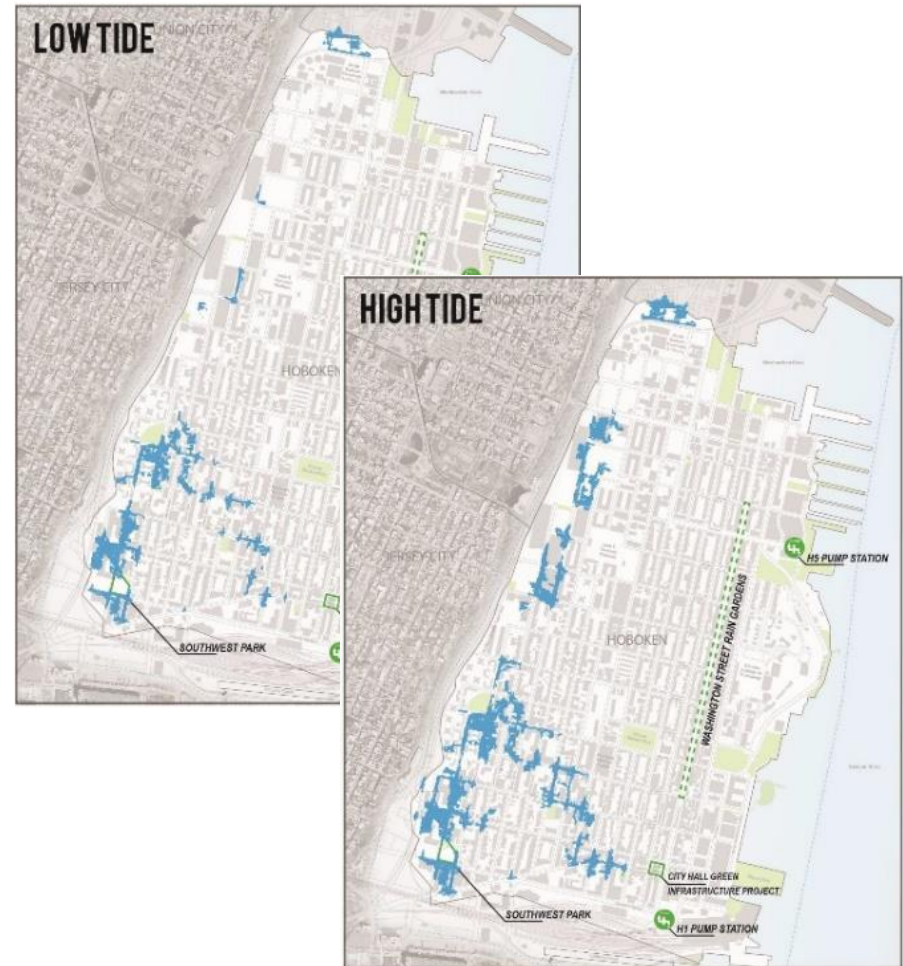
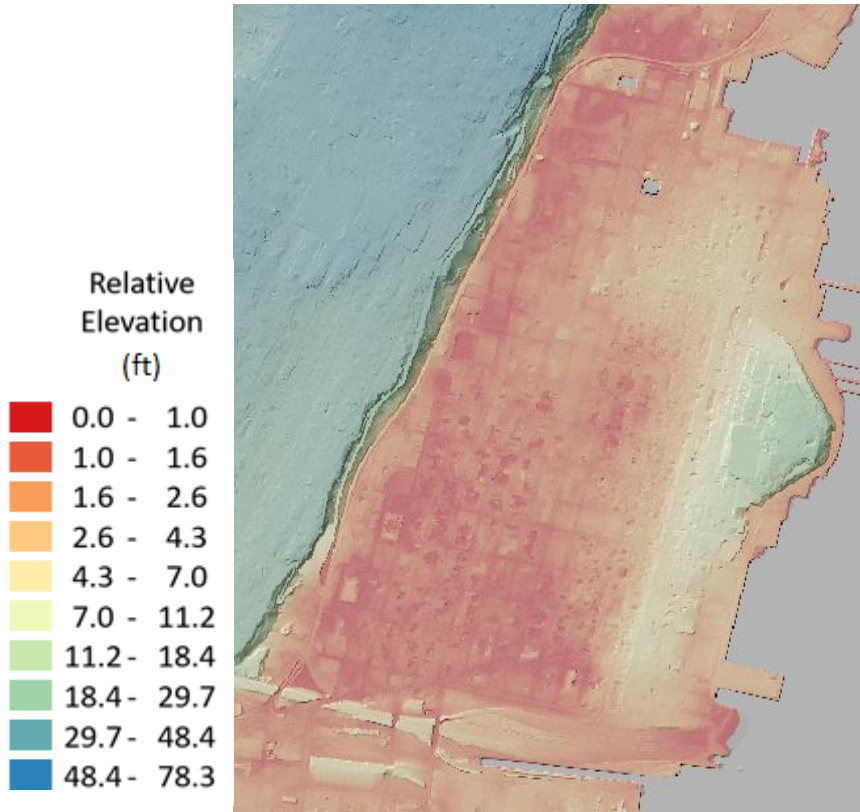
2nd step:
Loss of S
city exit



VHT: Vehicles Hours Traveled VMT: Vehicles Miles Traveled

Discussion

What urban characteristics lead to flood risk?





Objective and metrics

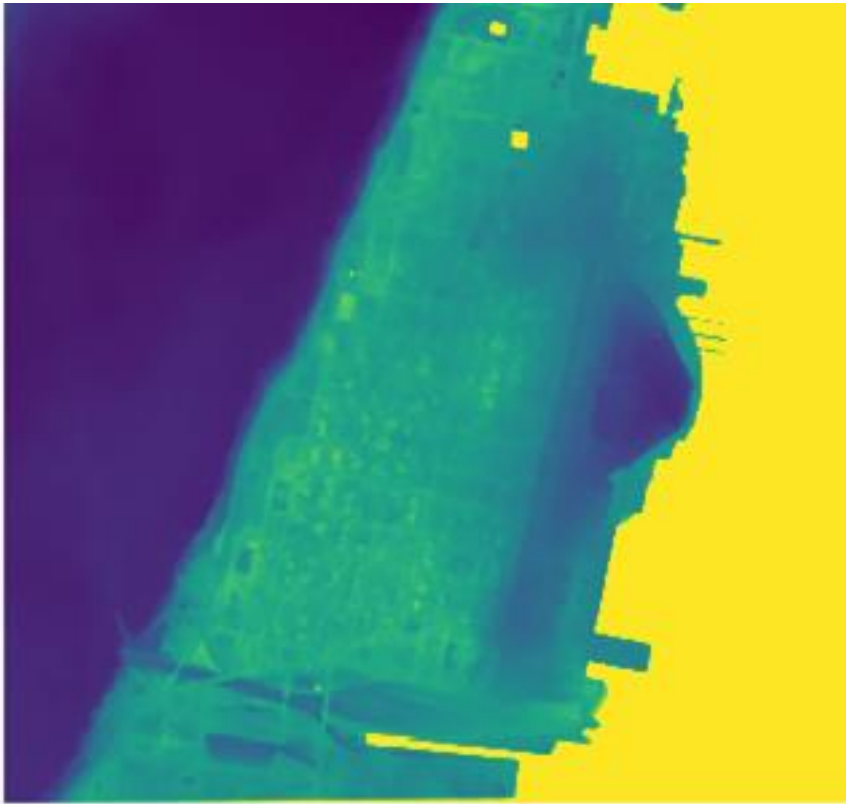
What urban characteristics lead to street flooding risk?

- Land cover and topography:
 - Elevation: The relative altitude at each street.
 - Slope: The inclination at each street.
 - Imperviousness: Ratio of area covered by impervious surfaces.
- Drainage system features:
 - Pipe Cross-Sectional Area (PCSA): Cross-sectional area of the pipe connected downstream from street manhole.
 - Pipe Distance to Closest Outfall or Pump (PDCOP): Pipe length downstream from street manhole until ejection or pumping units.

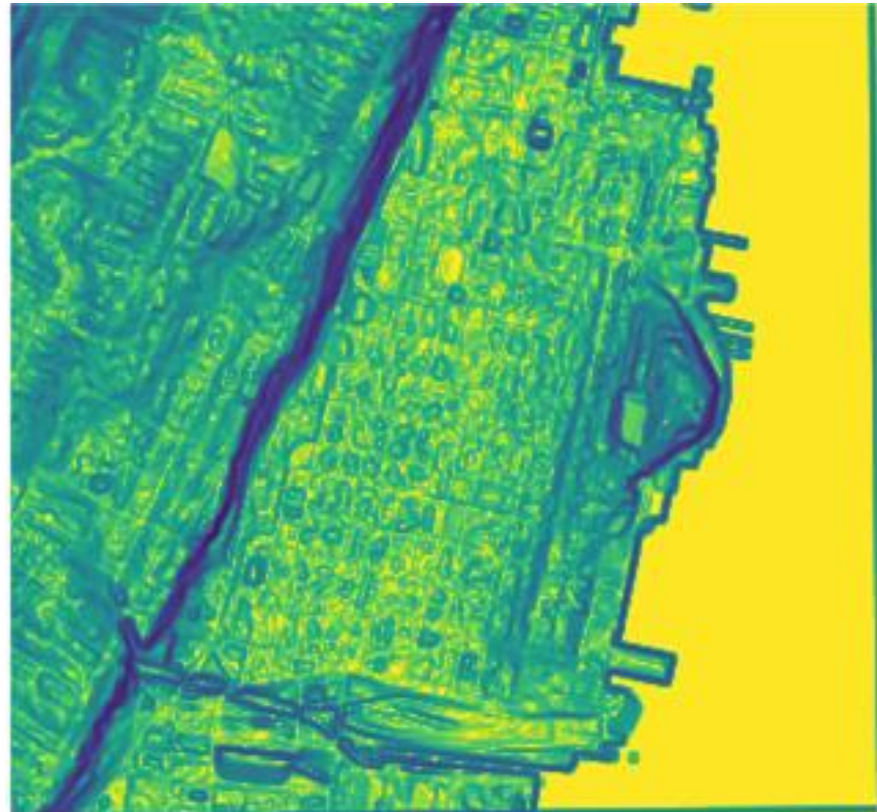
Methods

How to use machine learning to predict flood risk?

Elevation



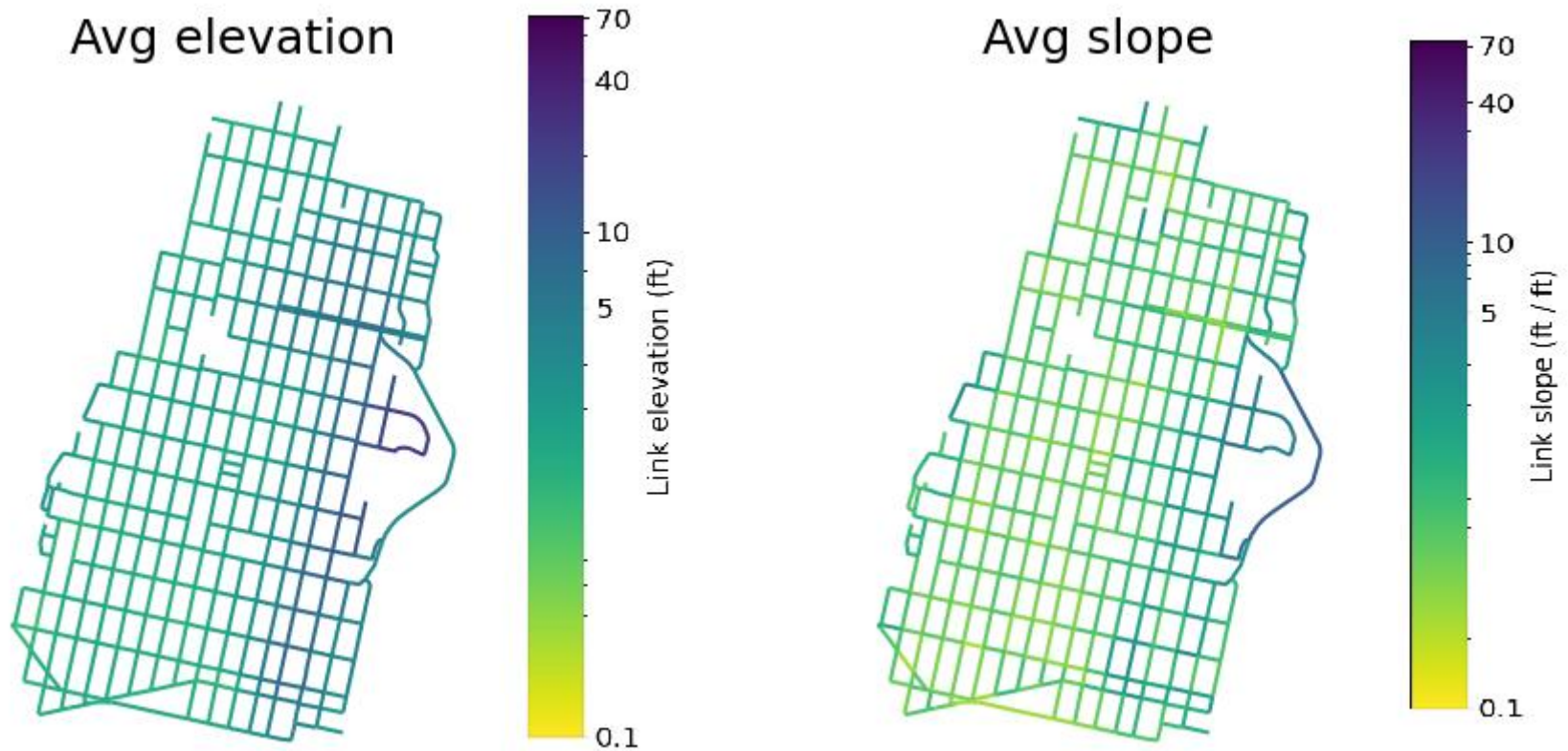
Slope



USGS NED one meter x58y451 NJ SdL5 2014 IMG 2015. 2015. Last visited 2019-05-22. URL: shorturl.at/acqIT

Methods

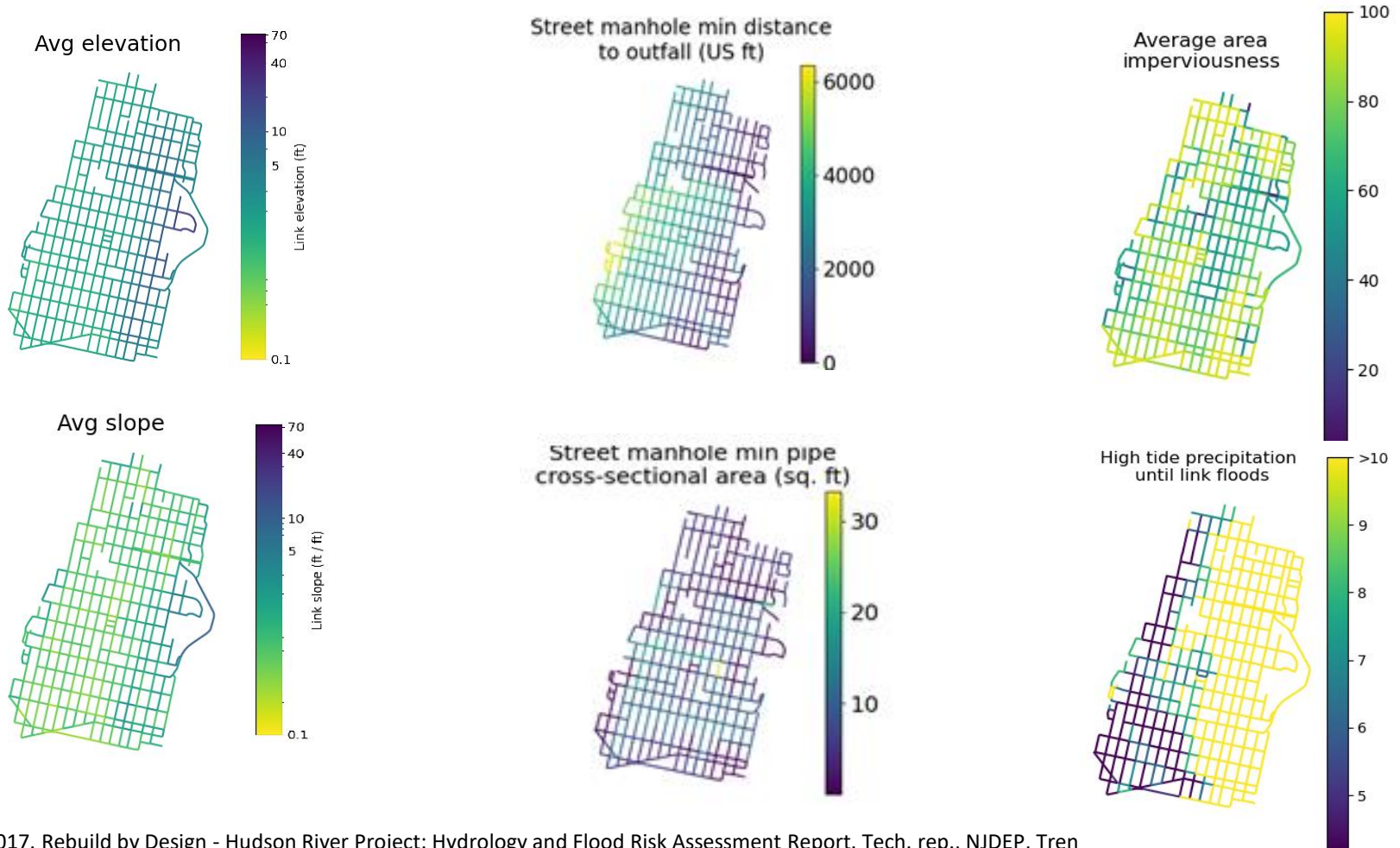
How to use machine learning to predict flood risk?



OpenStreetMap contributors. Planet dump retrieved from <https://planet.osm.org>, <https://www.openstreetmap.org>; 2017.
USGS NED one meter x58y451 NJ SdL5 2014 IMG 2015. 2015. Last visited 2019-05-22. URL: shorturl.at/acqIT

Methods

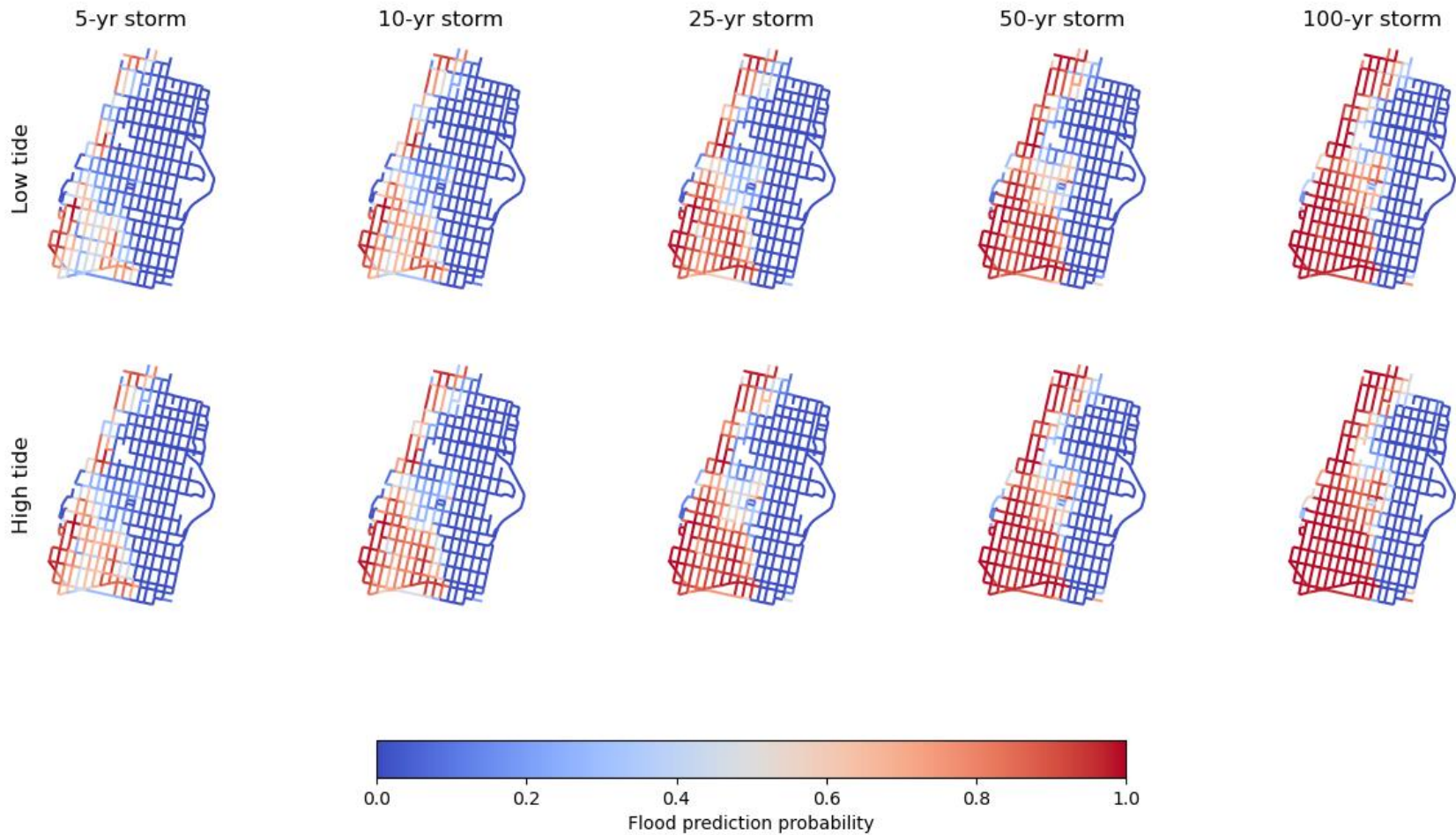
How to use machine learning to predict flood risk?



Dewberry, 2017. Rebuild by Design - Hudson River Project: Hydrology and Flood Risk Assessment Report. Tech. rep., NJDEP, Tren OpenStreetMap contributors. Planet dump retrieved from <https://planet.osm.org>. <https://www.openstreetmap.org>; 2017. USGS NED one meter x58y451 NJ SdL5 2014 IMG 2015. 2015. Last visited 2019-05-22. URL: shorturl.at/acqIT NHSA, 2015. North Hudson Service Area Sewer System. http://nhsahotline.com/Sewer/docs/Hoboken_Map_2015.pdf NJDEP, 2015. Land Use/Land Cover 2012 Update, Edition 20150217. <http://www.nj.gov/dep/gis/listall.html>

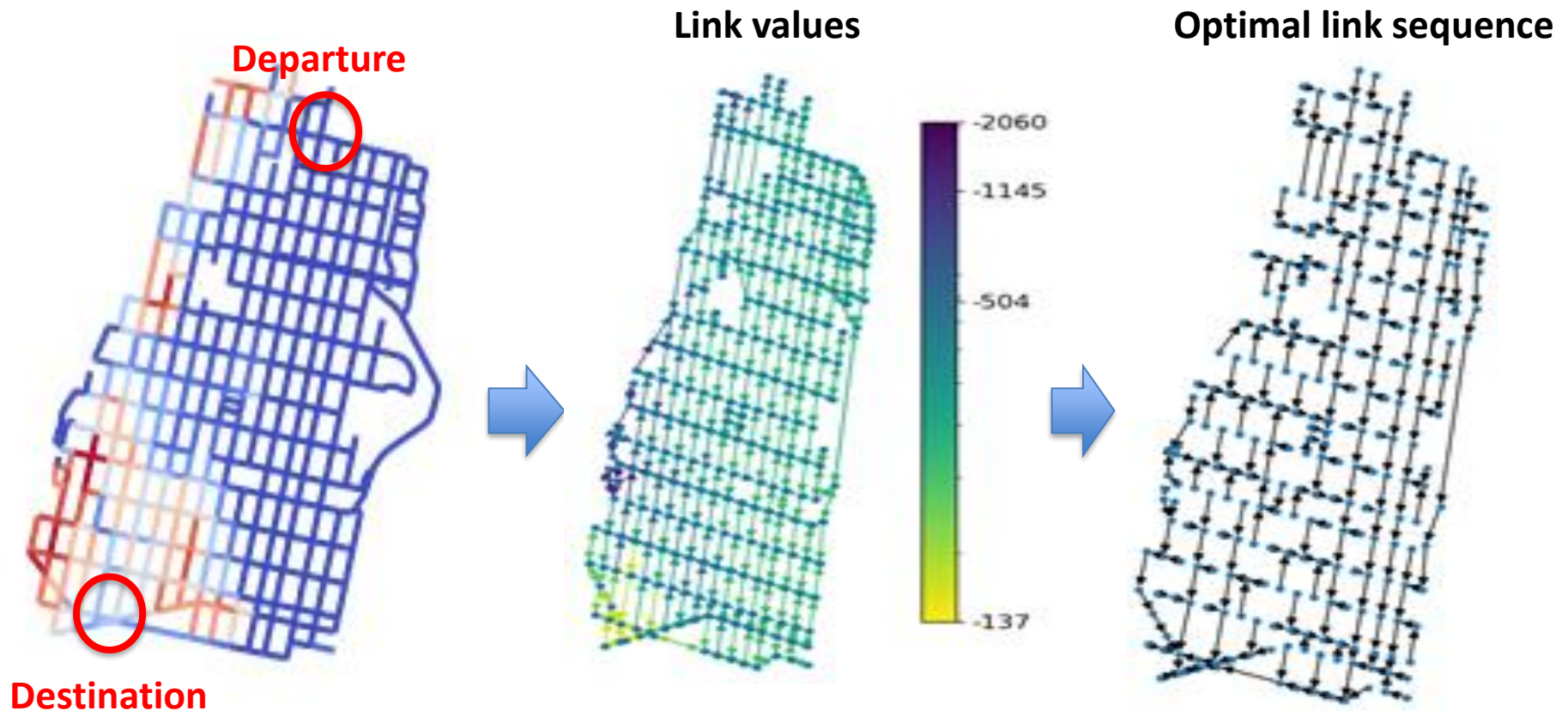
Methods

How to use reinforcement learning to devise paths?



Methods

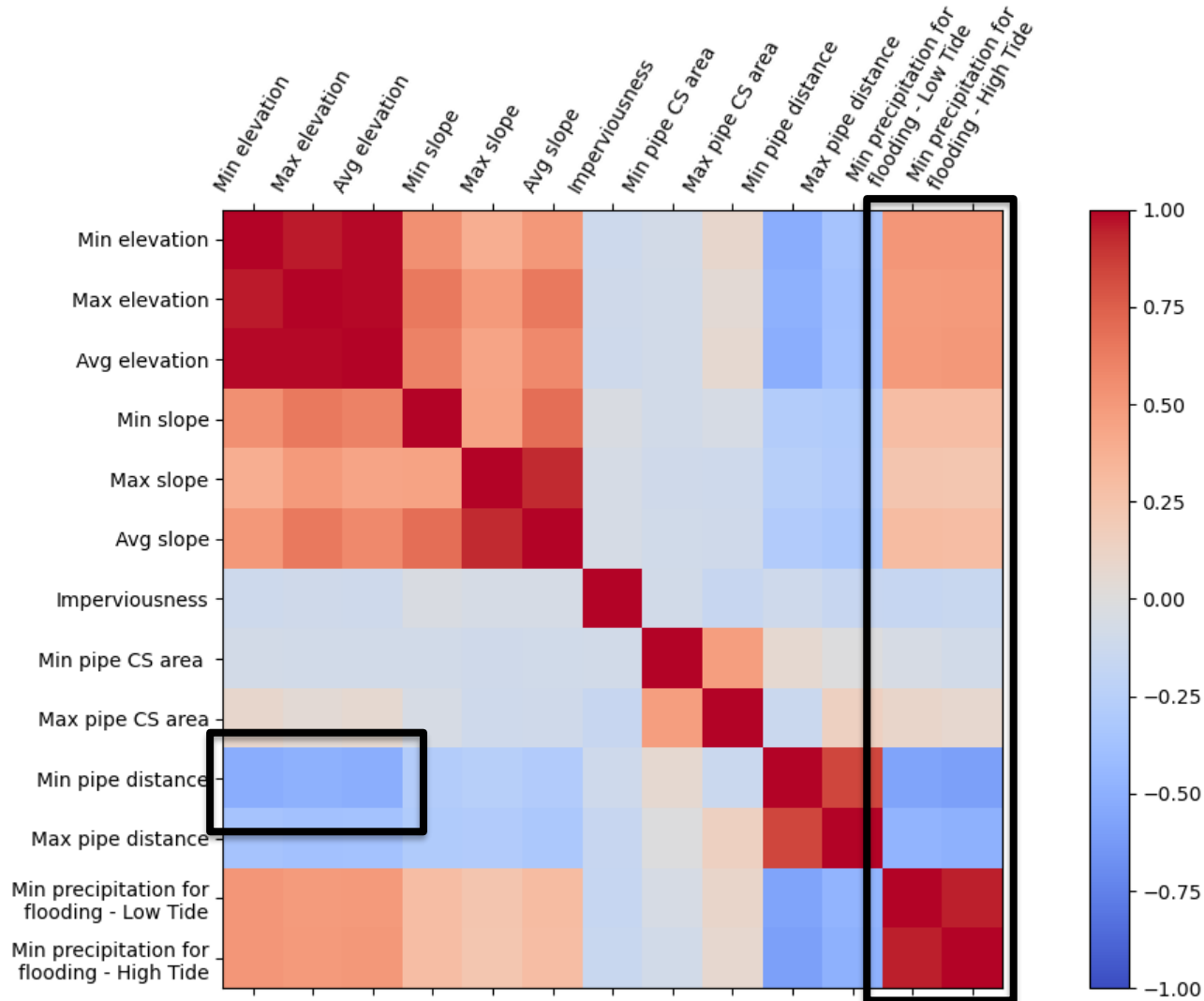
How to use reinforcement learning to devise paths?





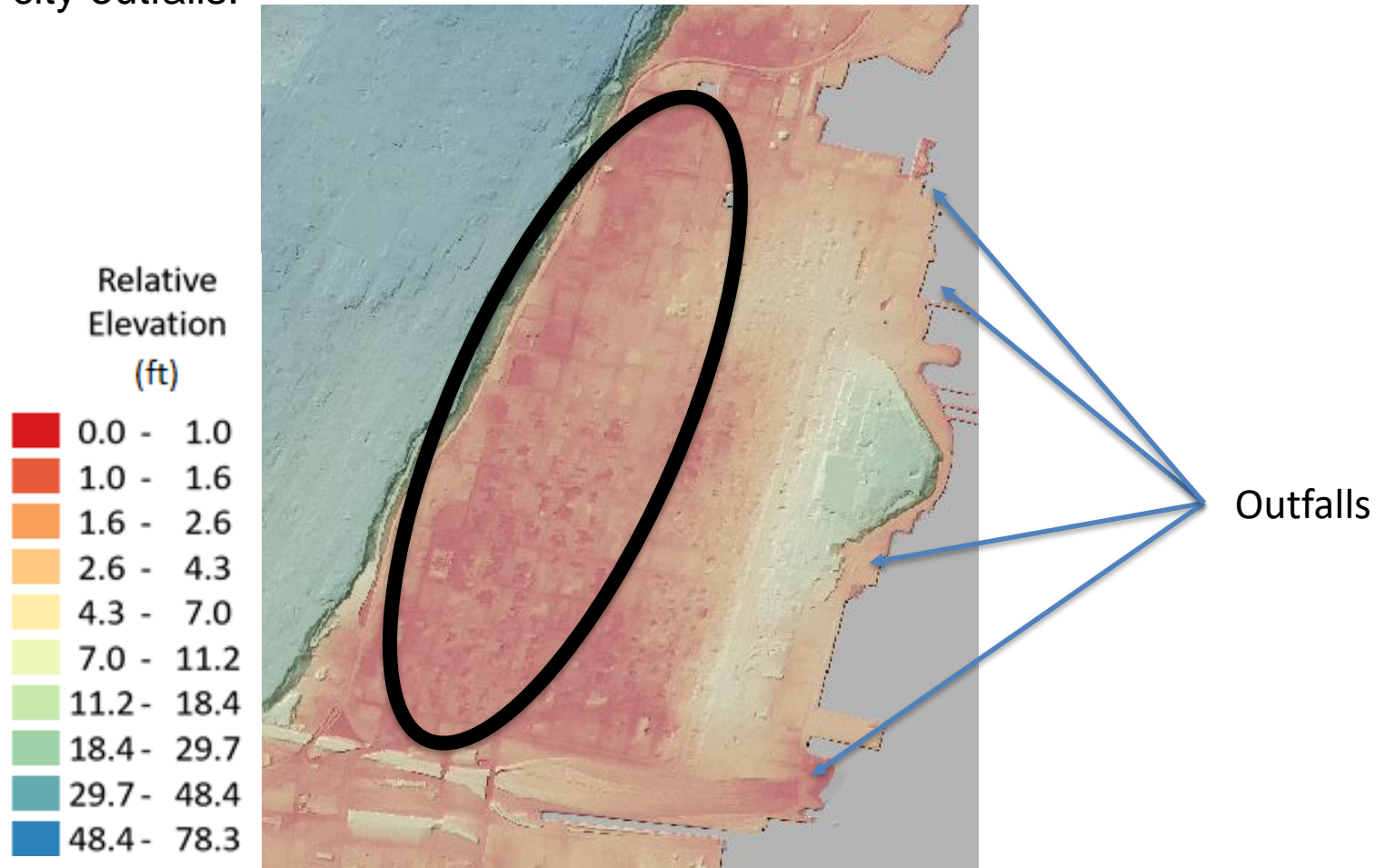
Results and discussion

What is the degree of correlation between features and flooding?



Results and discussion

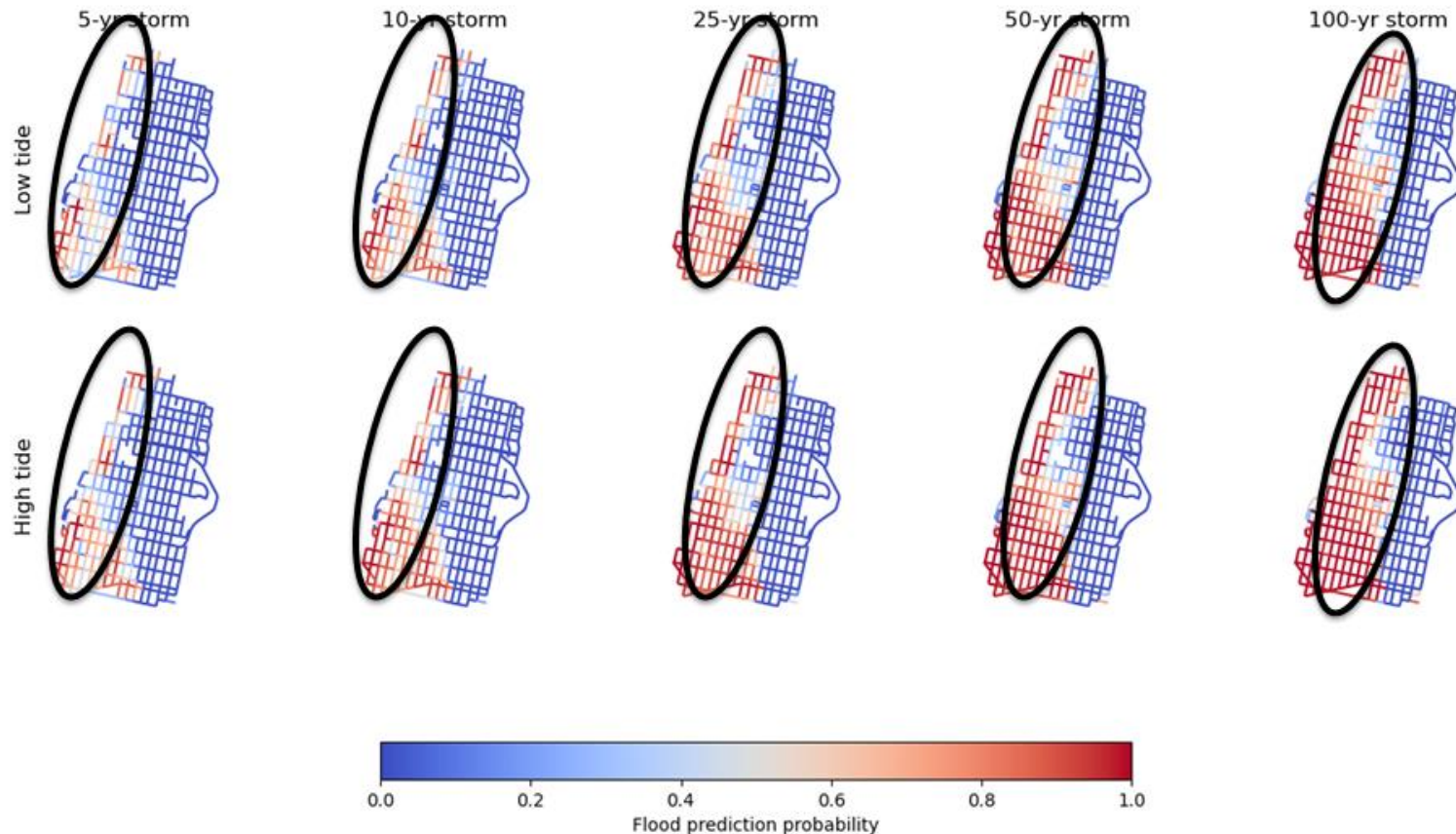
The lowest lying areas of the city are also the areas farthest from the Hudson River and the city outfalls.



Results and discussion

What features are more important in predicting flooding?

A “disruption boundary” forms starting on the West side, and propagates East during more intense events





Results and discussion

What features are more important in predicting flooding?

This occurs because elevation resulted in the most important predictor in our Machine Learning model.

Feature LR parameter	Value
Minimum elevation	-13.762
Precipitation	2.492
Minimum slope	-0.621
Minimum PDCOP	0.527
High tide	0.256
Imperviousness	0.097
Minimum PCSA	-0.012



Results and discussion

How use these predictions to improve driver navigation?

Path selection objectives:

- **Path shortness:** Provide paths that are not needlessly long.
- **Path reliability:** Provide paths that are less likely to be flooded.



Results and discussion

How use these predictions to improve driver navigation?

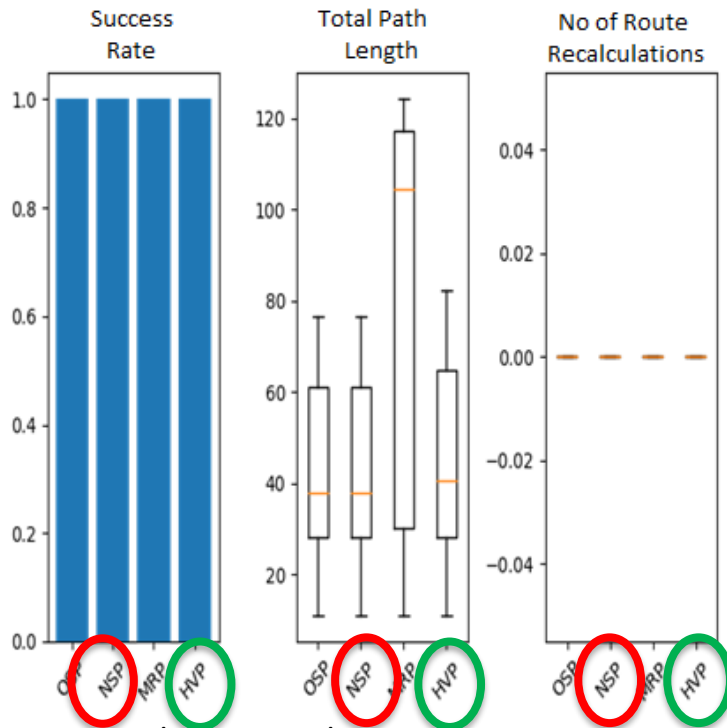
Evaluated routing algorithms:

- **Omniscient Shortest Path** (OSP, baseline): The shortest path under perfect information.
- **Naïve Shortest Path** (NSP): Take the shortest path and update it after reaching a flooded link.
- **Most Reliable Path** (MRP): Take the most reliable path and update it after reaching a flooded link.
- **Most Valuable Path** (MVP): Subsequently choose the available link with lowest reliability-adjusted travel time.

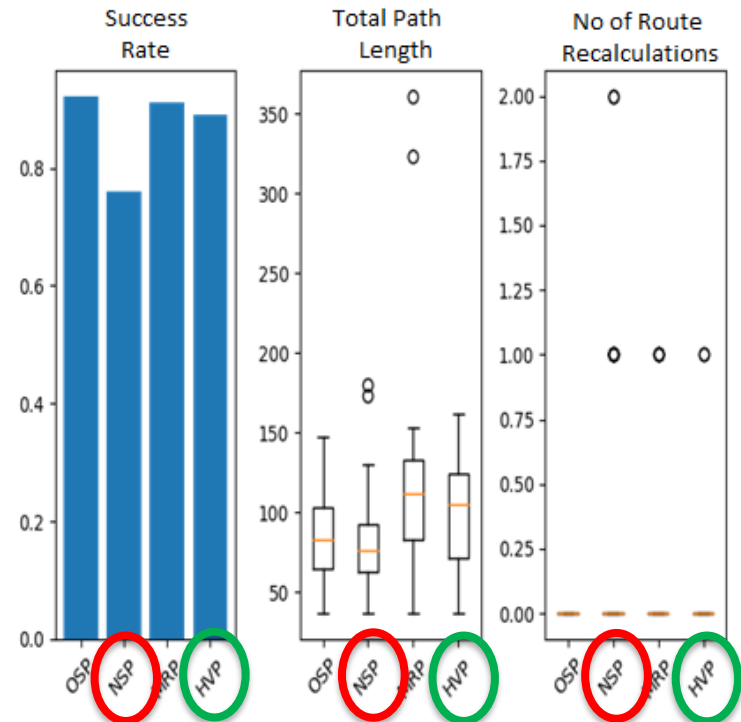
Results and discussion

Incorporating flood risk data reduces the risk of having to reroute or of reaching a dead end, while maintaining reasonable path length

Low flood risk regions



High flood risk regions



OSP: Omniscient Shortest Path.

NSP: Naïve Shortest Path.

MRP: Most Reliable Path.

MVP: Most Valuable Path.



Conclusions

Summary of findings

- Flood events have the potential to cause system-wide disruption to transportation systems by impacting both mobility and accessibility. These impacts can be estimated using traffic simulation techniques adapted to a disruptive setting and serve to guide flood resilience transportation planning.
- A city's particular characteristics influence its vulnerability to flooding. Such vulnerability spills over to transportation systems, posing risk to drivers. Flood risk can be predicted using statistical analysis, and the resulting information can guide flood advisories and assist drivers in navigating flood-prone regions or canceling trips altogether.



Future directions

Future work

- The traffic simulation model presented in the first module relies on SDUE assumptions. We are comparing these results against other traffic simulation techniques in order to validate our findings.
- We are further investigating actual drivers' behavior during flood events to better assess transportation flood resilience. Namely, we are investigating drivers' prior knowledge of flood risk and how they respond to new flood risk information.



Thank you for your attention.

**Questions
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