ADAPTIVE SAMPLING DESIGN FOR ESTIMATING SPATIOTEMPORAL PATHOGEN PREVALENCE IN CITIES

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OUTLINE

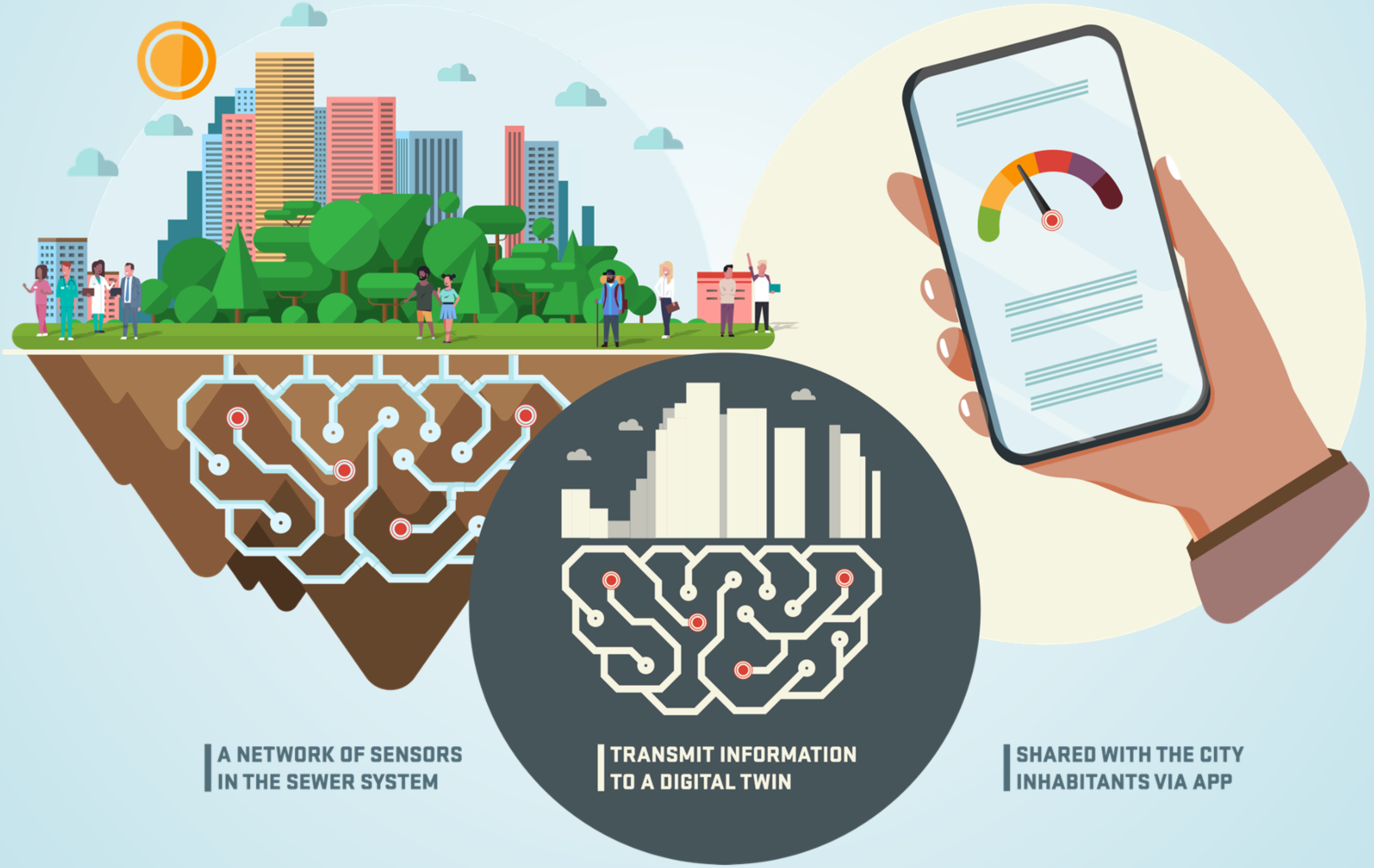
- Pandemic Resilient Cities Project
- Motivating examples
- Conceptualizing the adaptive sampling design
  - Creating sewersheds
  - Aligning with Census data
  - Unequal probability sampling
- Results
  - Viral concentration estimation
  - Preliminary results in City 1

PANDEMIC RESILENT CITIES PROJECT

- *Goal*: Partner with communities to create systems that produce city-level infectious disease forecasts
  - Build interdisciplinary partnerships between science & academia, public health professionals, and community leaders
  - Build mathematical models that demonstrate stepping back across epidemic tipping points
  - Identify feedback loops that predict and alter transmission rates
- Key components
  - Wastewater-based epidemiology
  - Surveillance by sequencing
  - Adaptive sampling

LONG-RANGE GOAL

PANDEMIC-RESILIENT CITY



A NETWORK OF SENSORS IN THE SEWER SYSTEM

TRANSMIT INFORMATION TO A DIGITAL TWIN

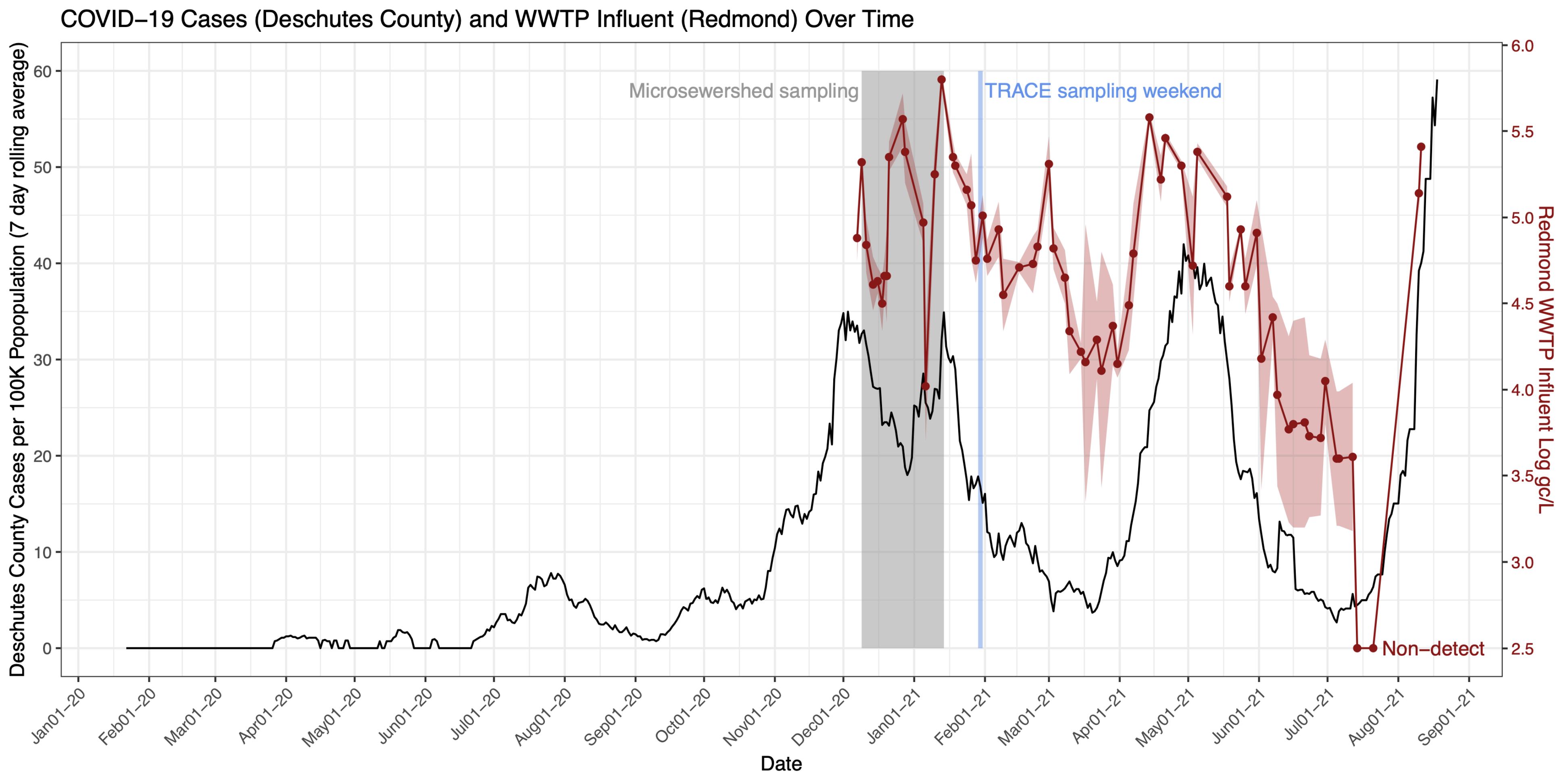
SHARED WITH THE CITY INHABITANTS VIA APP

WORK WITH CITIES

- Workshop last spring/summer with community stakeholders (public health, utilities, etc.)
- Prototype development starting this flu season, continuing through next
- Weekly wastewater monitoring at different point in city and at influent of wastewater treatment plant for 4 pathogens:
  - Influenza A
  - Influenza B
  - SARS-CoV-2 (COVID)
  - RSV
- Have time series of data from 3 cities

MOTIVATING EXAMPLES

WHY WASTEWATER?



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WHY UNEQUAL PROBABILITY SAMPLING?

Simulation example:

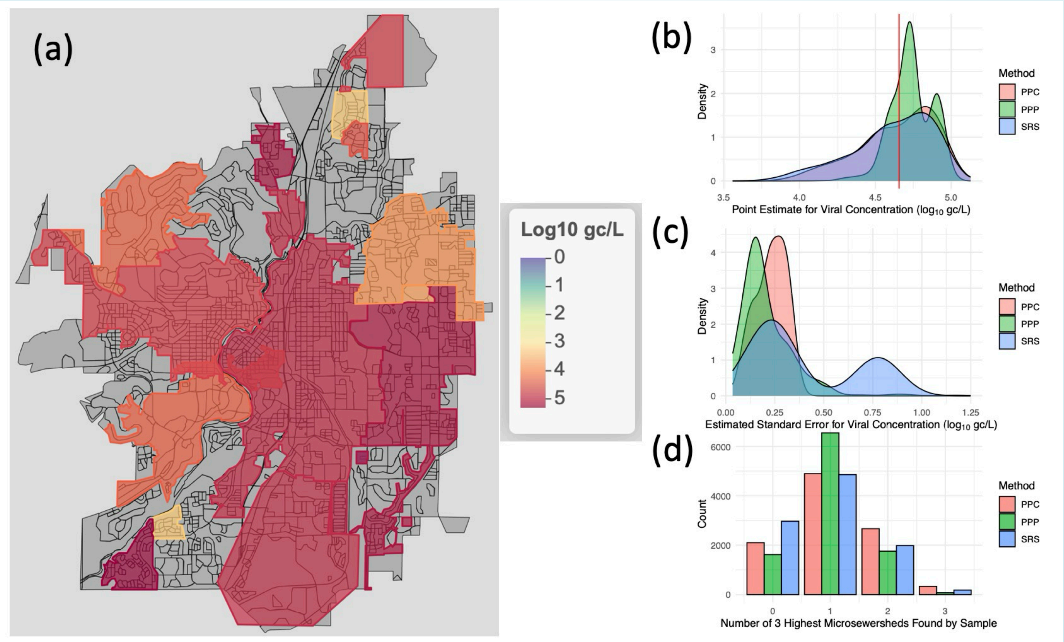
- A city has been split into 16 sampling locations
- Take 10,000 samples of size 5 using:
  - simple random sample (SRS)
  - probability proportional to population (PPP)
  - probability proportional to viral concentration (PPC)

WHY UNEQUAL PROBABILITY SAMPLING?

(a) Viral concentration data

(b) Point estimates and (c) SE of estimates by method for 10,000 simulated samples

(d) PPC is the best method at sampling higher concentration MH, resulting in samples that contain at least two of the three highest concentration MH 29.8% of the time, compared with 18.1% of the time for PPP and 21.2% for SRS.



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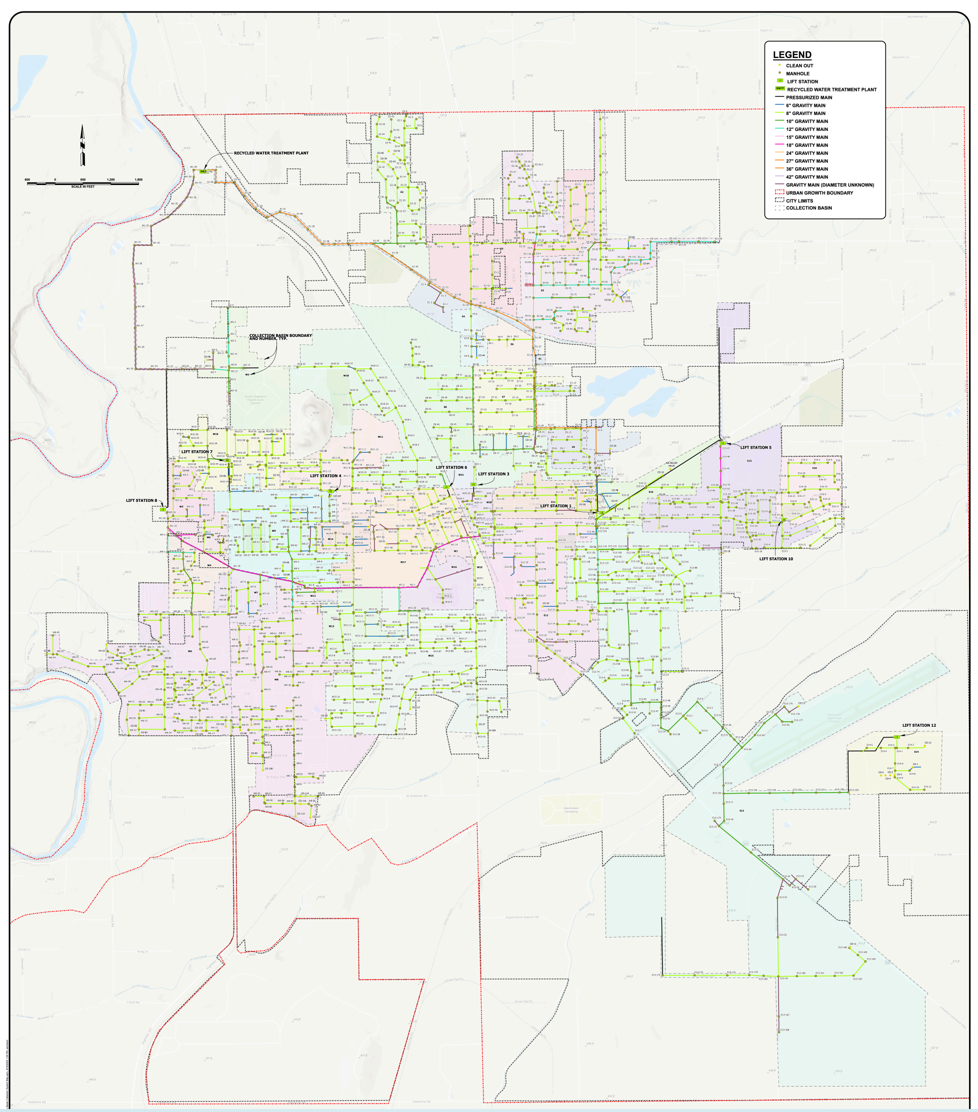
CREATING THE SAMPLING FRAME

CREATING SEWERSHEDS



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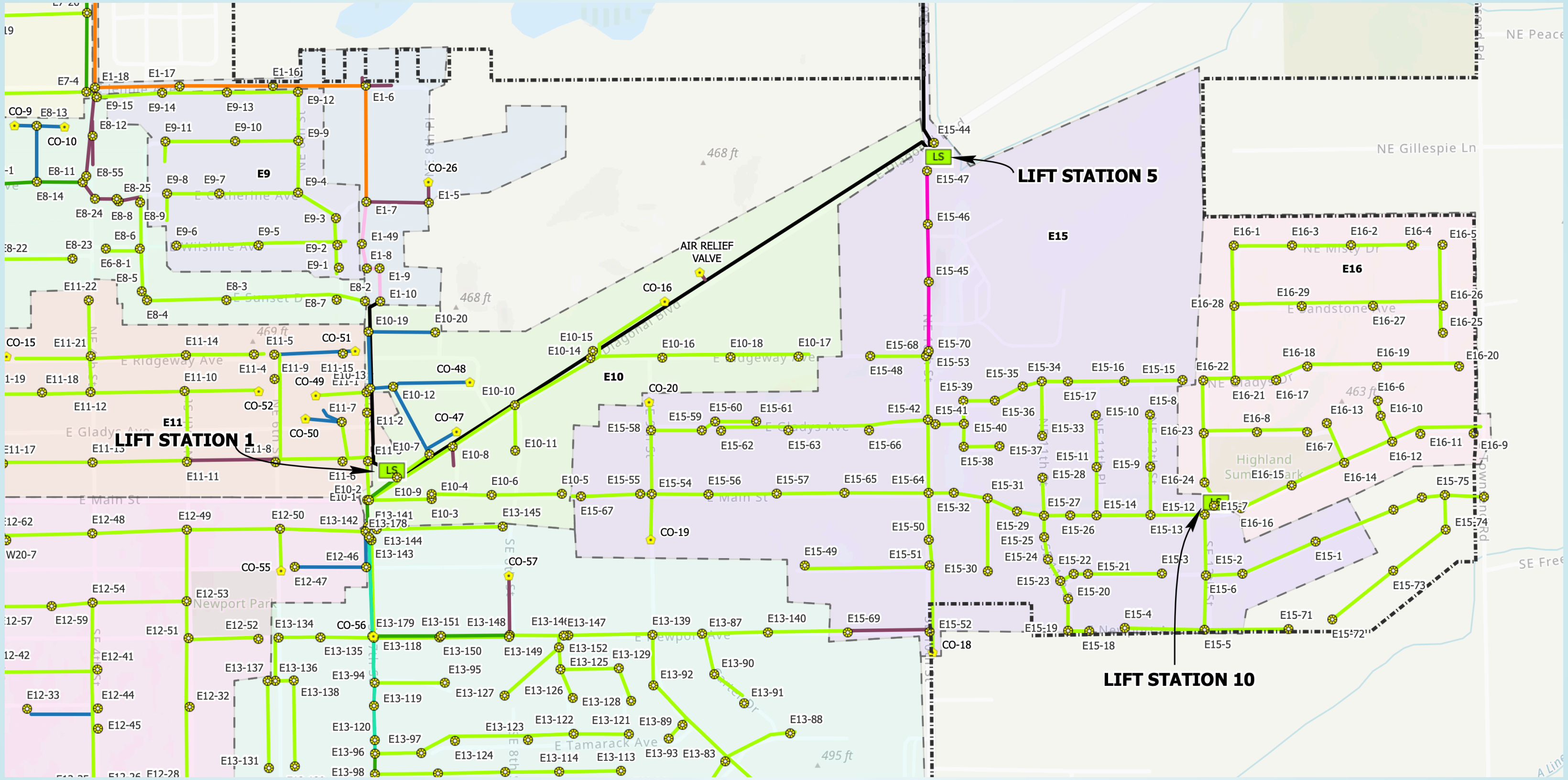
CREATING SEWERSHEDS



- How many?
- Identify Maintenance Hole (MH) that captures all flow from sewershed
- Attempt to make sewersheds disjoint

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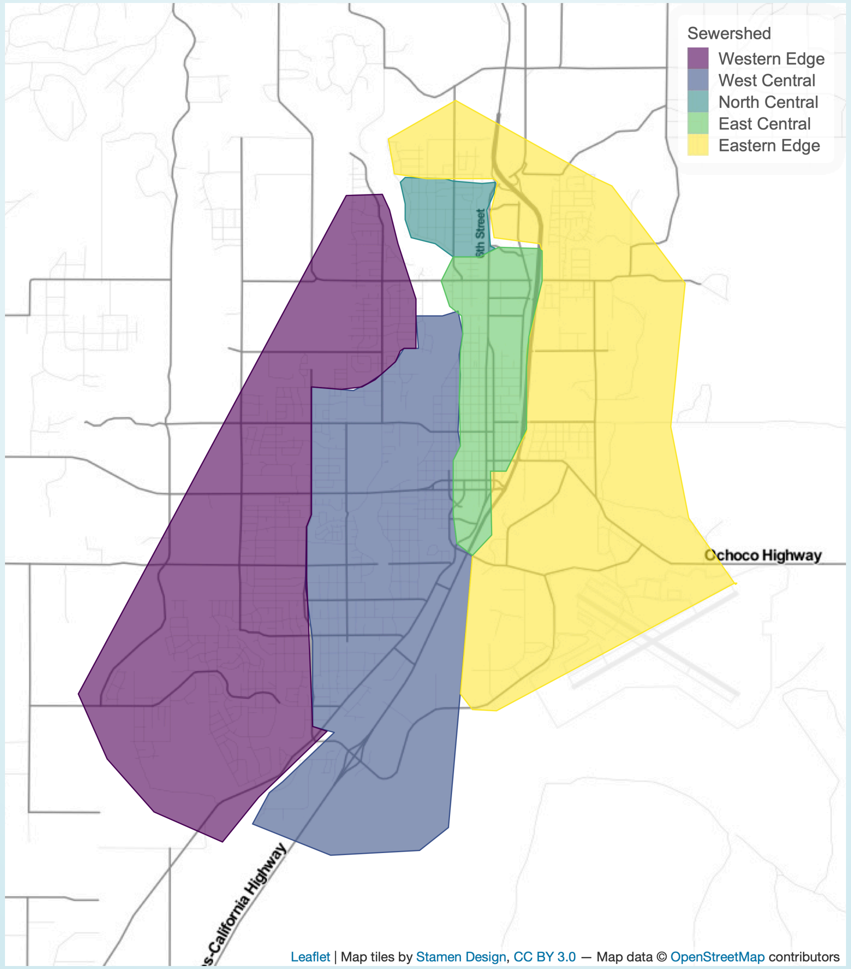
SEWERSHEDS

- Each sewershed will be a sampling unit



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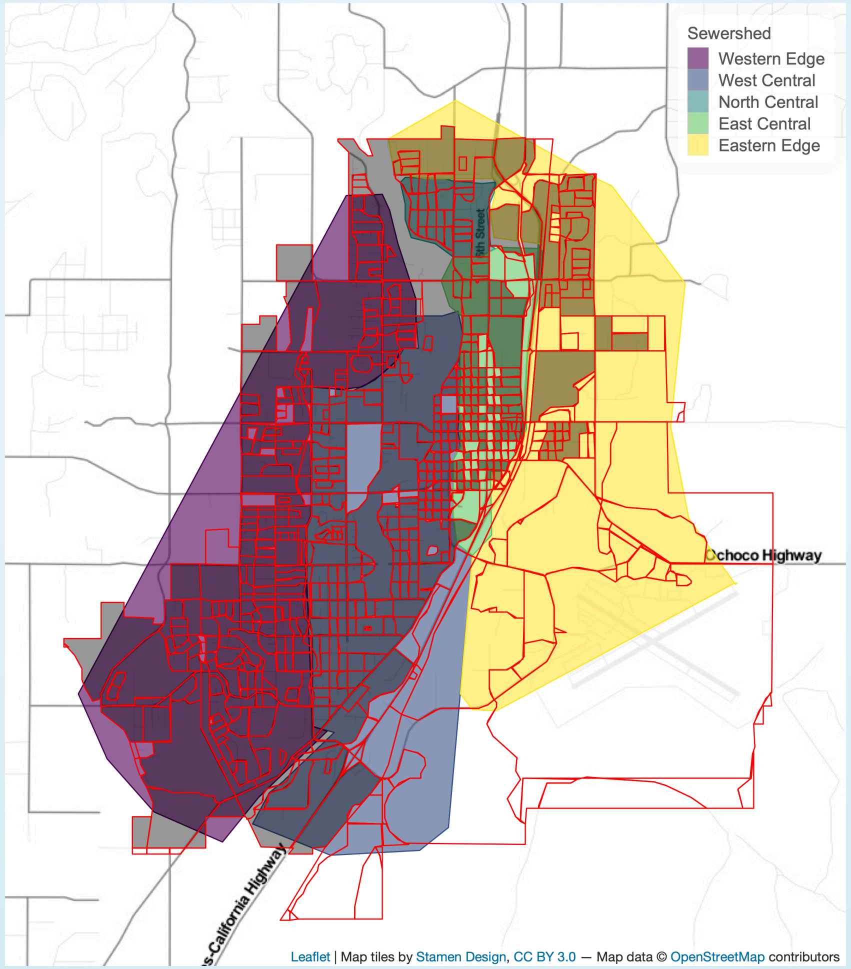
CENSUS BLOCKS

- Use Census data to add auxiliary information to inform selection probabilities



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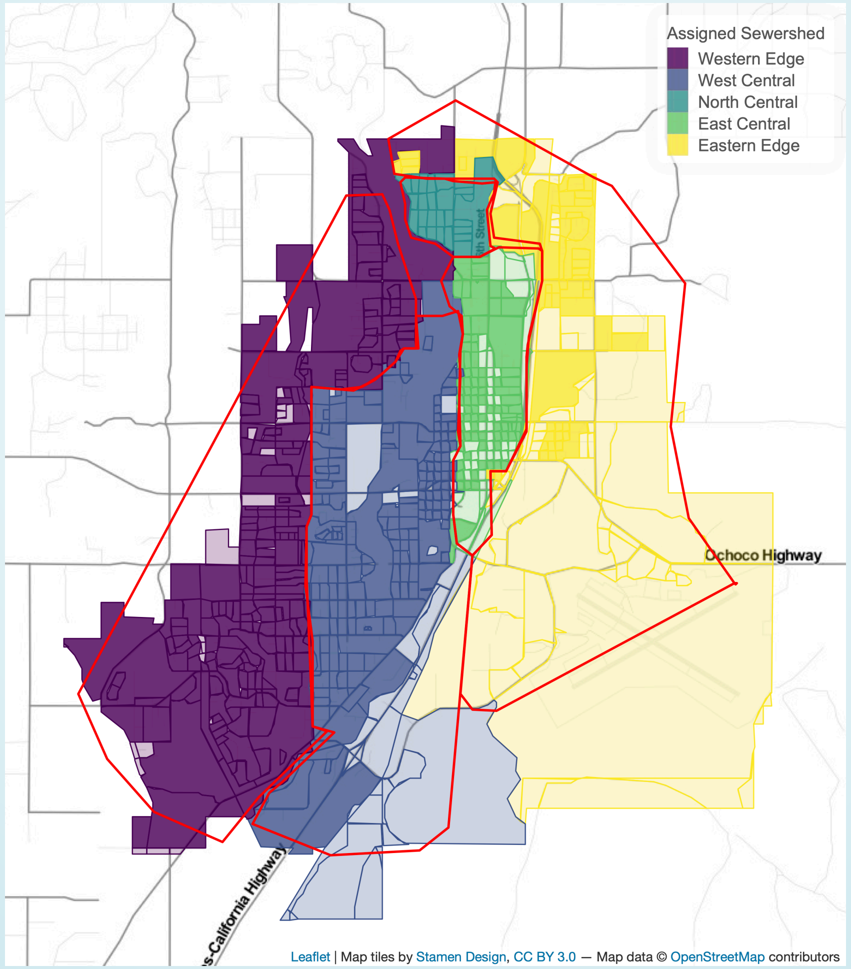
DEVELOPMENT OF SAMPLING FRAME

- Intersect Census blocks and sewersheds to assign demographic variables



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UNEQUAL PROBABILITY SAMPLING DESIGN

- Selection probabilities for each sewershed are determined by a weighted average of population size and viral concentration of pathogen targets
- Updated each week based on previous weeks' data and logistical constraints

The probability of selecting sewershed i during week k is

$$\pi_i^{(k)} = \frac{\sum_{t \in \tau} \left(\frac{w_t^{(k)} x_{it}^{(k-1)}}{\sum_{i \in M} x_{it}^{(k-1)}} \right)}{\sum_{t \in \tau} w_t^{(k)}}$$

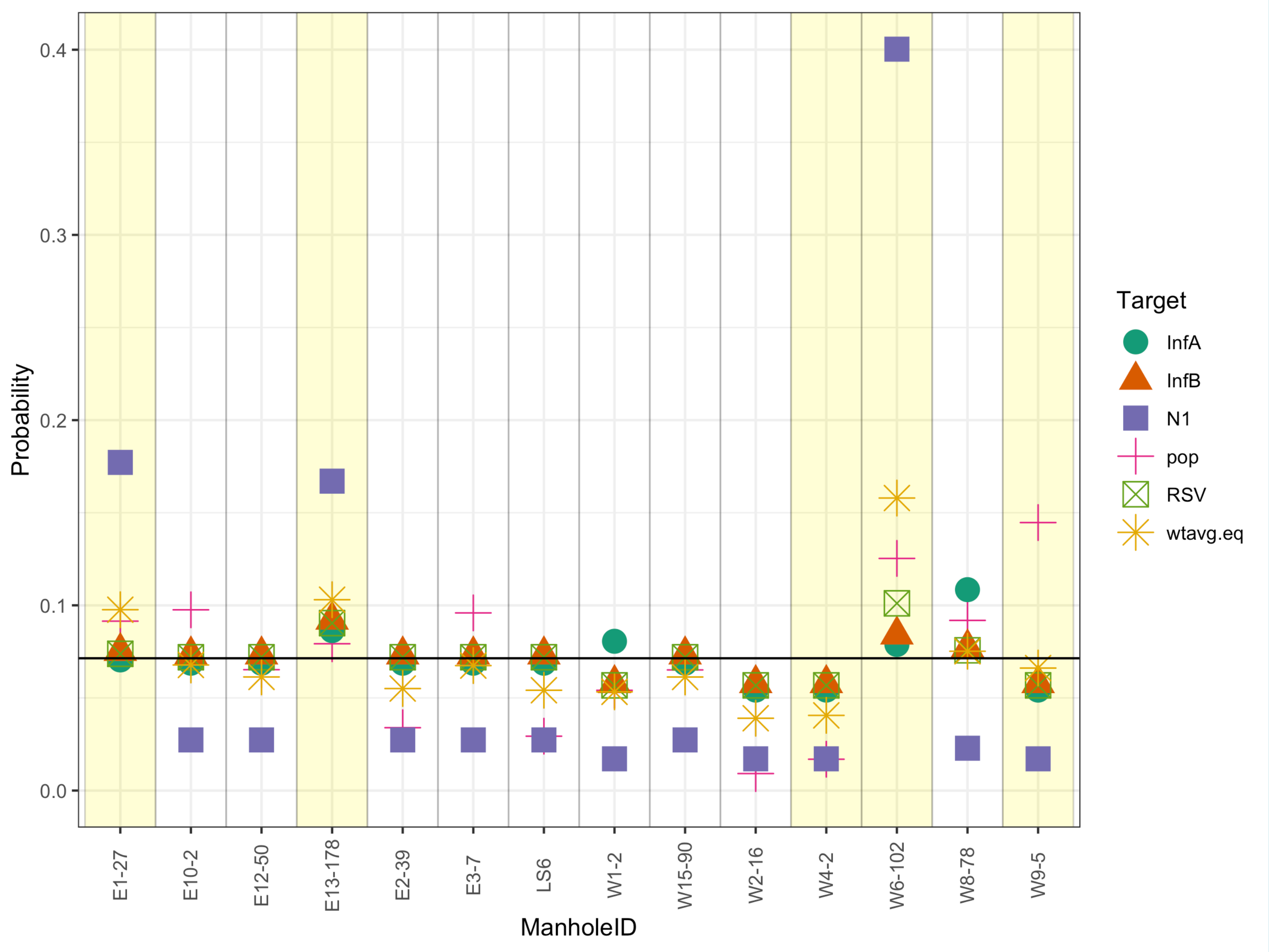
where

- τ is the set of targets used to determine probabilities (including population size and pathogen targets)
- $w_t^{(k)}$ is the weight given to item t of τ for week k
- $x_{it}^{(k-1)}$ is the value of item t for week $k-1$ (for example, the measured viral concentration of SARS-CoV-2 during the previous week)

ADVANTAGES OF THIS APPRAOCH

- Combines information from multiple targets and demographic variables (or other auxiliary sources)
- Allows information from past week(s) to be incorporated
- Can be tuned based on local needs, expert opinion (e.g. give influenza a lower weight when it is not flu season)
- Flexible pipeline that can handle delayed/missing data
- Sample with higher probability from 'hotspots' and other areas of interest
- Still a random, probability-based sample and allows generalizable inference

EXAMPLE



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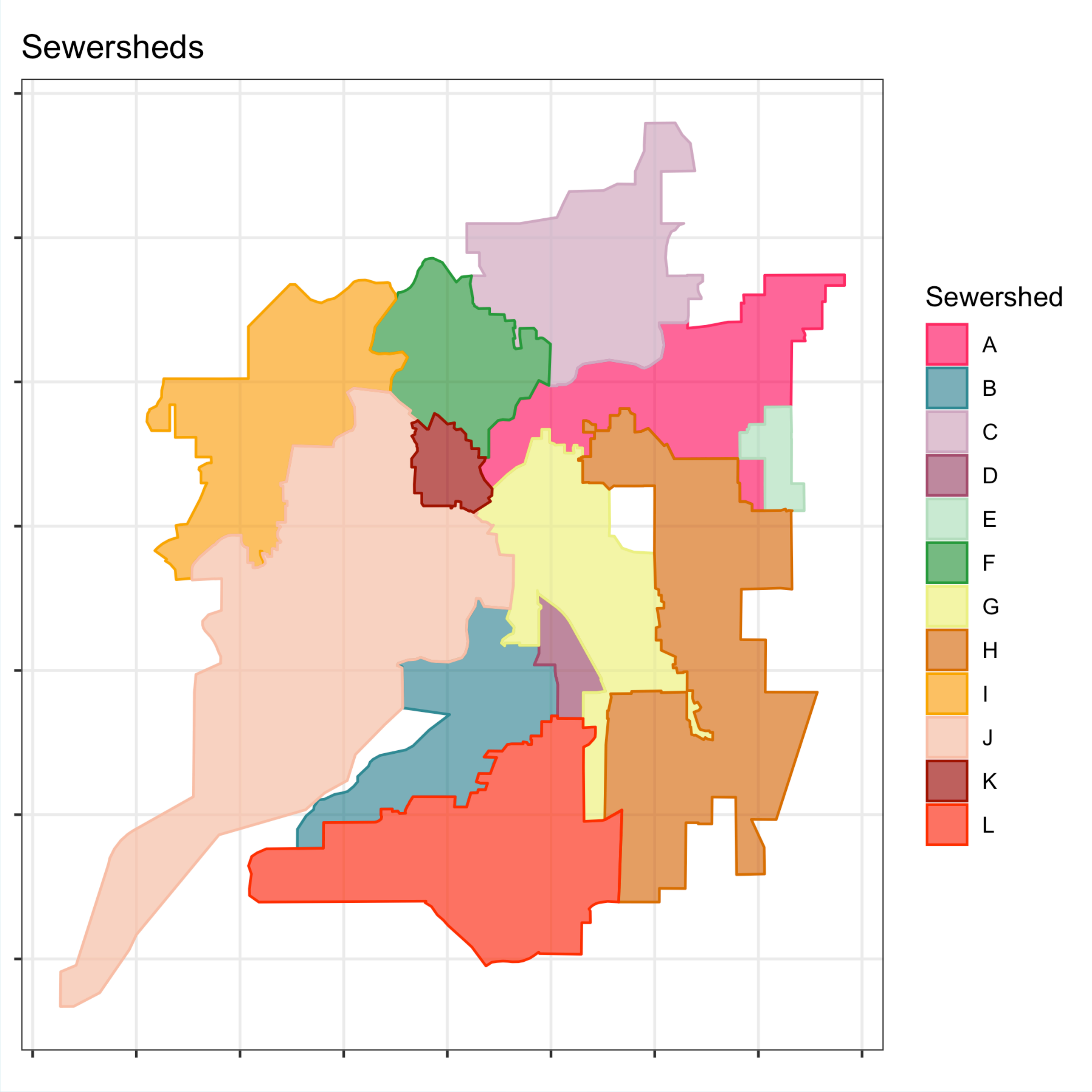
RESULTS



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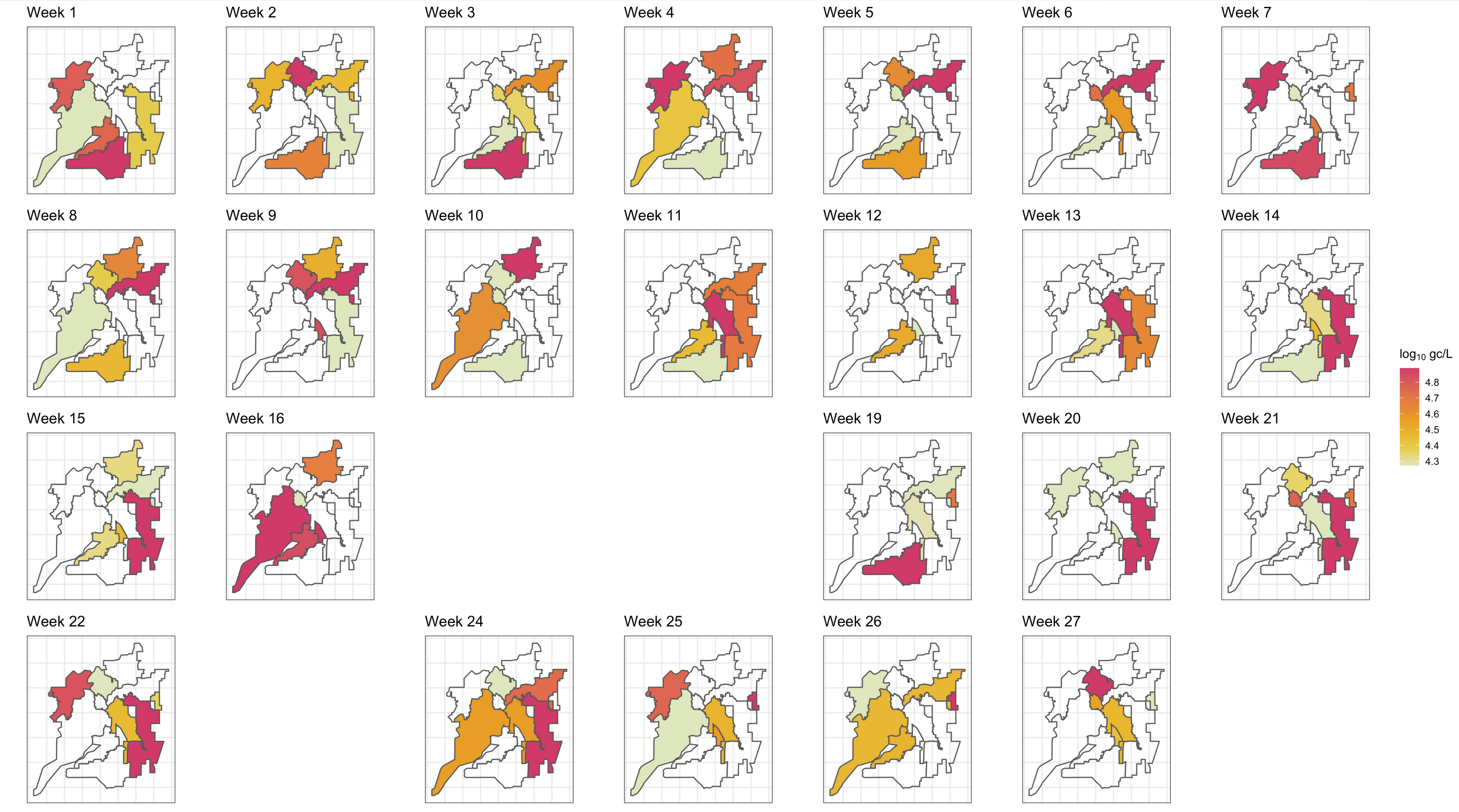
VIRAL CONCENTRATION OF SARS-COV-2



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VIRAL CONCENTRATION ESTIMATION

The estimated viral concentration based on the unequal probability sampling design can be found using a Horvitz-Thompson estimator:

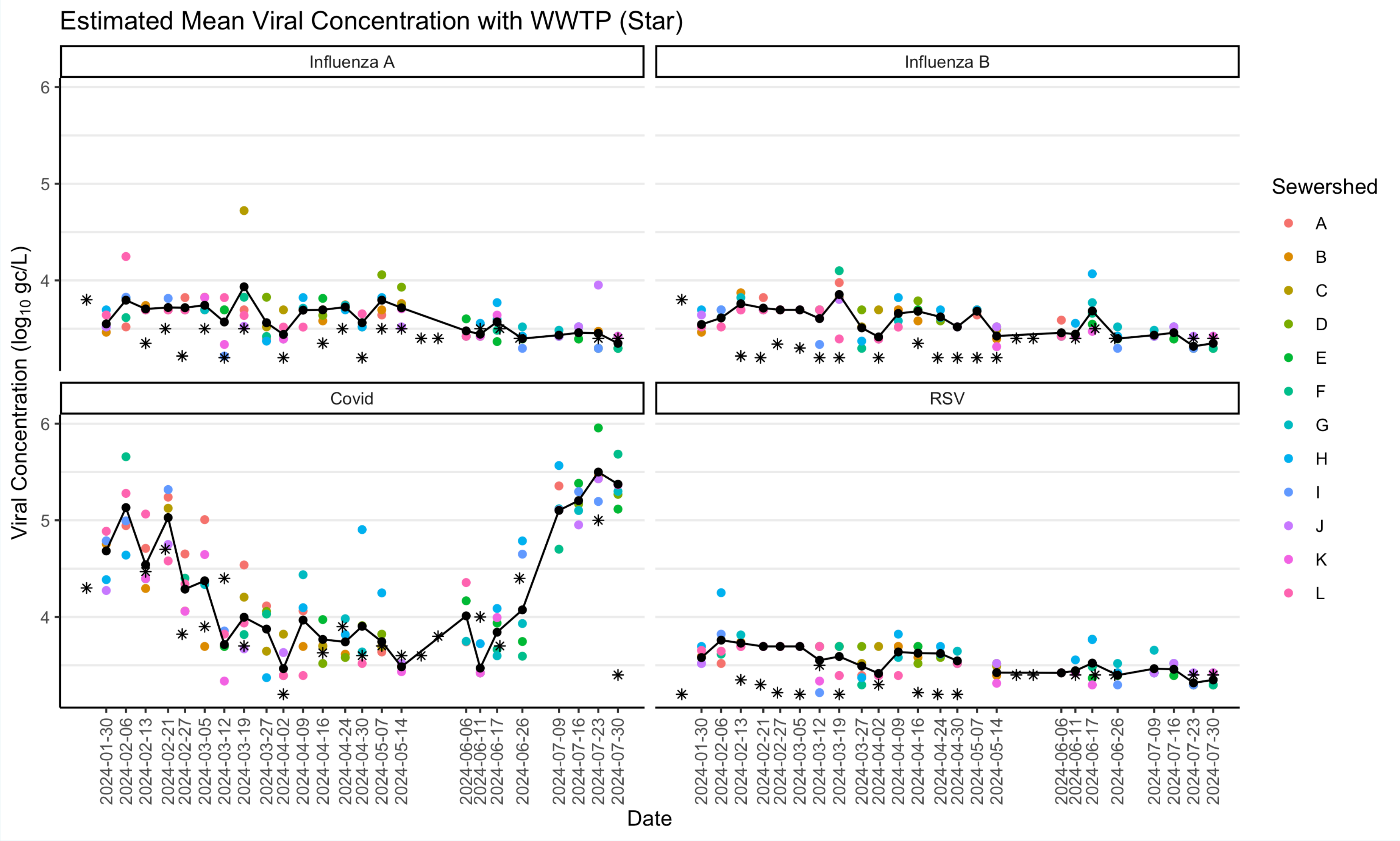
$$\hat{\bar{x}}^{(k)} = \frac{\sum\limits_{i \in \mathcal{S}^{(k)}} x_i^{(k)} / \pi_i^{(k)}}{\sum\limits_{i \in \mathcal{S}^{(k)}} 1 / \pi_i^{(k)}}$$

where

- $\pi_i^{(k)}$ is the selection probability for sewershed i during week k
- $x_i^{(k)}$ is the observed viral concentration (of the particular target being estimated) in sewershed i during week k

Implementation via the survey package in R.

RESULTS IN CITY 1



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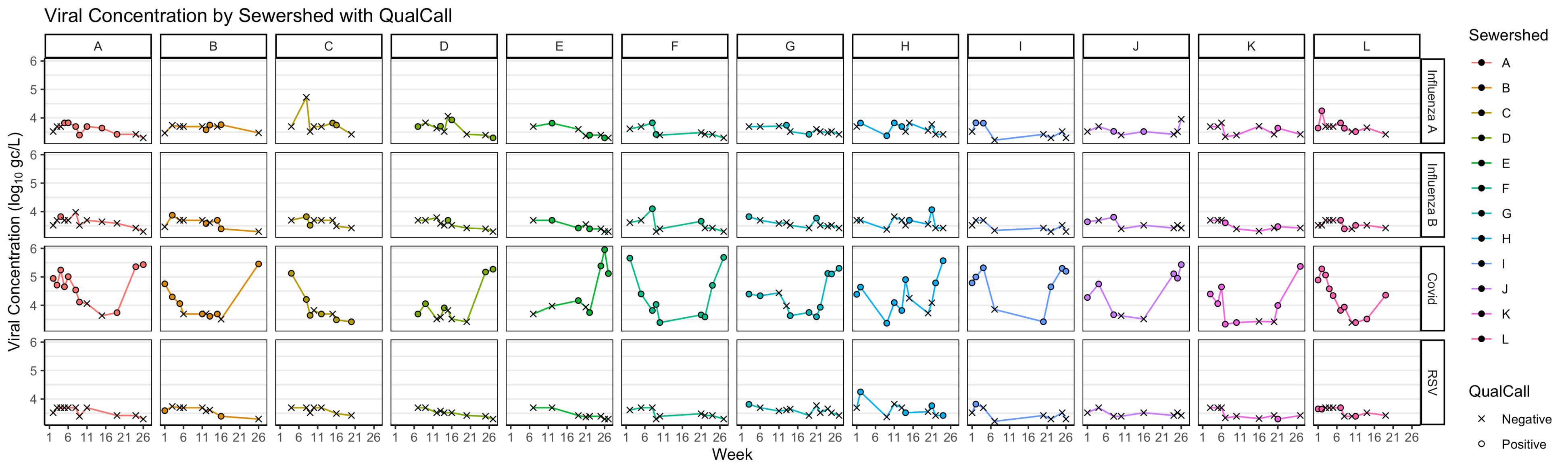
CITY 1 BY SEWERSHED



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NEXT STEPS

- Use 'Rosetta Stone' to translate between log_{10} gc/L to cases
- Incorporate sampled data into mathematical models to nowcast and forecast case counts
- Incorporate other data streams (e.g. hospitalizations, demographic data)
- Infer concentrations for non-sampled locations at a point in time to create a heatmap
- Work with community partners on how to make the data products most actionable

CONCLUSIONS

- Flexible design-based sampling framework that incorporates previous weeks of data
- Cooperative feedback loop with wastewater & mathematical modeling teams, as well as community partners
- Potential for incorporation of a variety of data streams
- Can be tailored for unique characteristics, needs of cities
- Still a work in progress!!

THANK YOU!

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