Automated Redistricting and Communities of Interest (COI)

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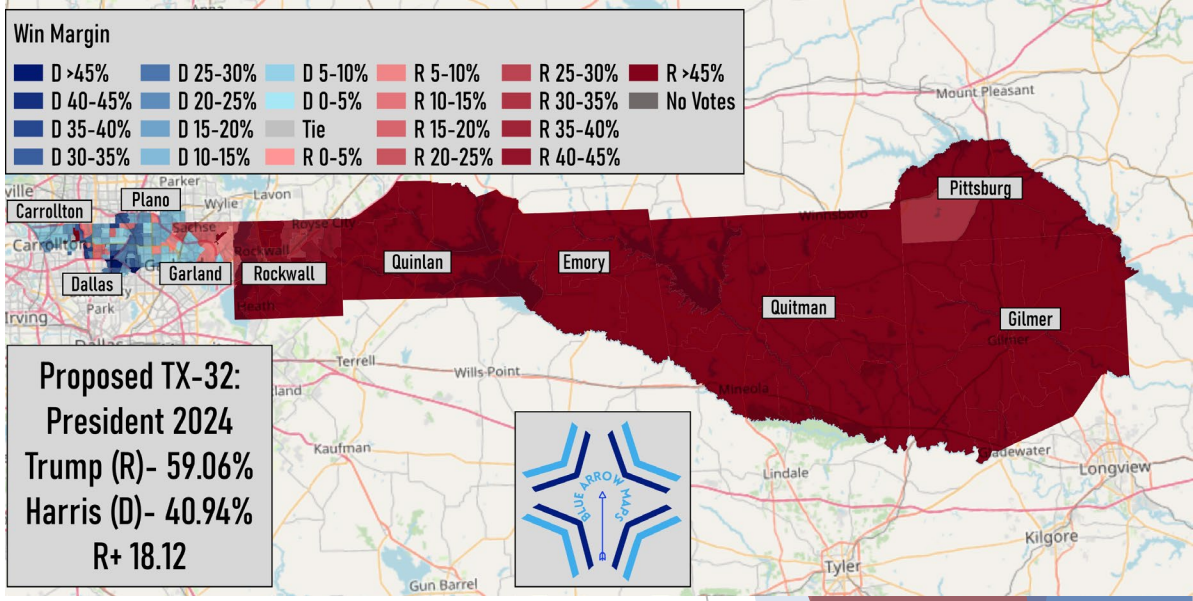
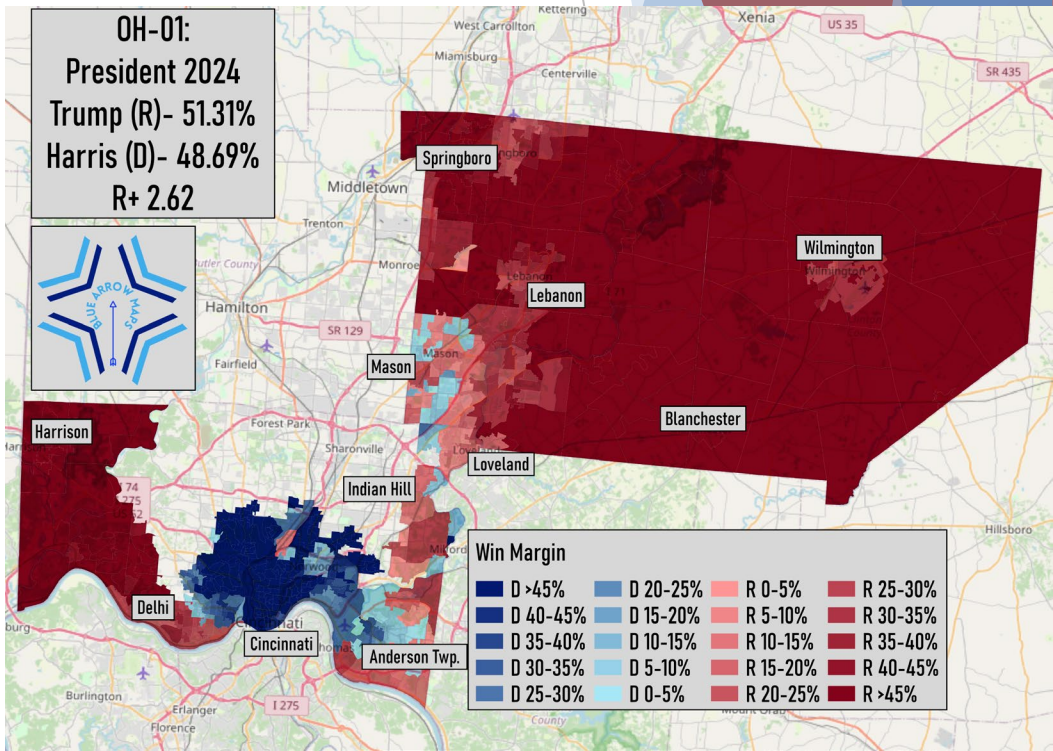
SPSA 2026 Conference

Background

- Present “Redistricting Wars” after Trump asked Texas to redistrict before the 2026 midterms
- COI- the elusive “gold standard” of redistricting
- Questions of how best to go about ascertaining and utilizing COI
- Literature- COI is a mess





The Objectives

1. Create means of determining COI for redistricting analysis and algorithms
2. Assess how districts created with COI in mind compare to enacted districts

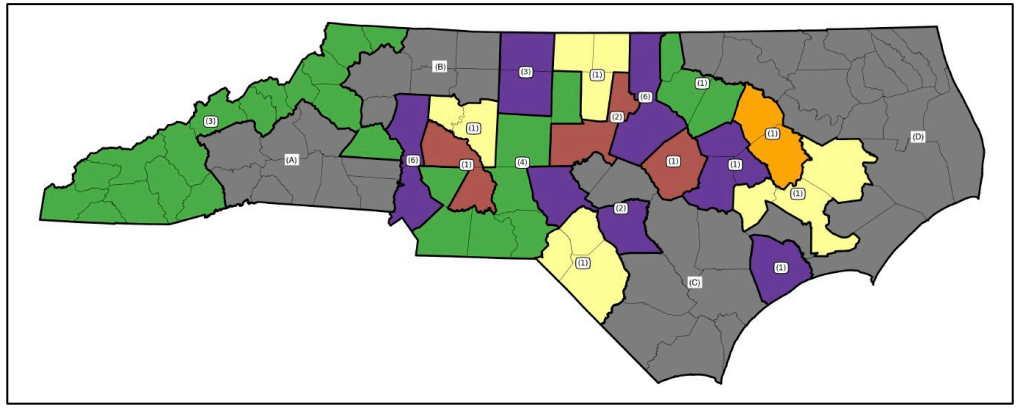
The Hypothesis

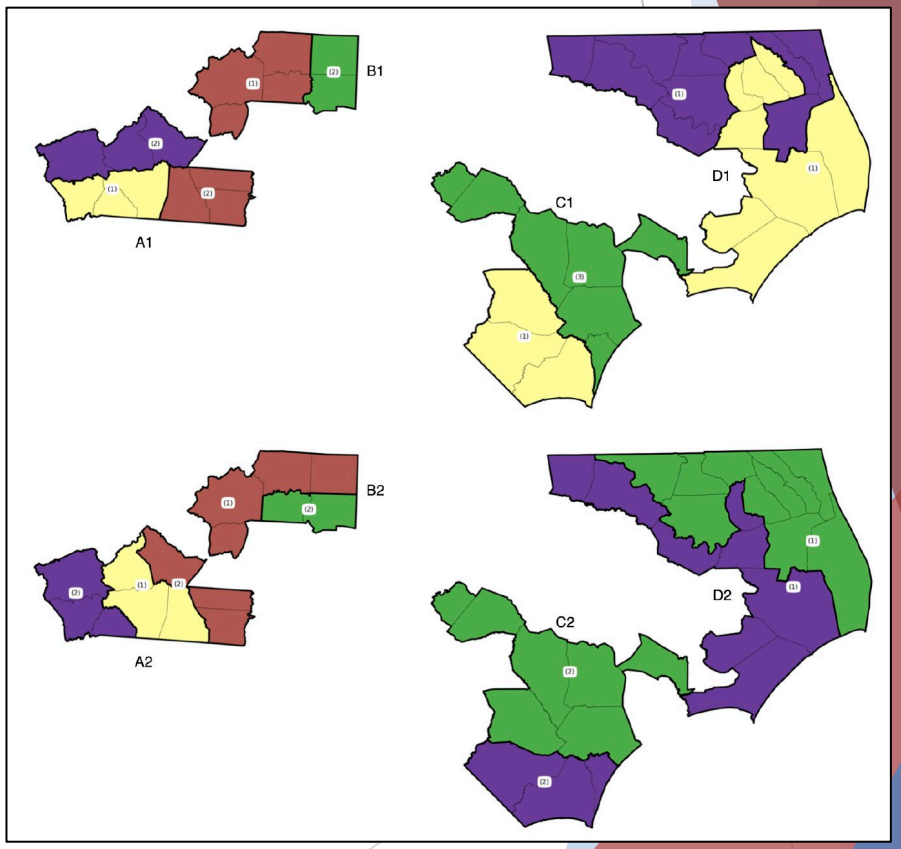
- Districts created through a COI-minded process will perform better across a variety of redistricting metrics relative to districts created via other means

Data and Case Selection

- Data sourced from Redistricter for North Carolina, sourced and disaggregated from Census and American Community Survey (ACS) data
- Plans compared to enacted State Senate maps from the 2020 and 2024 redistrictings
  - 2020- fair maps mandated by State Supreme Court
  - 2024- Republicans won the right to re-gerrymander the state legislative lines and Congressional district
- Two sets of enacted maps in a short period of time, multiple bases for comparison
- State uses Stephenson Clustering for redistricting

Stephenson Clusters for NC State Senate



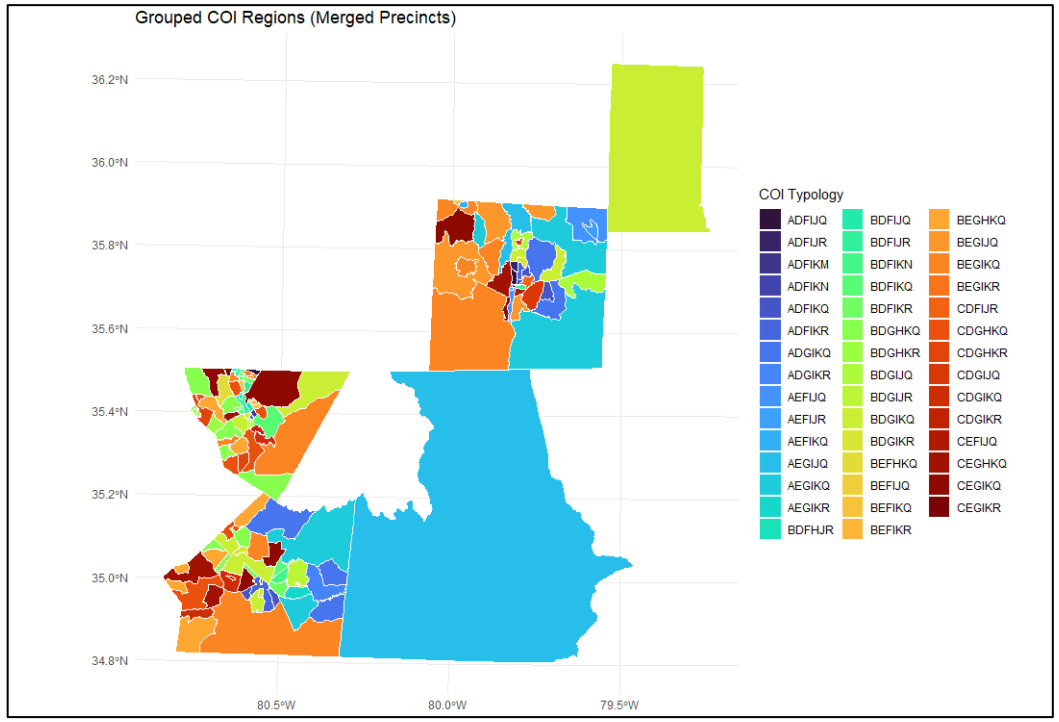


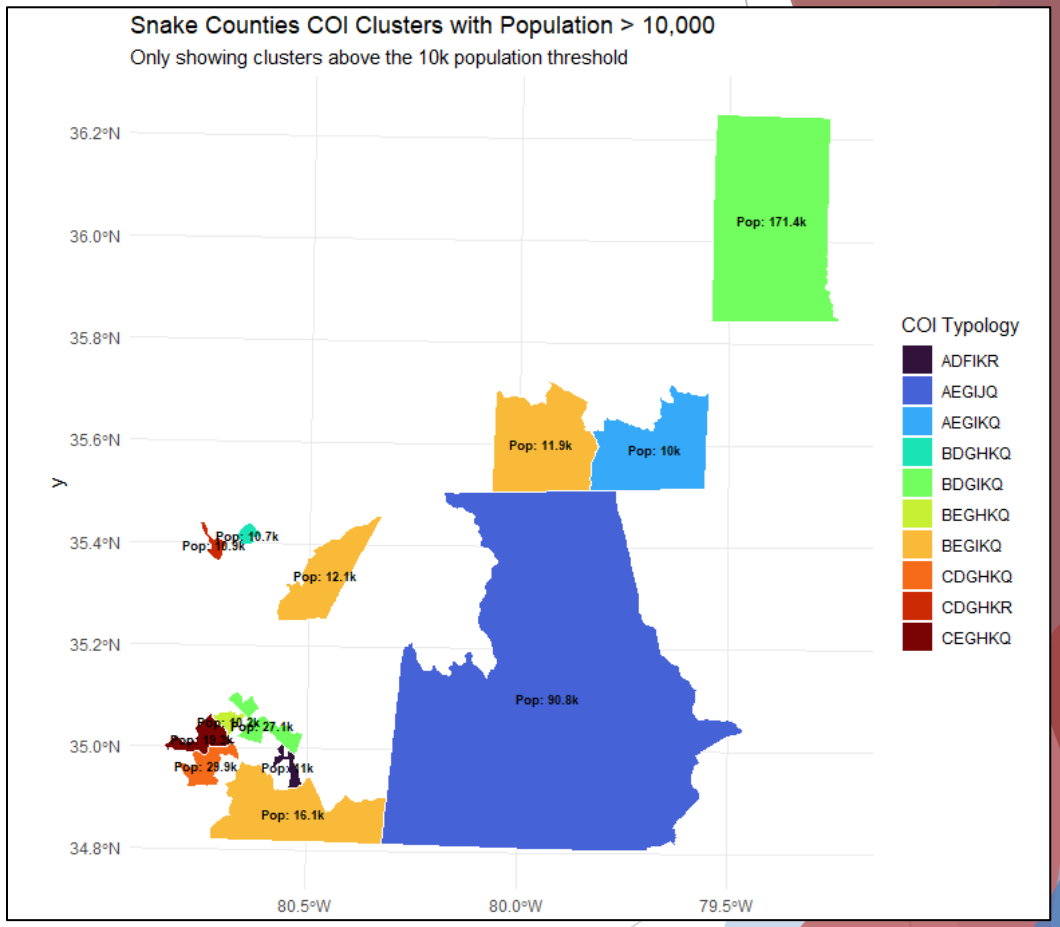
Source: Cooper et al., 2021

Methods

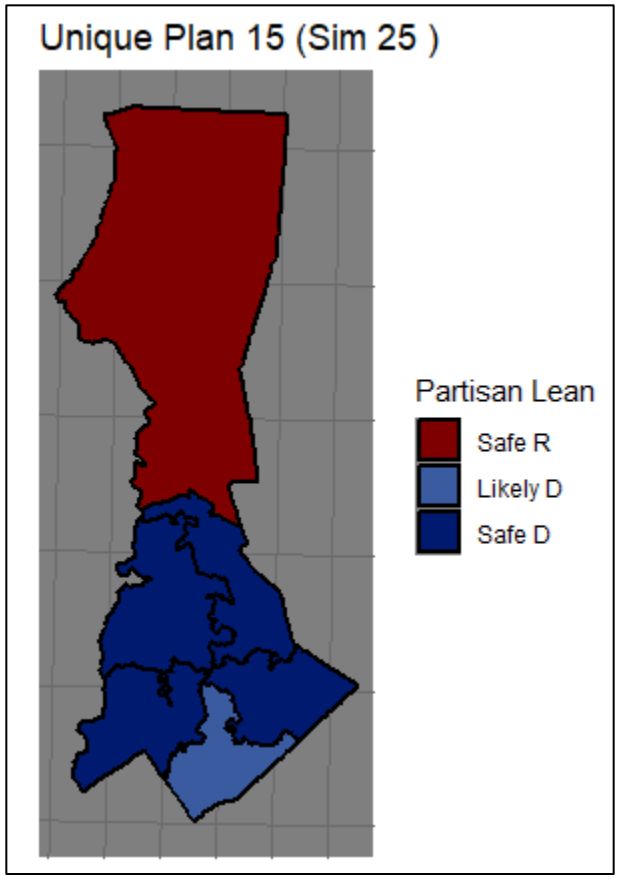
- Utilizes Redist package in R
- Sequential Monte Carlo (SMC) algorithms will be used to redistrict the four counties into the appropriate number of districts based on a set of socioeconomic variables
  - Includes race, employment sector, poverty, homeownership, education, and age
- Three means of doing so
  - Shotgun- each method on its own, establish a baseline for comparison (10k simulations)
  - Multi- consider all of the variables equally at once (1k simulations each)
  - Cluster- determine typologies of each Block Group (BG) based on outlier values of the variables, find contiguous groups of BGs with the same typologies, and prioritize typology clusters with over 10,000 residents in redistricting (10k simulations)
- Averages of each method/set of methods will be compared to the 2020 and 2024 State Senate maps
  - Results filtered to unique plans as to not inflate results (around 70% efficiency)

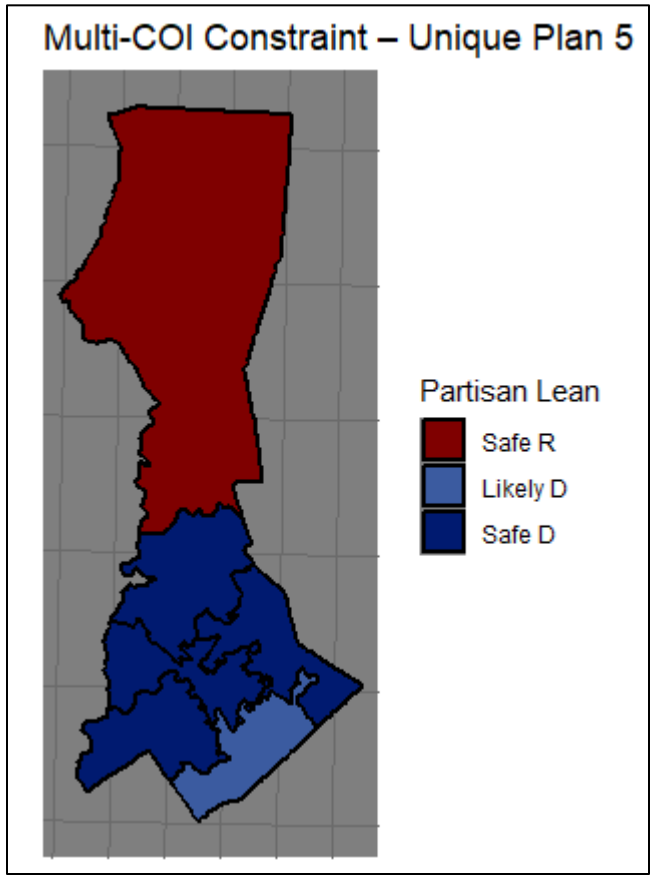
Clustering Examples

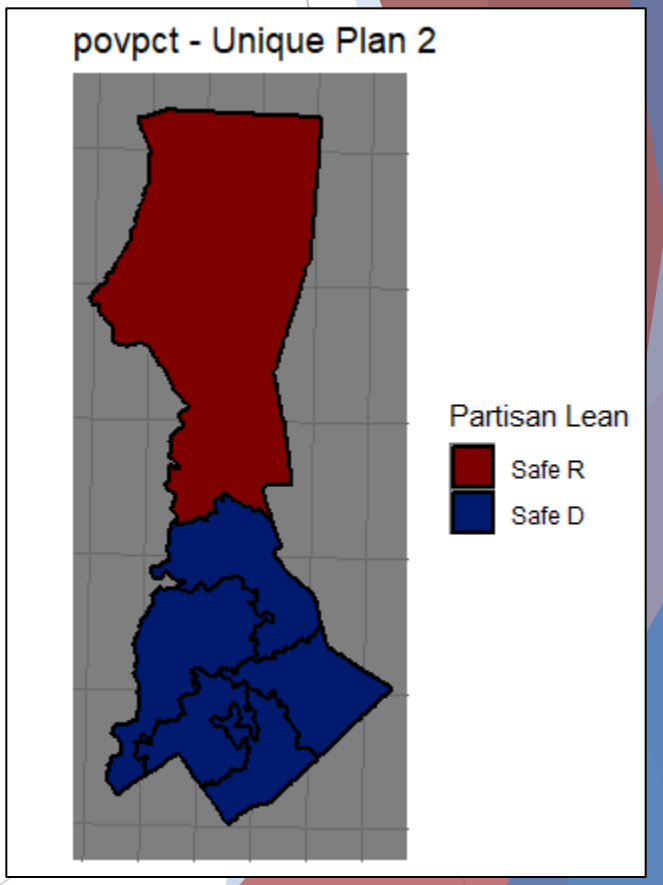




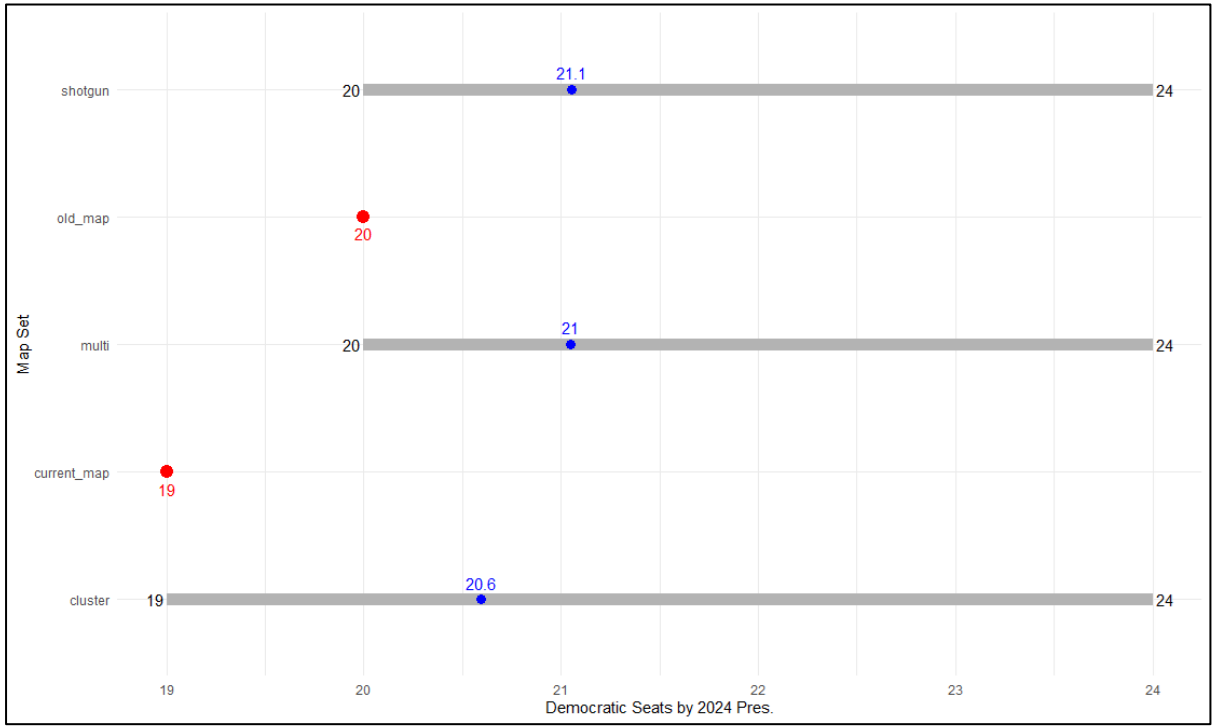
Sample Maps


Unique Plan 15 (Sim 25)
Partisan Lean
Safe R
Likely D
Safe D


Multi-COI Constraint – Unique Plan 5
Partisan Lean
Safe R
Likely D
Safe D

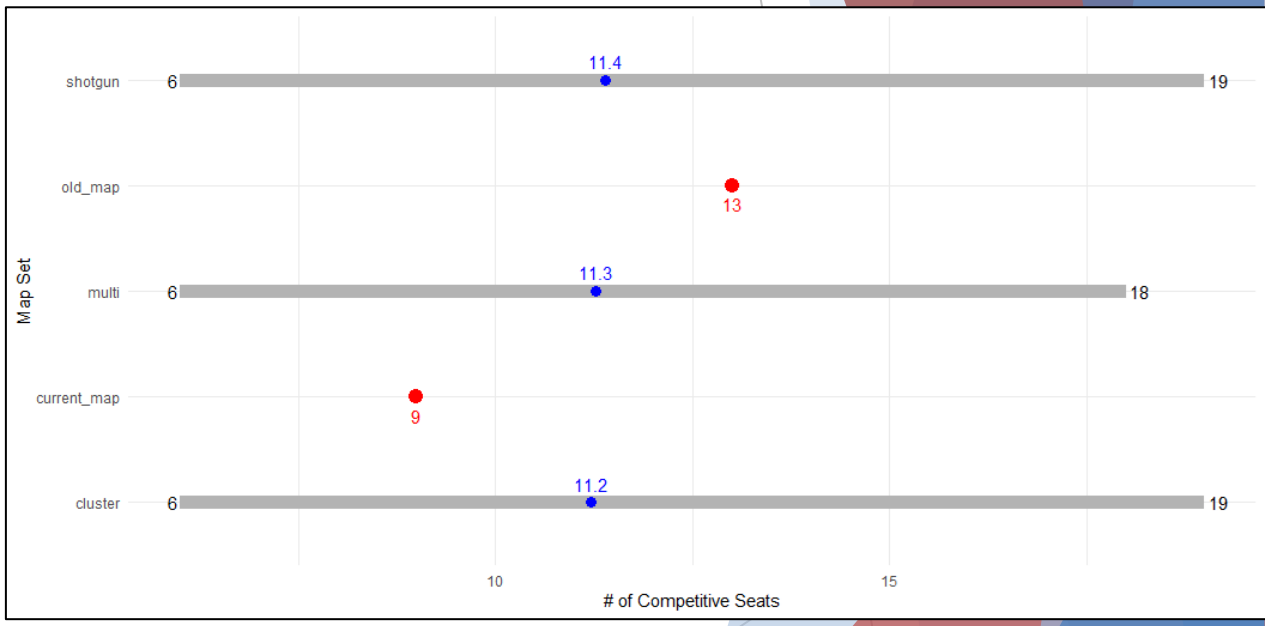

povpct - Unique Plan 2
Partisan Lean
Safe R
Safe D

Results

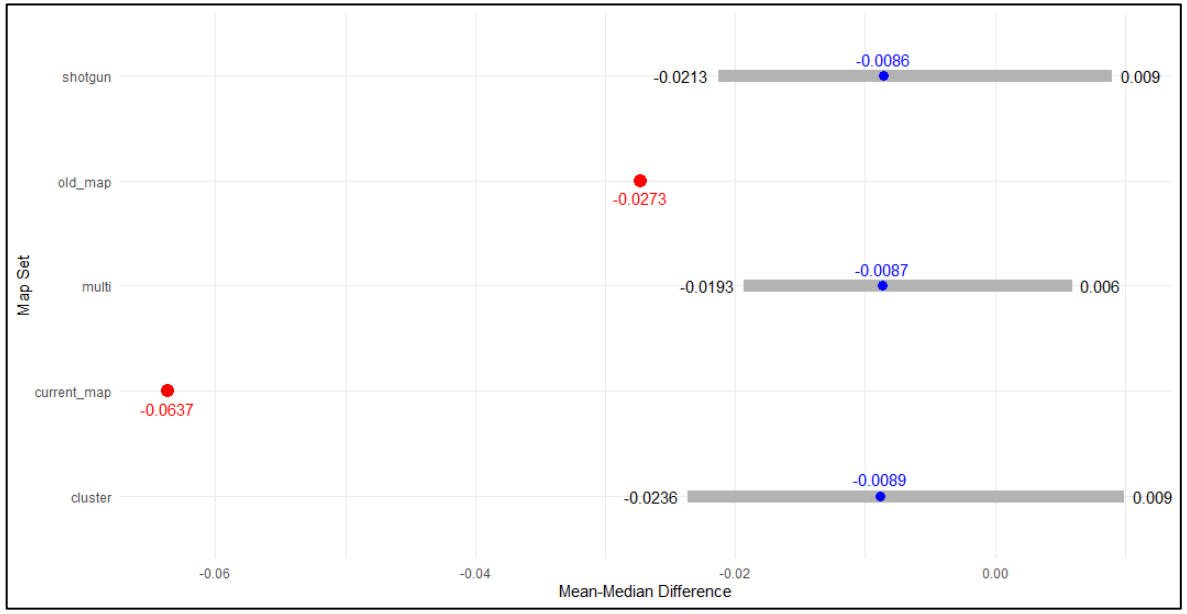


Democratic Seats (2024 Pres. Lean)

Competitive Seats (Within 15 Points)

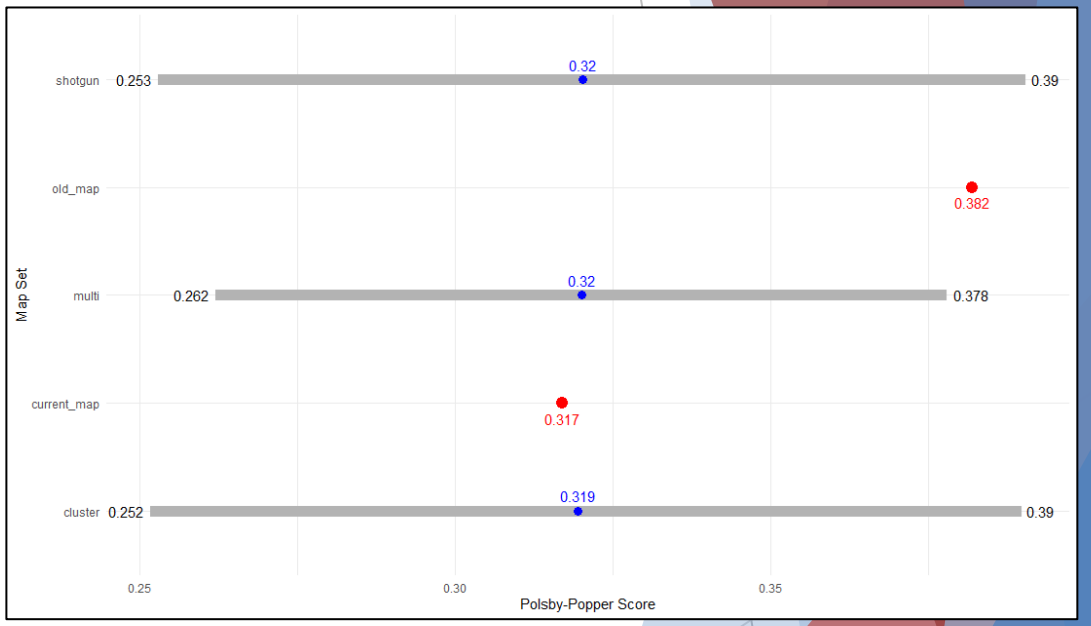


Results

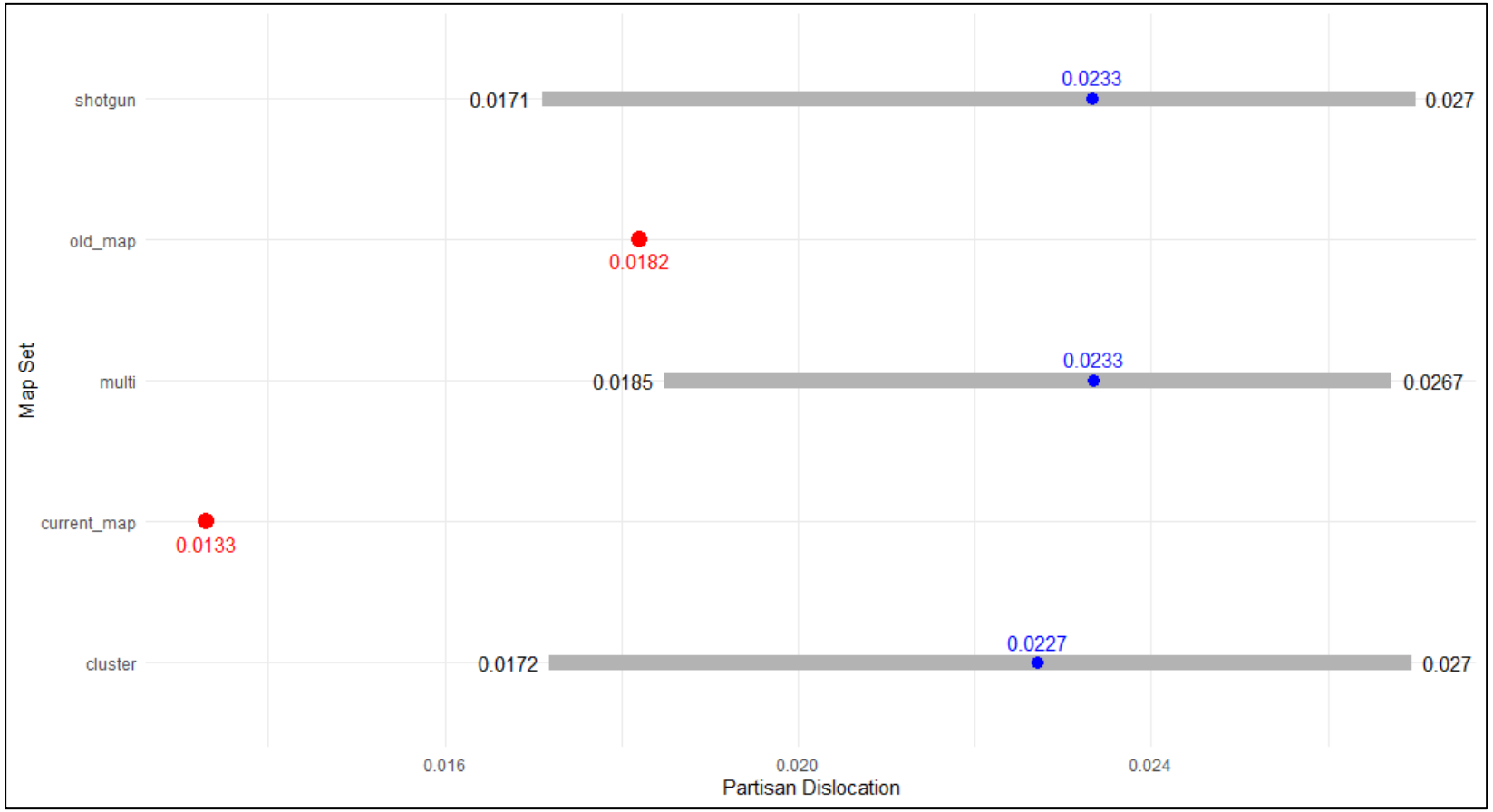


Mean-Median Difference

Polsby Popper Scores



Results



Partisan Dislocation

Results

- Initial Analysis
  - COI-driven district drawing does not necessarily produce better performing districts
  - Comparisons suggest that the new State Senate maps became less fair across most dimensions of analysis
- For the most part, the simulated map averages are statistically different from each other and the measures of the enacted maps
- Method can be reproduced relatively easily for creating districts in a variety of contexts

Future Directions

- Expand research to both legislative chambers of NC, and add other states to redistricting sample
- Add other methods where:
  - COI typologies are considered, but not in predefined clusters
  - Network analysis-driven clustering method
    - (Louvain and/or Leidan)
- Further refine algorithms; explore more of the theoretical basis of COI enactment as to refine/modify cluster sizes
- Explore the application of this in regards to referenda voting, more akin to Makse (2012)