# Alternative Fueling Infrastructure Location Optimization

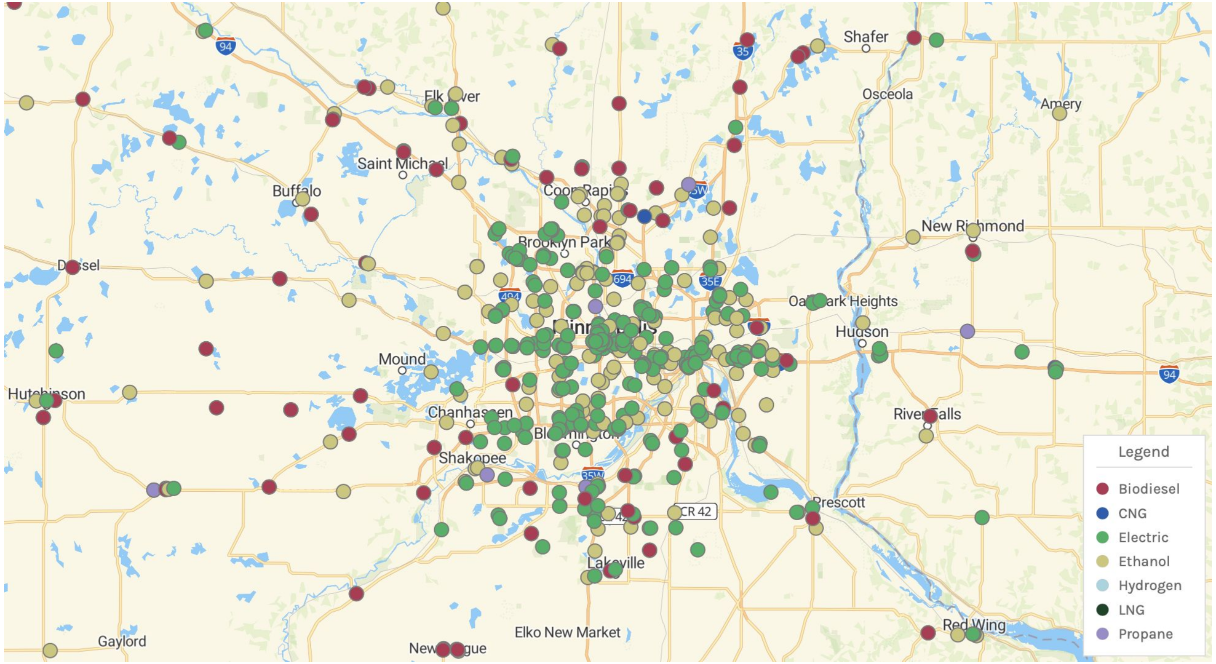
GIS 5571: ArcGIS I

Luke Zaruba
December 14, 2022

# Problem

Where are the best locations to invest limited resources while ramping up access to alternative fuel sources?

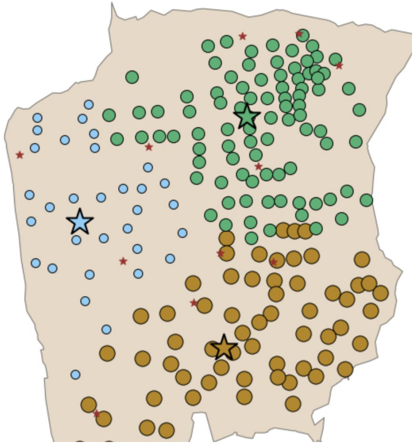
How can funding be optimized to most efficiently serve people?

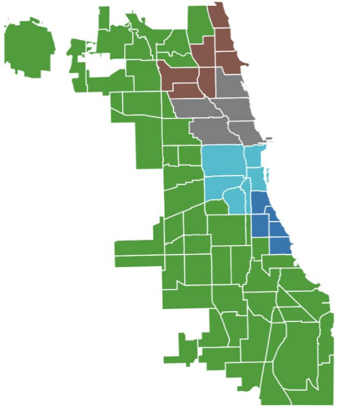



Credit: U.S. Department of Energy AFDC (2022)

# Solution

- Spatial optimization can determine which locations will most efficiently provide access over an area, in conjunction with one another (location-allocation)
- Other applications of spatial optimization could include routing, OD cost matrices, regionalization, etc…





(L to R): P-Median, Skater
Credit: PySAL/spopt Developers (2022)

# Spatial Optimization Techniques

Two algorithms selected:

- Location Set Coverage Problem (LSCP)
  - Toregas, et al. (1971)
  - Minimize number of facilities such that **all** demand is within a defined threshold distance
  - “Minimize Facilities” option in ArcGIS

- Maximal Coverage Location Problem (MCLP)
  - Church & ReVelle (1974)
  - Maximize amount of demand covered within a defined thres
    based on a **fixed** number of facilities
  - “Maximize Coverage” option in ArcGIS

$$
\begin{array}{lllr}
\textbf{Minimize} & \sum_{j=1}^{n} x_j & & (1) \\
\textbf{Subject to:} & \sum_{j \in N_i} x_j \geq 1 & \forall i & (2) \\
 & x_j \in 0,1 & \forall j & (3)
\end{array}
$$

**Where:**

$$
\begin{array}{lll}
i & = & \text{index referencing nodes of the network as demand} \\
j & = & \text{index referencing nodes of the network as potential facility sites} \\
S & = & \text{maximal acceptable service distance or time standard} \\
d_{ij} & = & \text{shortest distance or travel time between nodes} i \text{and} j \\
N_i & = & \{j | d_{ij} < S\} \\
x_j & = & \begin{cases} 1, \text{if a facility is located at node} j \\ 0, \text{otherwise} \end{cases}
\end{array}
$$

$$
\begin{array}{lllr}
\textbf{Maximize} & \sum_{i=1}^{n} a_i y_i & & (1) \\
\textbf{Subject to:} & \sum_{j \in N_i} x_j \geq y_i & \forall i & (2) \\
 & \sum_{j} x_j = p & \forall j & (3) \\
 & y_i \in \{0,1\} & \forall i & (4) \\
 & x_j \in \{0,1\} & \forall j & (5)
\end{array}
$$

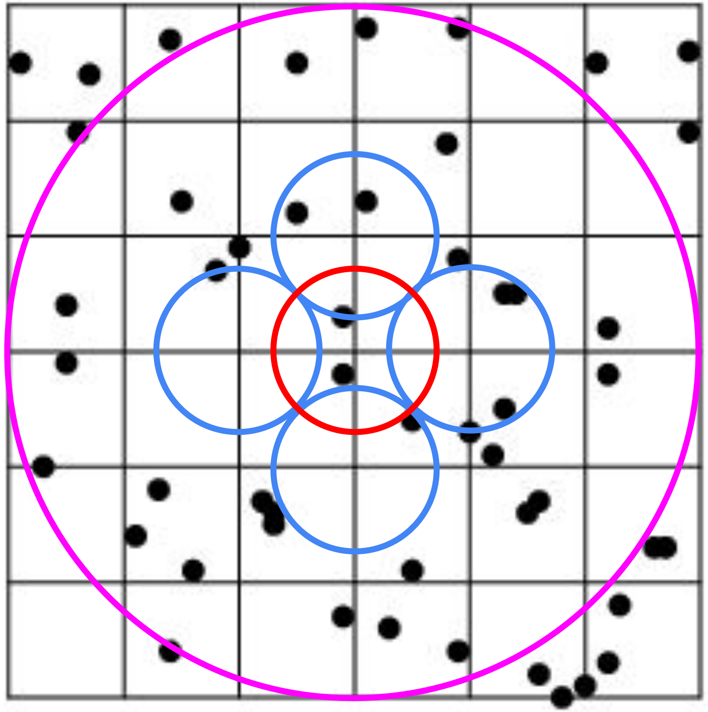
**Where:**

$$
\begin{array}{lll}
i & = & \text{index referencing nodes of the network as demand} \\
j & = & \text{index referencing nodes of the network as potential facility sites} \\
S & = & \text{maximal acceptable service distance or time standard} \\
d_{ij} & = & \text{shortest distance or travel time between nodes} i \text{and} j \\
N_i & = & \{j | d_{ij} < S\} \\
p & = & \text{number of facilities to be located} \\
x_j & = & \begin{cases} 1, \text{if a facility is located at node } j \\ 0, \text{otherwise} \end{cases} \\
y_i & = & \begin{cases} 1, \text{if demand } i \text{ is covered within a service standard} \\ 0, \text{otherwise} \end{cases}
\end{array}
$$

Credit: PySAL/spopt Developers (2022)

# ETL Part 1: Candidate Locations

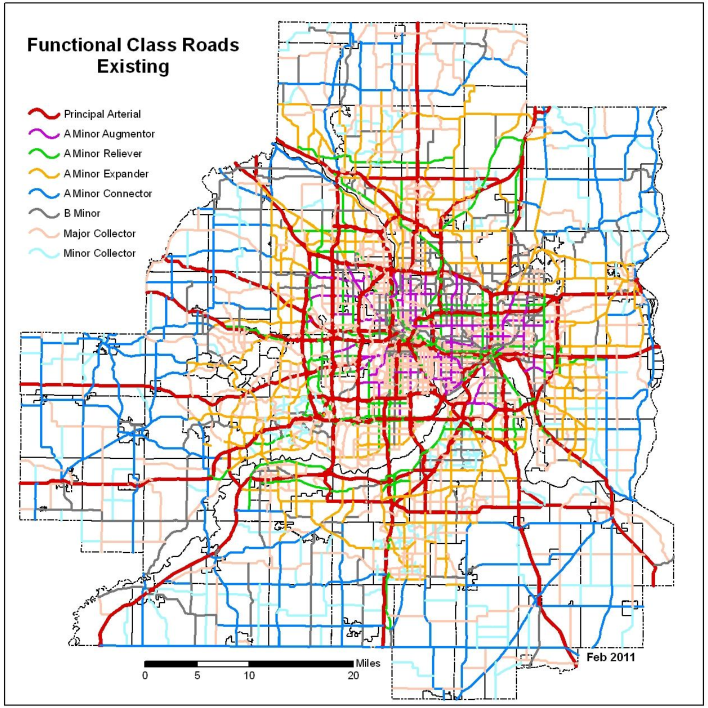
- What are ideal candidates?
- Why not just one search with a big radius?
- Iteratively make calls to API, by using a grid pattern to create overlap and capture all of the potential locations
- How to deal with spatial overlap/redundancy?
- Good solution when you don’t need to pay for credits



Credit: GDAL & author (2022)

# ETL Part 2: Network & Demand

- Network: Simple but not ideal solution
- Two ways to simulate demand
  - Create fixed number of randomly located points across the study area
  - Distribute random points, based on some weight (e.g., population, % people that drive EVs, etc.) within an area

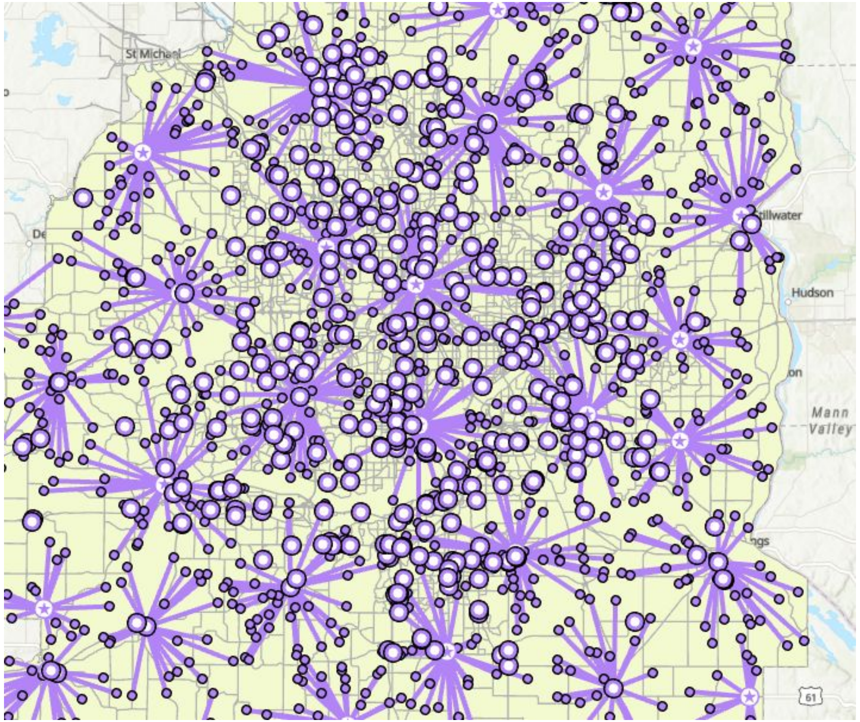



Credit: Metropolitan Council (2021)

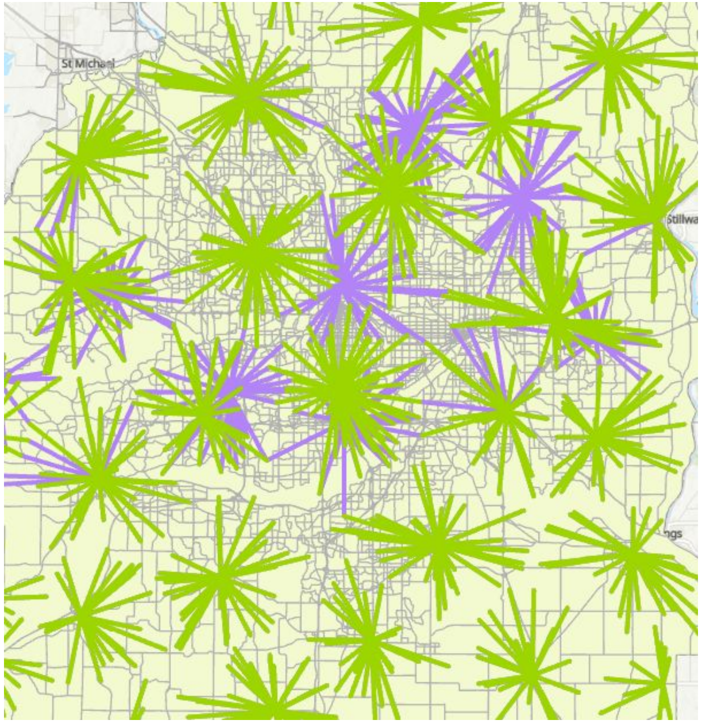
# Location-Allocation Analysis

1. Iterate through distance weights (LSCP) or # of facilities (MCLP)
   a. For MCLP, a linear impedance transformation was used (no weight value needed)
   b. Impedance transformation is comparable to the “power” parameter in IDW
2. Iterate through different demand datasets (nested loop)
3. Create LA layer & add in necessary datasets
   a. One key parameter: threshold of 15,000 km
4. Solve
5. Calculate # facilities chosen (LSCP) or # demand points covered (MCLP)
6. After all iterations, calculate summary statistics to find # of times each facility was chosen out of all models
   a. LSCP: best value could be 12, MCLP: best value could be 9

# LSCP Results

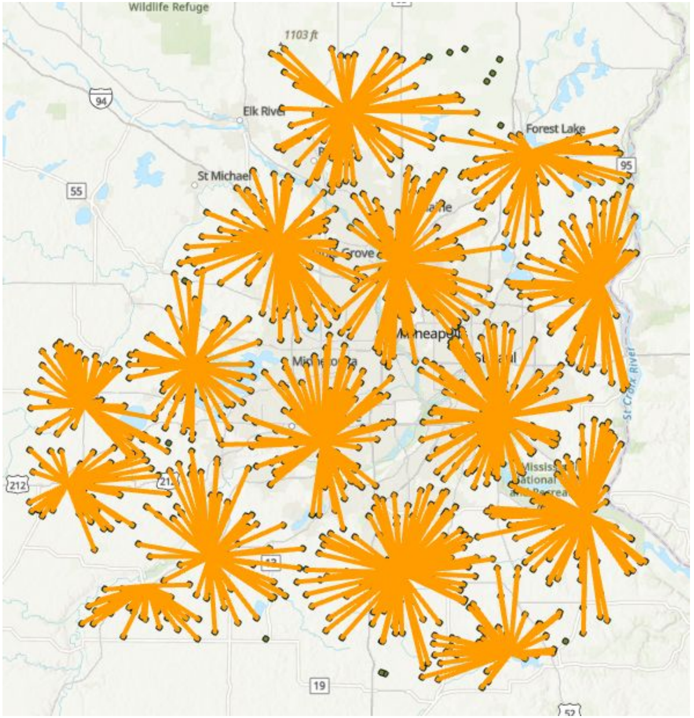



LSCP with power of 0.5 on demand dataset 0

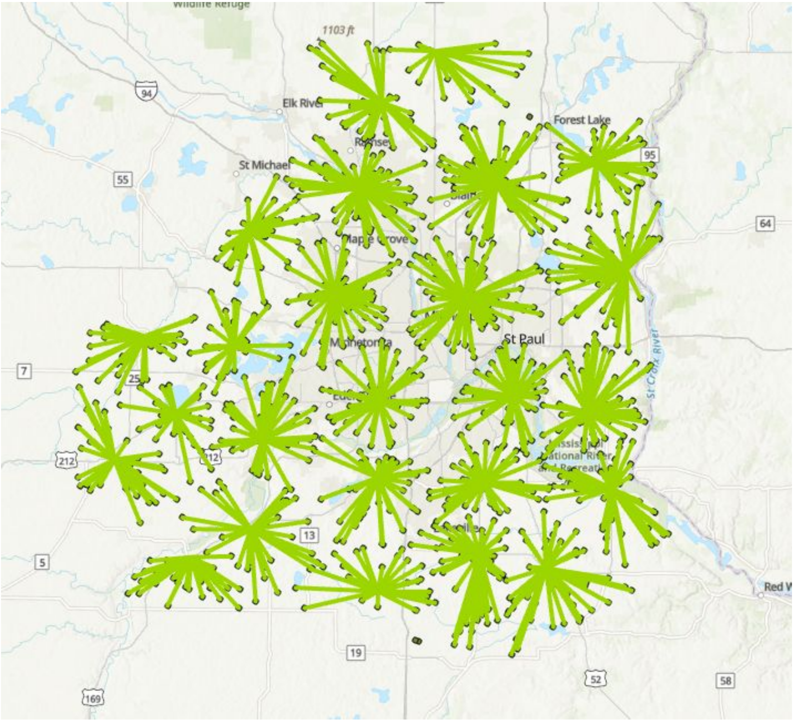



Comparing weight of 0.5 with weight of 2.0

# MCLP Results

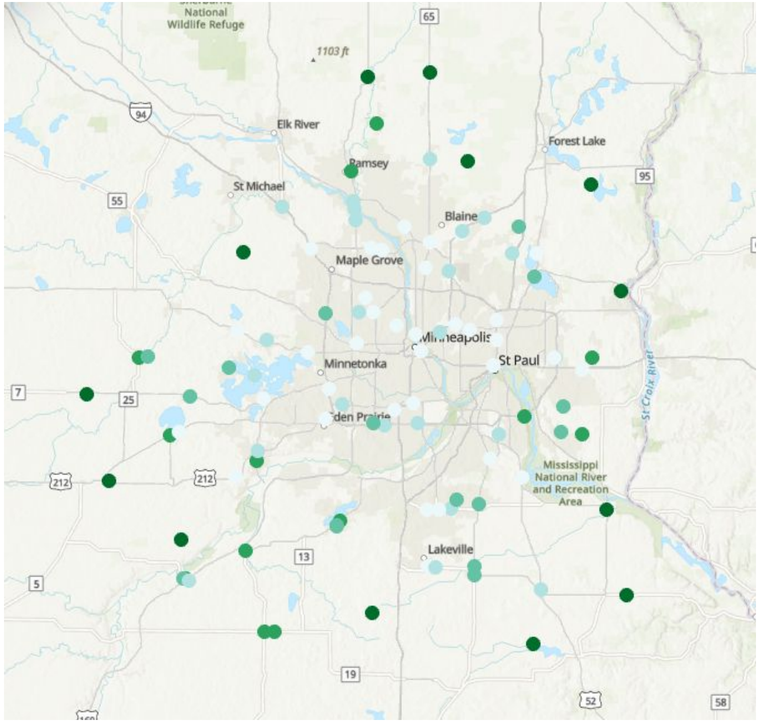



MCLP with 15 facilities on demand dataset 2

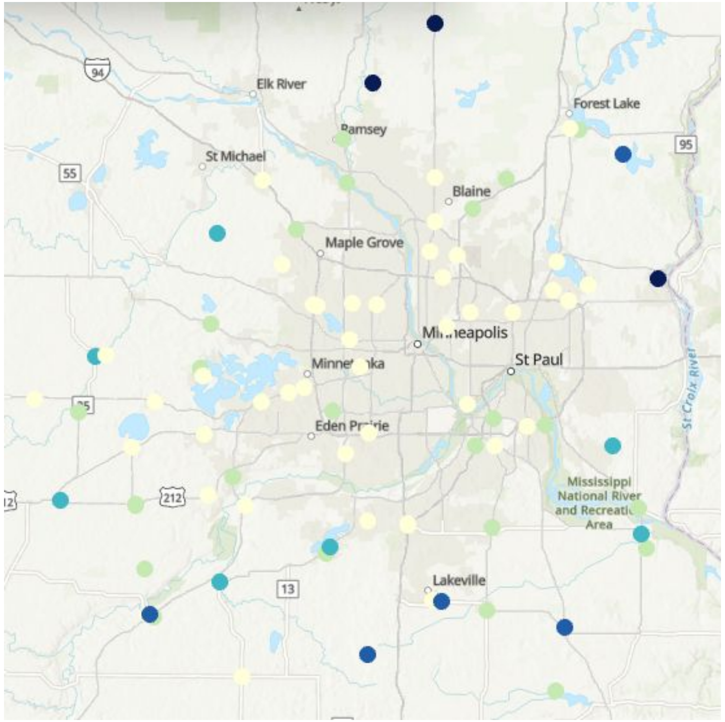



MCLP with 25 facilities on demand dataset 2

# Final Results




LSCP




MCLP

# Discussion & Conclusion

- Pattern of results shows that facilities near the edge of the AOI were chosen more frequently
    - Boundary effect?
    - Less urban and getting more rural
- Between 33 and 35 facilities chosen in all LSCP models
- Between 982 and 997 (of 1000) demand points covered in all MCLP models, with 15, 20, and 25 facilities
    - Change of impedance transformation in LSCP and MCLP could be primary factor

Questions?