Universiteit van Amsterdam

GerrySort

An Agent-Based Model for Simulating Gerrymandering and Geographical Partisan Sorting

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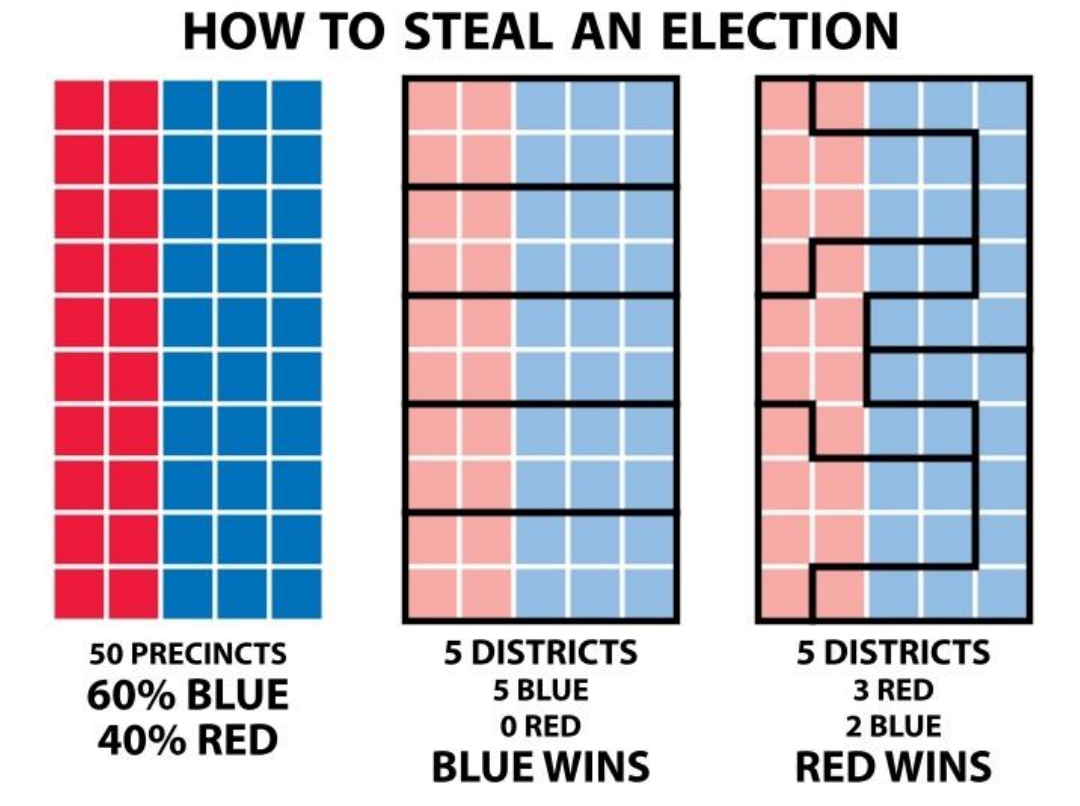
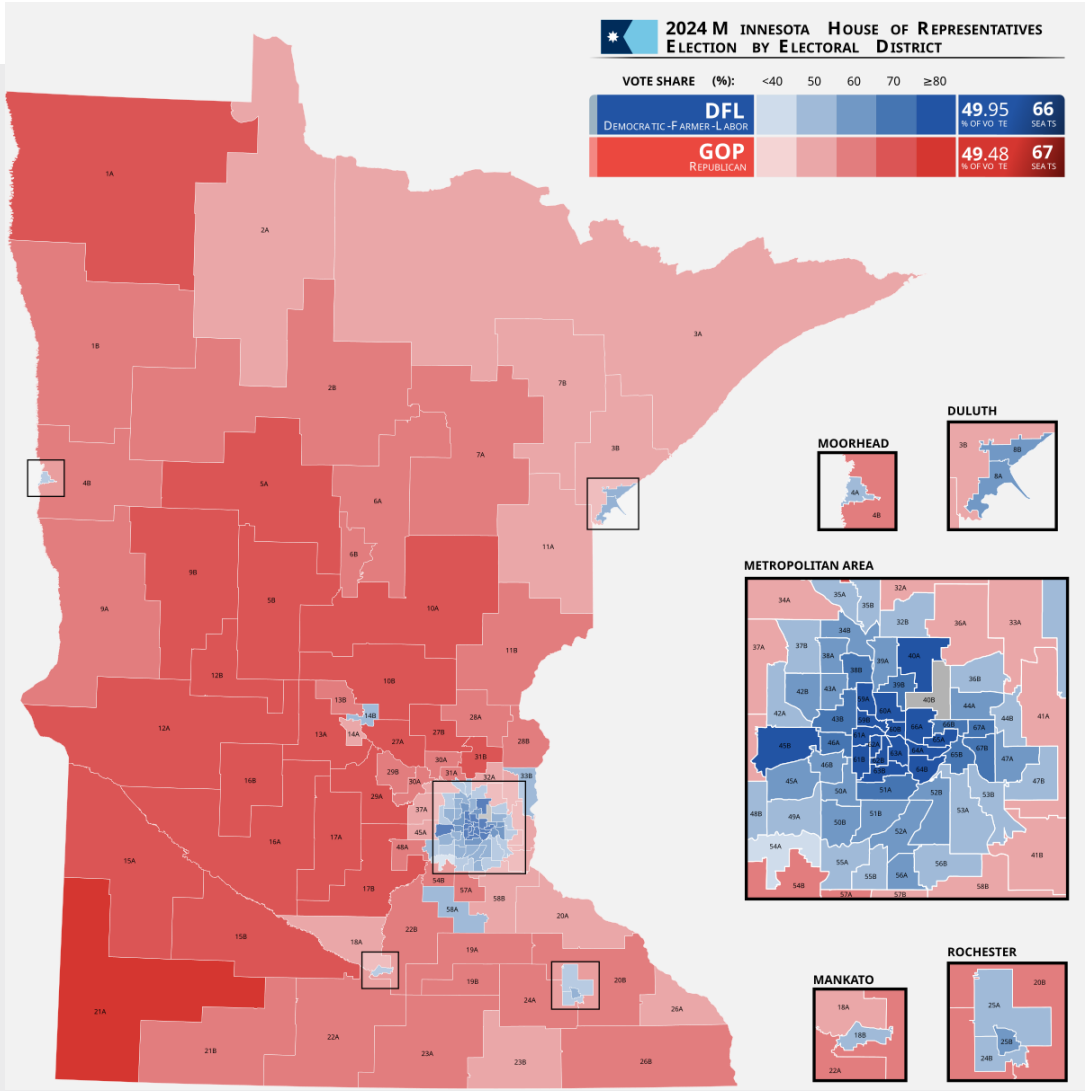
Core Concepts



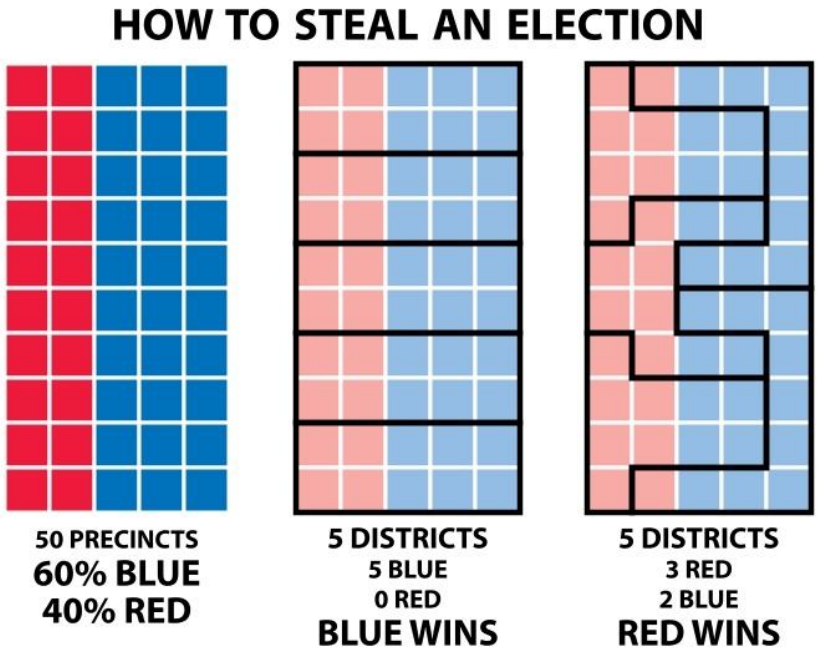
Gerrymandering



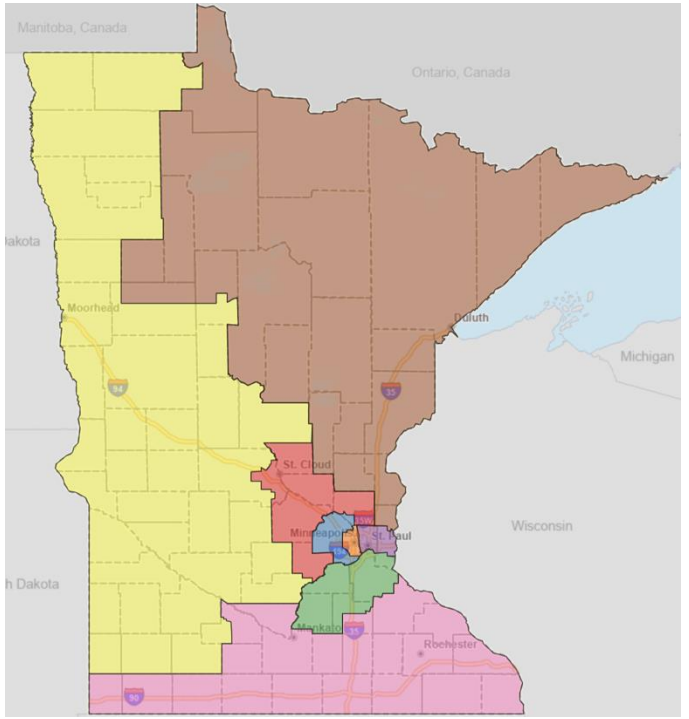
Geographical Partisan Sorting

Gerrymandering

- Single-member districts
- Redistricting Cycle
- Controlled by state legislatures



MN 2023 Congressional Map

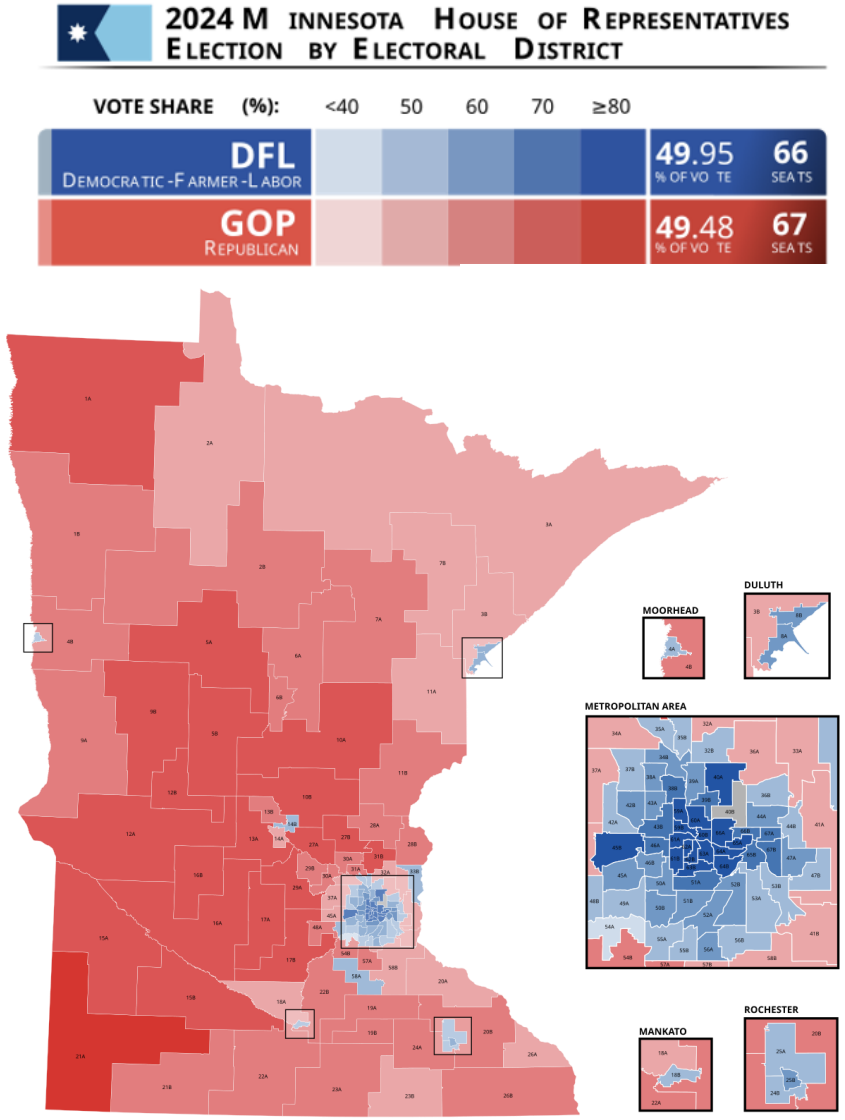


- **Problems**: Skewed representation, Less competitiveness, Less responsiveness
- **Federal rules**: Equal population + No racial gerrymandering
- **State reforms**: Compactness, Competitiveness, Independent commissions

Geographical Partisan Sorting

- People cluster by politics (urban = Dem, rural = Rep)

- **Problems**:
  - Increased polarization
  - Leads to “unintentional gerrymandering”

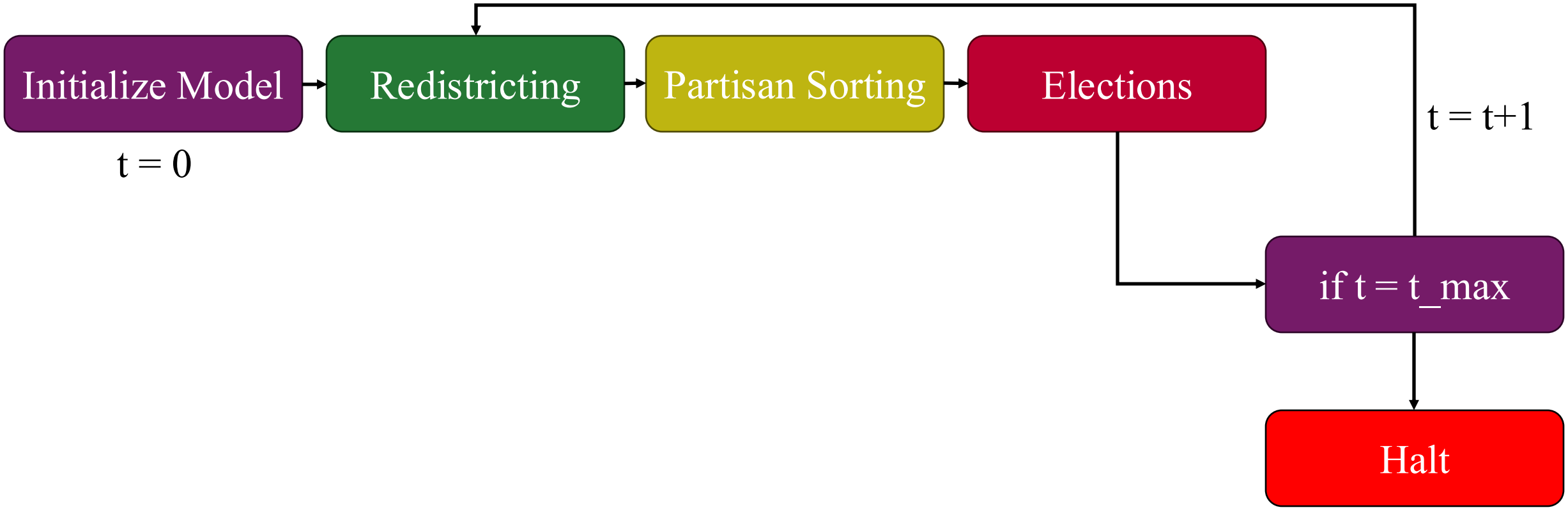


Research Objectives

- Investigate isolated and combined effects of **gerrymandering** and **geographical partisan sorting** on fairness of electoral maps
- Test the role of **different spatial voter distributions** on fairness of electoral maps
- Measuring the efficacy of **competitiveness/compactness** reforms to mitigate adverse effects of gerrymandering and geographical partisan sorting

Approach: Agent-Based Modelling

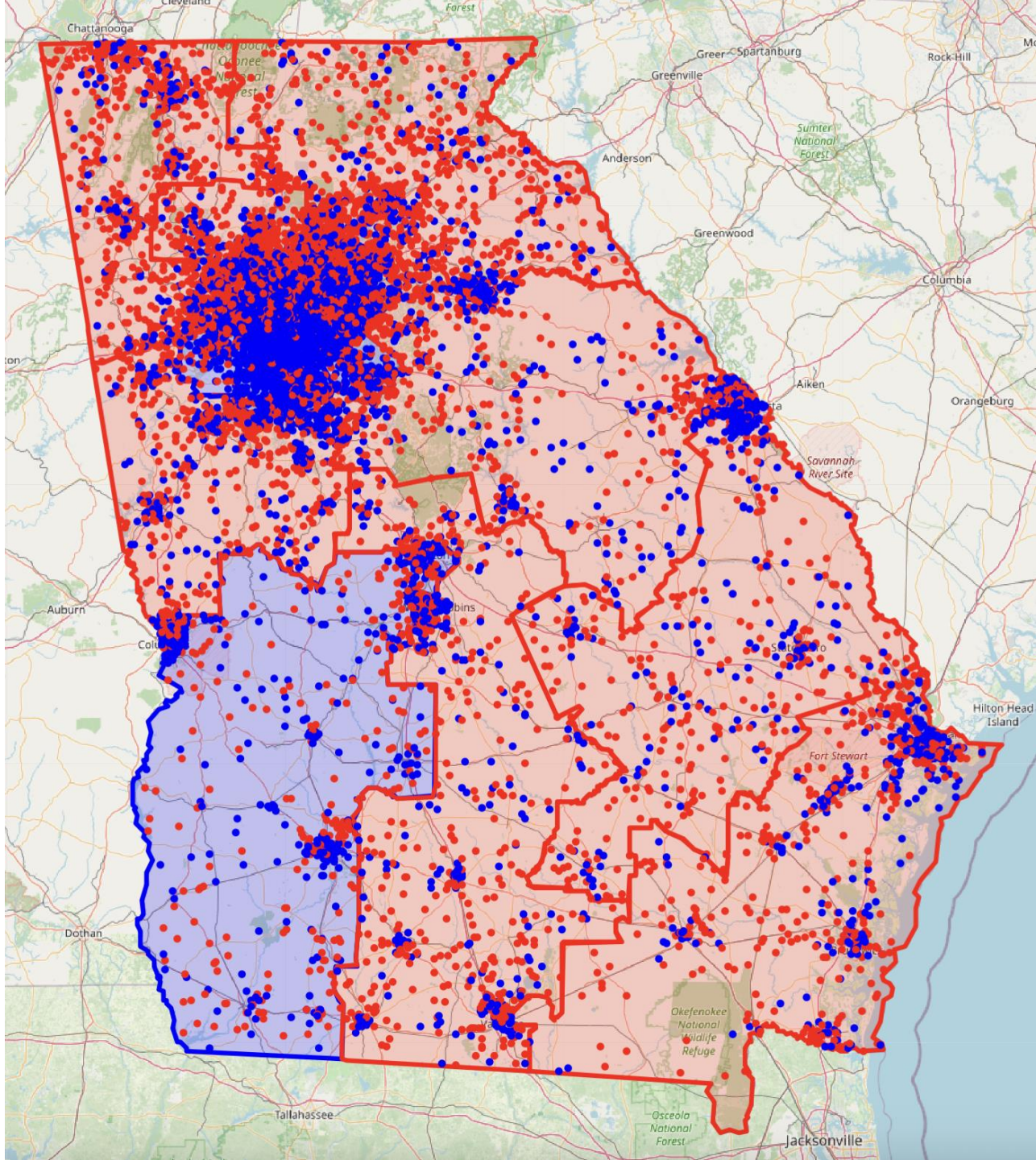
Model Description – Processes



Model Description – Initialization

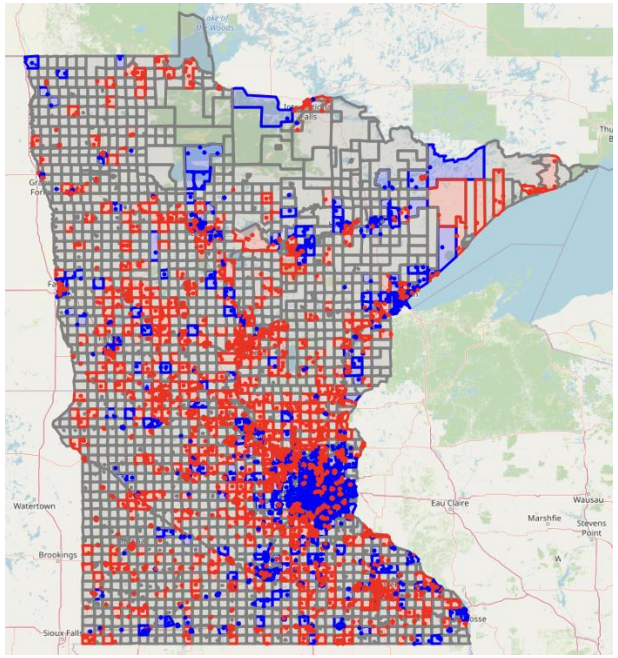
Real-World Data:

- 2020 Congressional District Map
- Precinct-Level:
  - 2020 Presidential Election Results
- County-Level:
  - Demographic Data → Capacity
  - Rural-Urban Commuter Area (RUCA) Codes → Partisan preferences

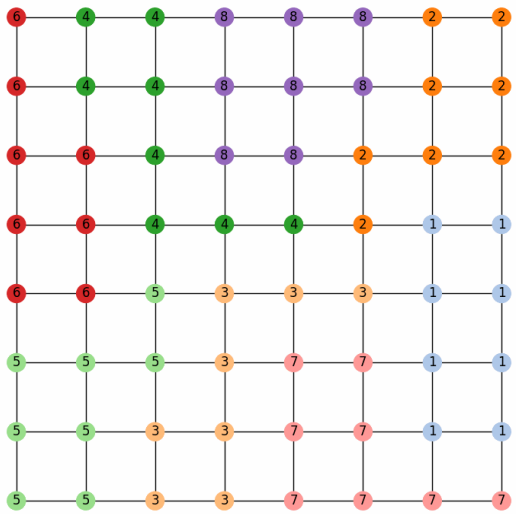


Model Description – Redistricting

- Generate Congressional Map → GerryChain

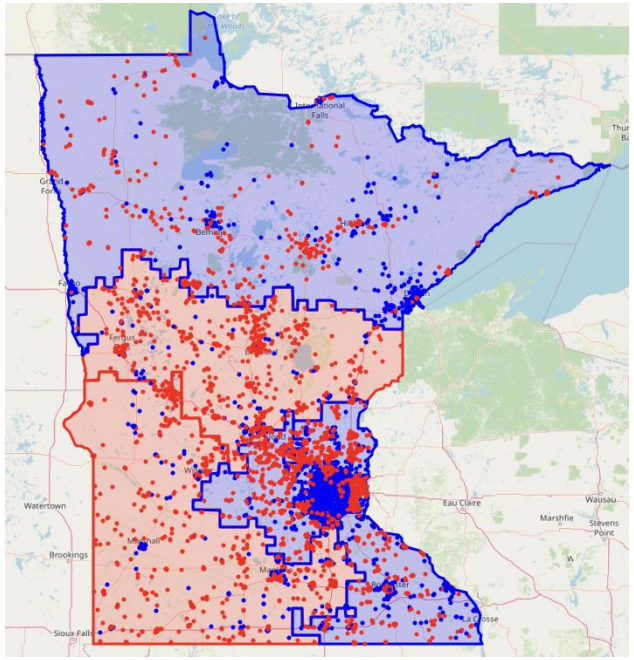


Collect precinct data (at t)



Generate new map

Constraints →
Population + Contiguity



Replace map

Model Description – Redistricting

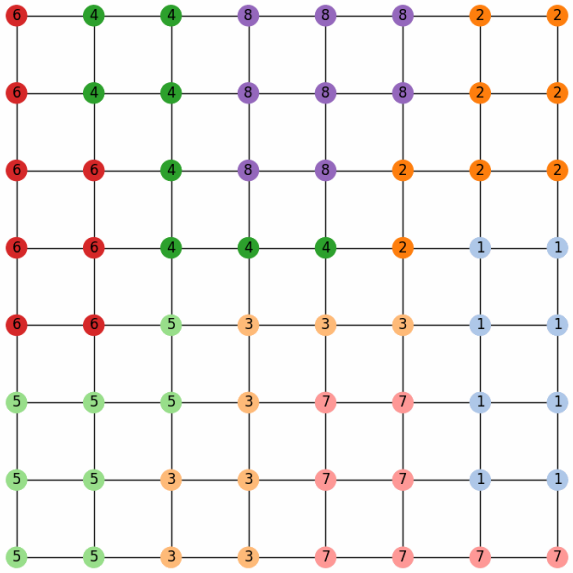
- Optimize according to function:

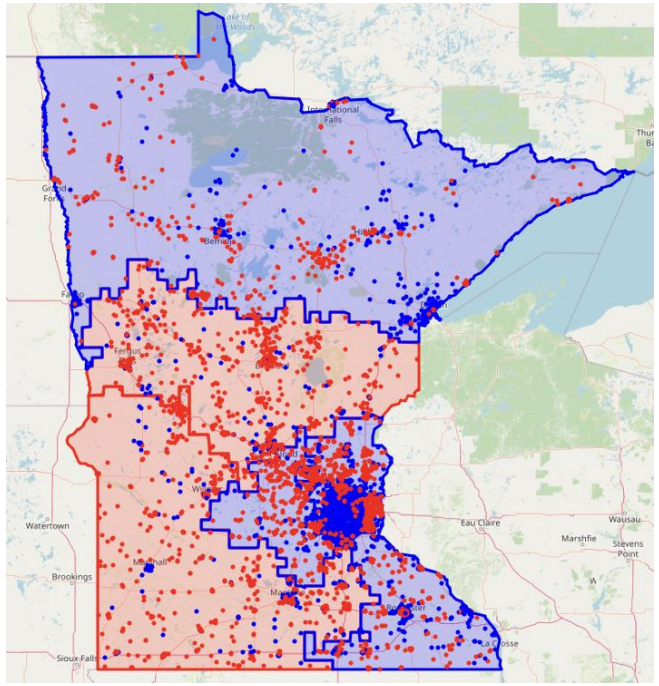
Partisan Gerrymandering

Number districts won / Total number of districts

Fairness Optimization

State-wide % match District %



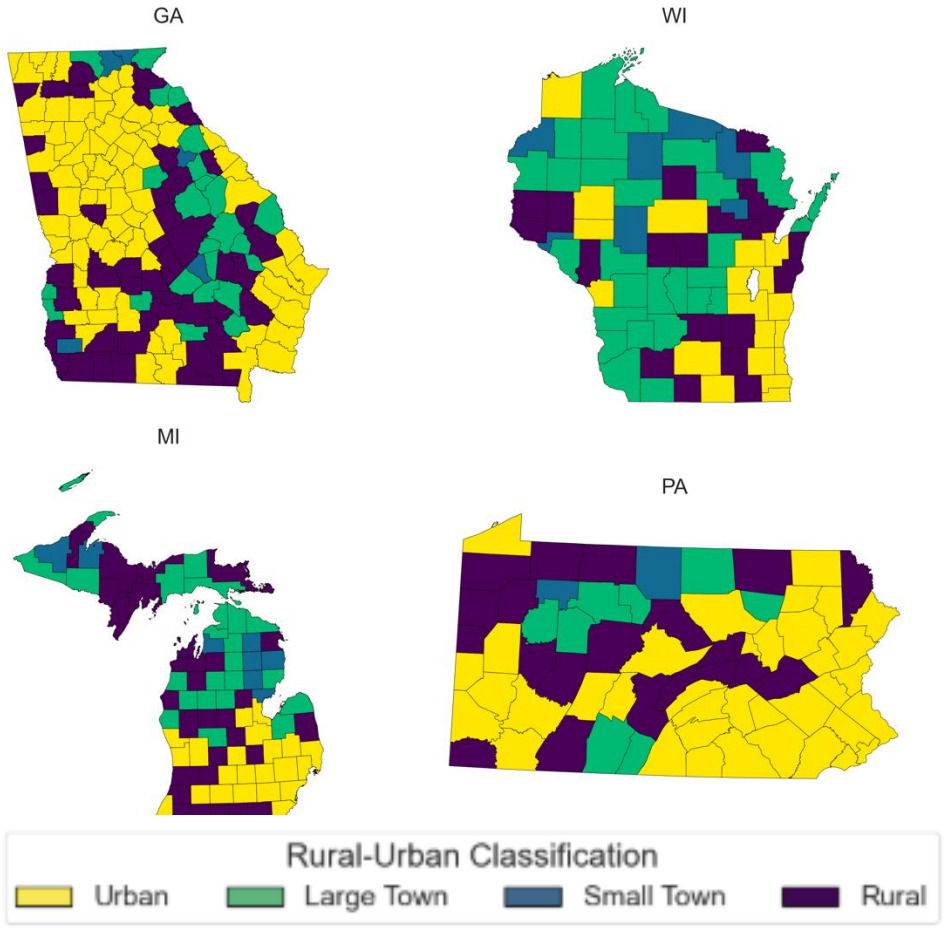


Model Description – Partisan Sorting

- Utility Function: $U_{loc} = X_1 \cdot a_1 + X_2 \cdot a_2 + X_3 \cdot a_3$

  - ***X1:*** Precinct Partisan Alignment
  - ***X2*:** County Partisan Alignment
  - ***X3***: Urban-Rural Political Preferences

Weights: a1=a2=a3=1/3

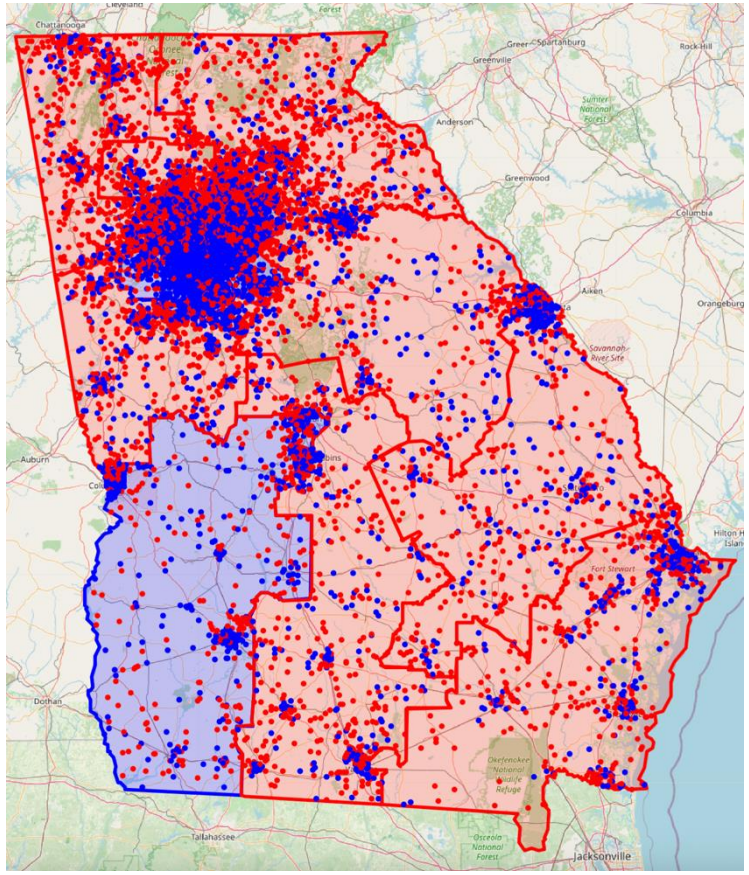


Model Description – Partisan Sorting

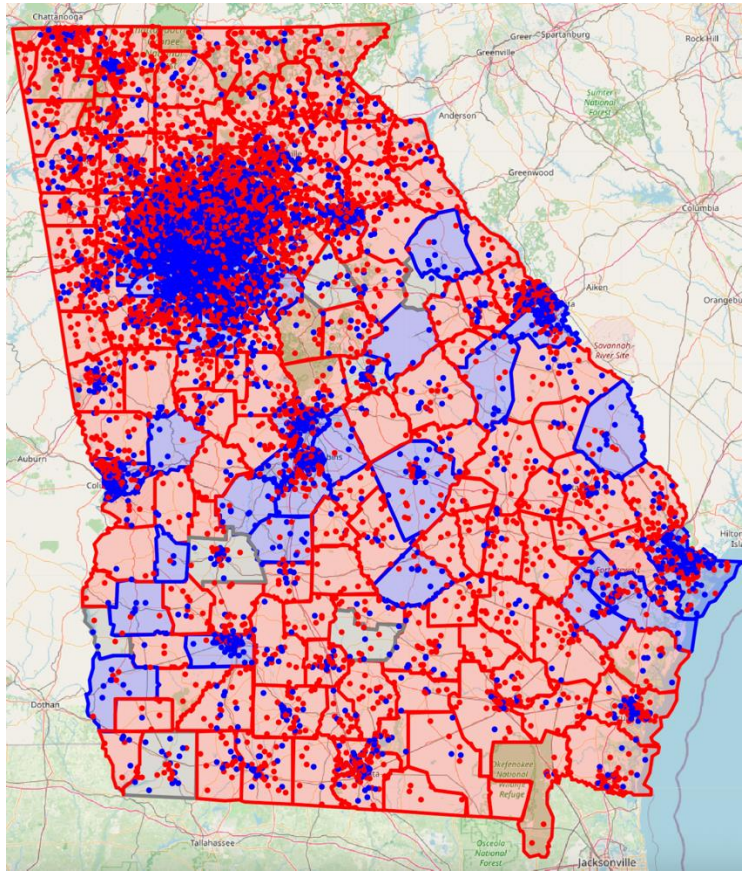
- Agents move if **Utility < Tolerance** (*T* parameter)

- Decision-Making Model:
  - x random move options (counties) drawn
  - Utility calculated for each option
  - Choice influenced by randomness (β parameter)

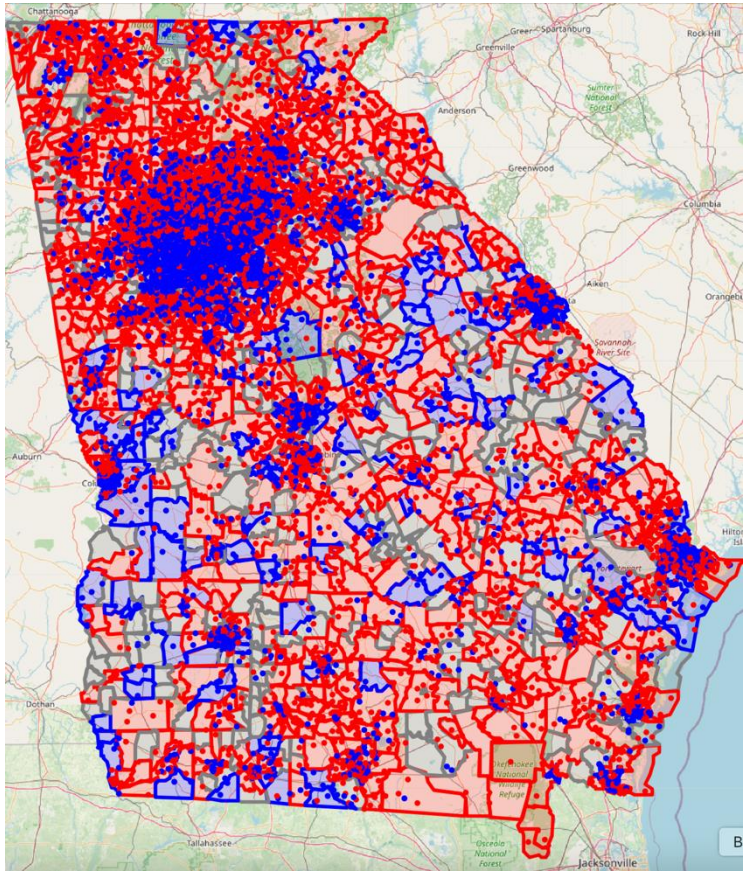
Model Description – Elections



Congressional



County



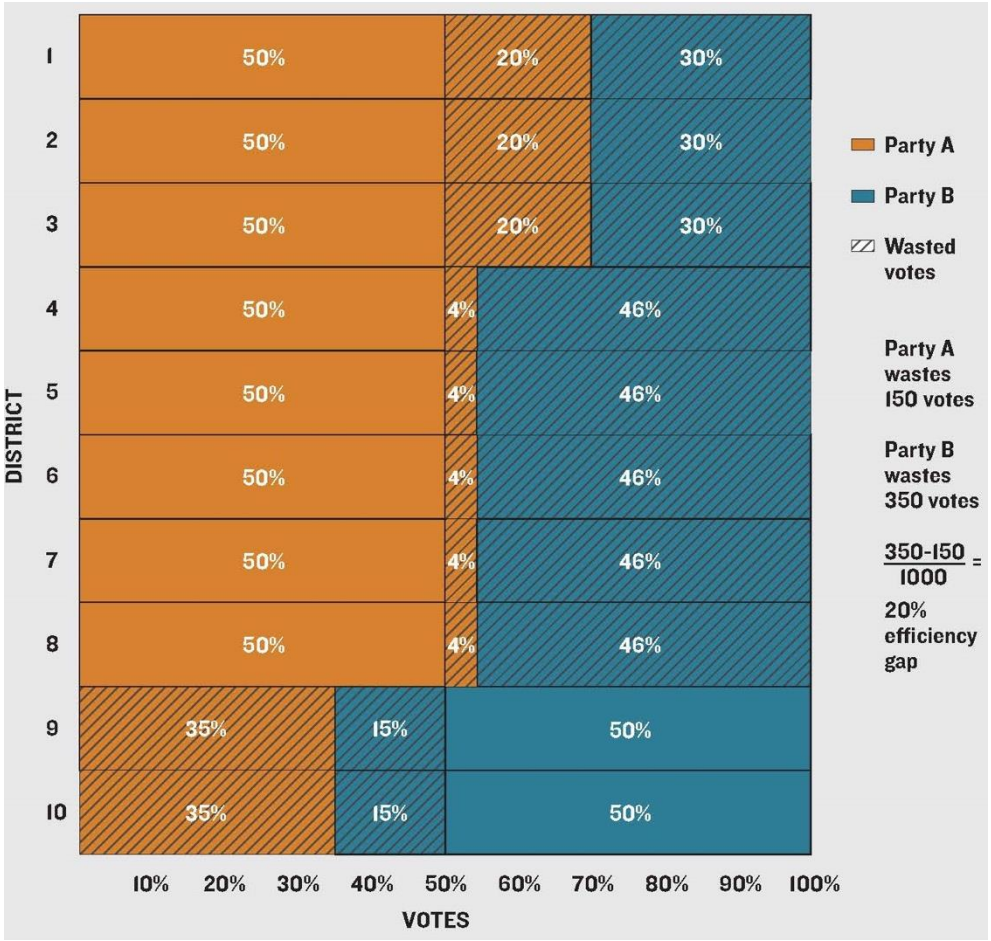
Precinct

Model Description – Outputs

- **Quantifying Fairness**:

$$\text{Efficiency Gap} = \frac{W_D - W_R}{V_D + V_R}$$

- Range: -1 (Dem) to +1 (Rep) → 0 perfect fairness

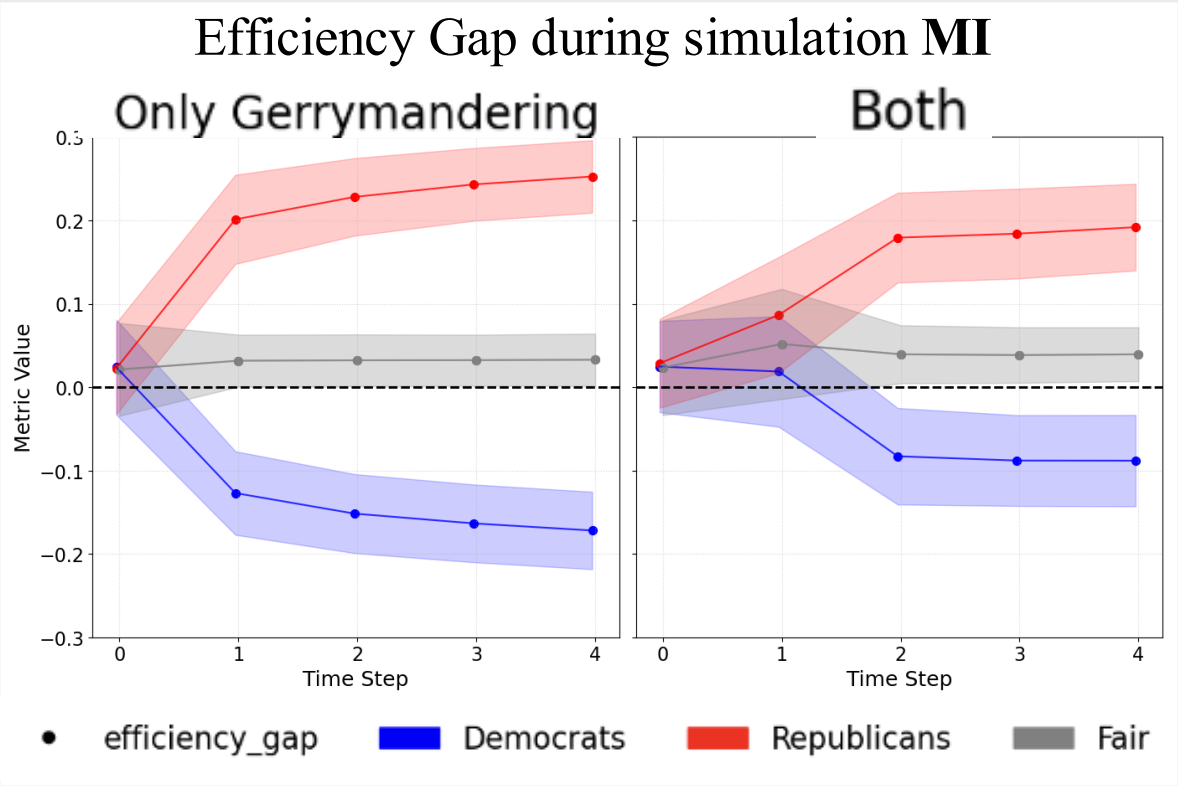


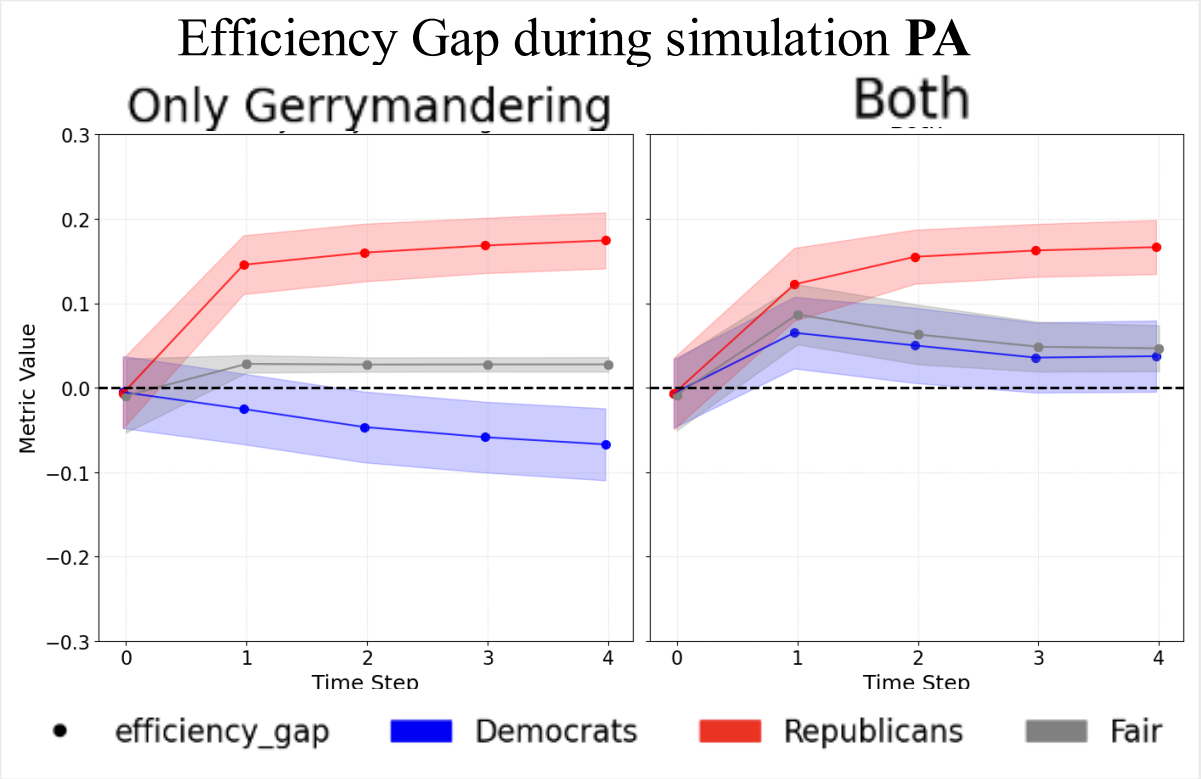
Baseline Experiments – Set-Up

- **States:** GA, WI, MI, PA (swing states)
- **Experiments**:
  - Only Gerrymandering
  - Both: Gerrymandering + Partisan Sorting
- **Control Scenarios:**
  - Fixed: Democrat / Republican / Fair
- **Runs:** 1000 sims per setup

Parameter	Default Value
T	0.5
β	100.0
E_S	250
σ	0.01
M_O	10
D_D	0.0
C_M	1.0

Baseline Experiments – Results





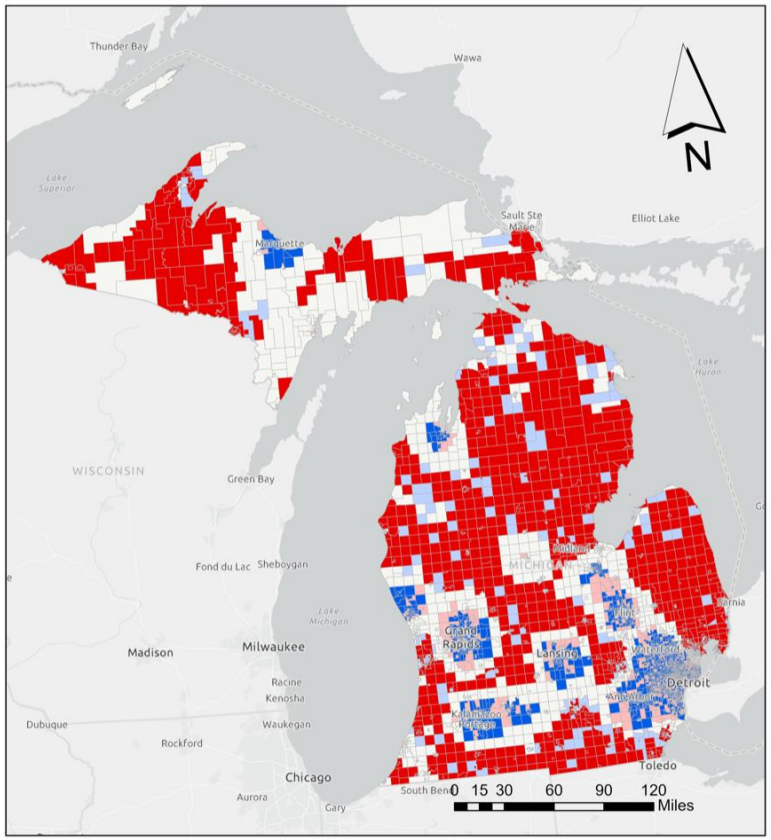
- Both parties can gerrymander
- Democrats disadvantaged
- Similar results for GA & WI

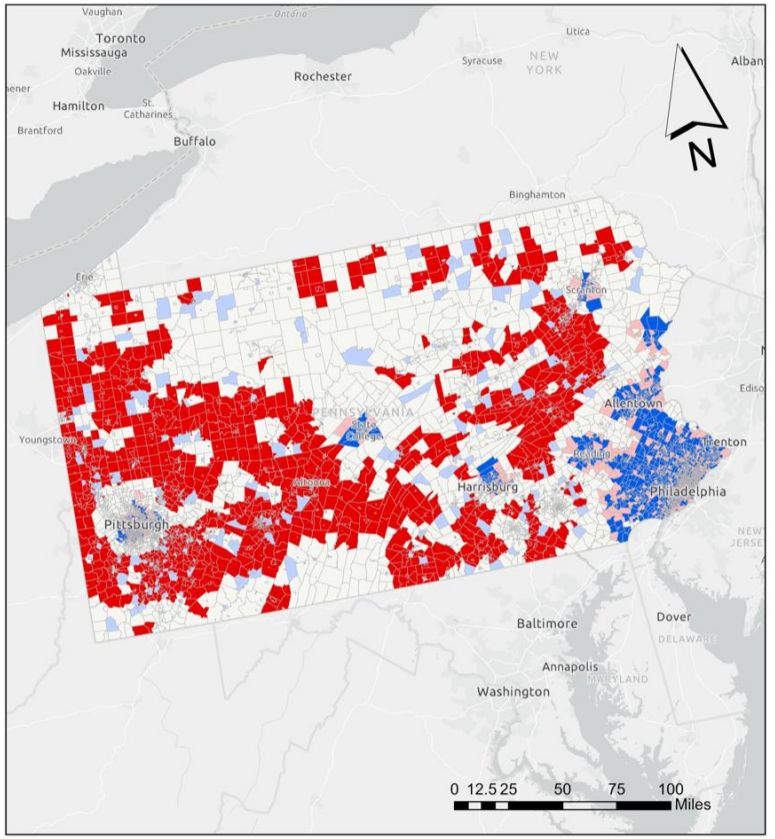
- PA: Outlier — Dems severely disadvantaged
- Likely due to spatial distribution of voters

  → Unintentional Gerrymandering

Testing Role of Political Geography – Set-Up

Partisan clustering in **MI** and **PA** (at t=END)

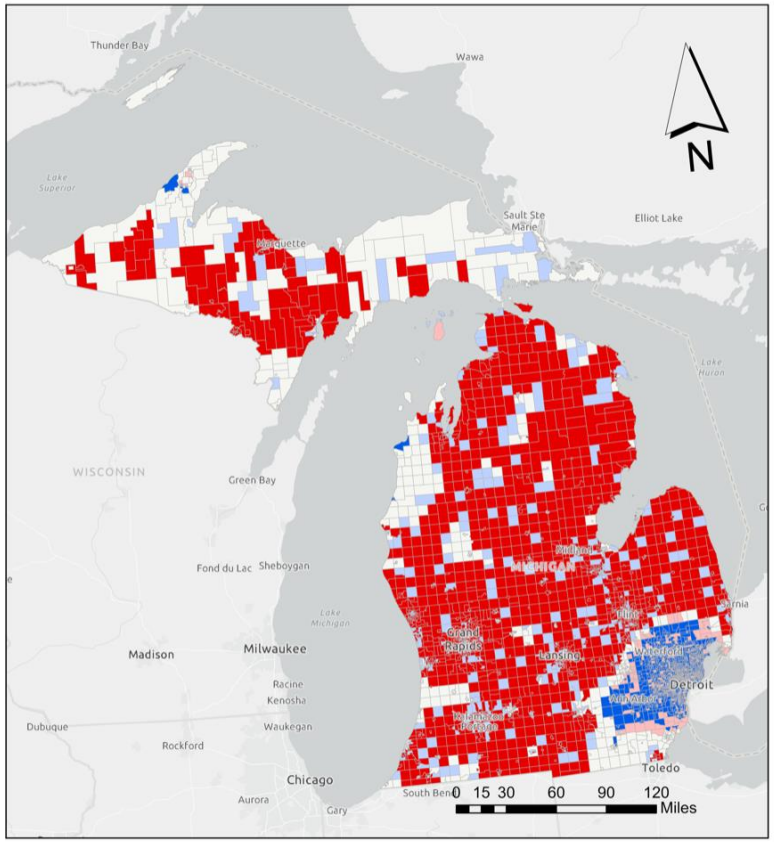


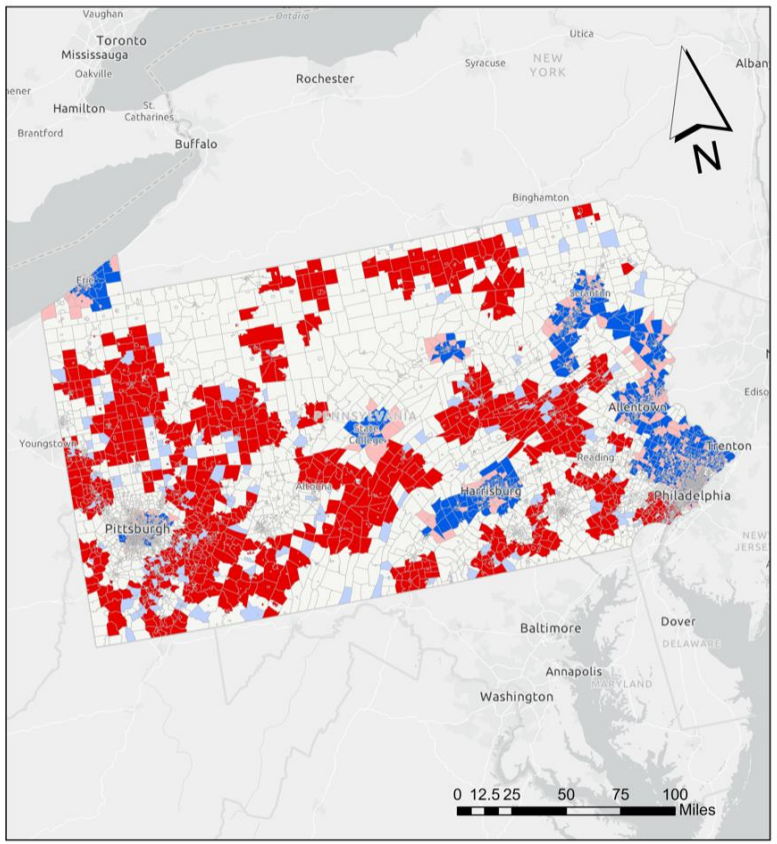


- 50% of Democrats in Detroit
- 60% of Democrats in Philadelphia

Testing Role of Political Geography – Set-Up

Partisan clustering in **MI** and **PA using fabricated initial voter distribution** (at t=END)

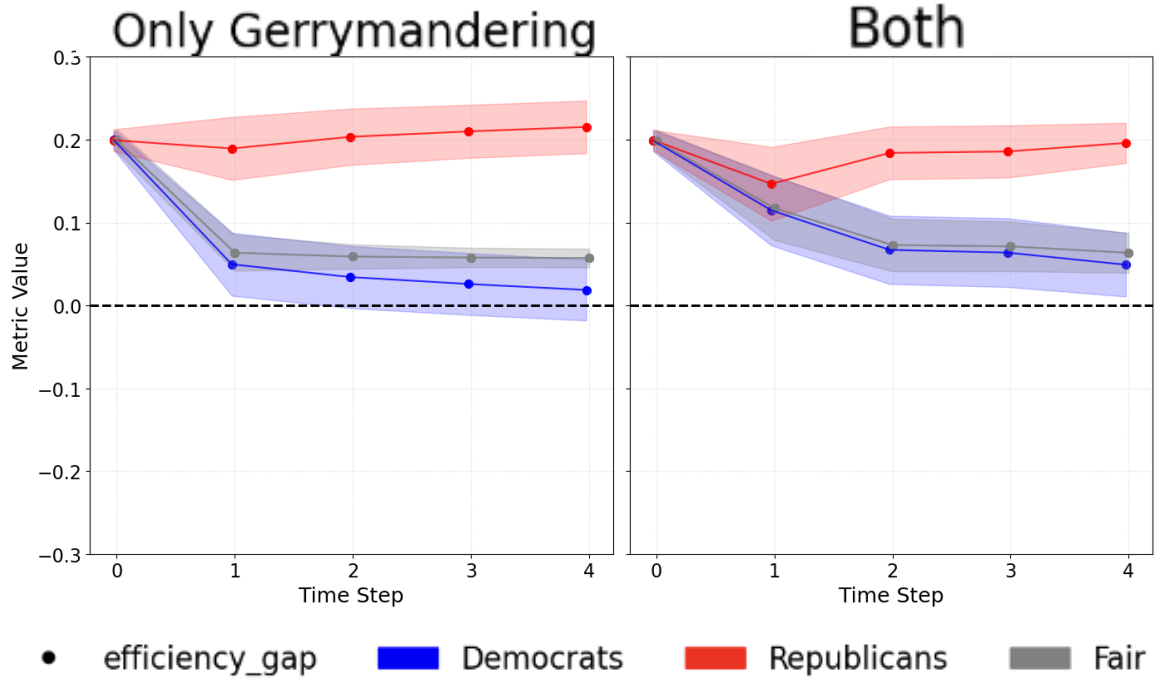




- 67% of Democrats in Detroit
- 44% of Democrats in Philadelphia

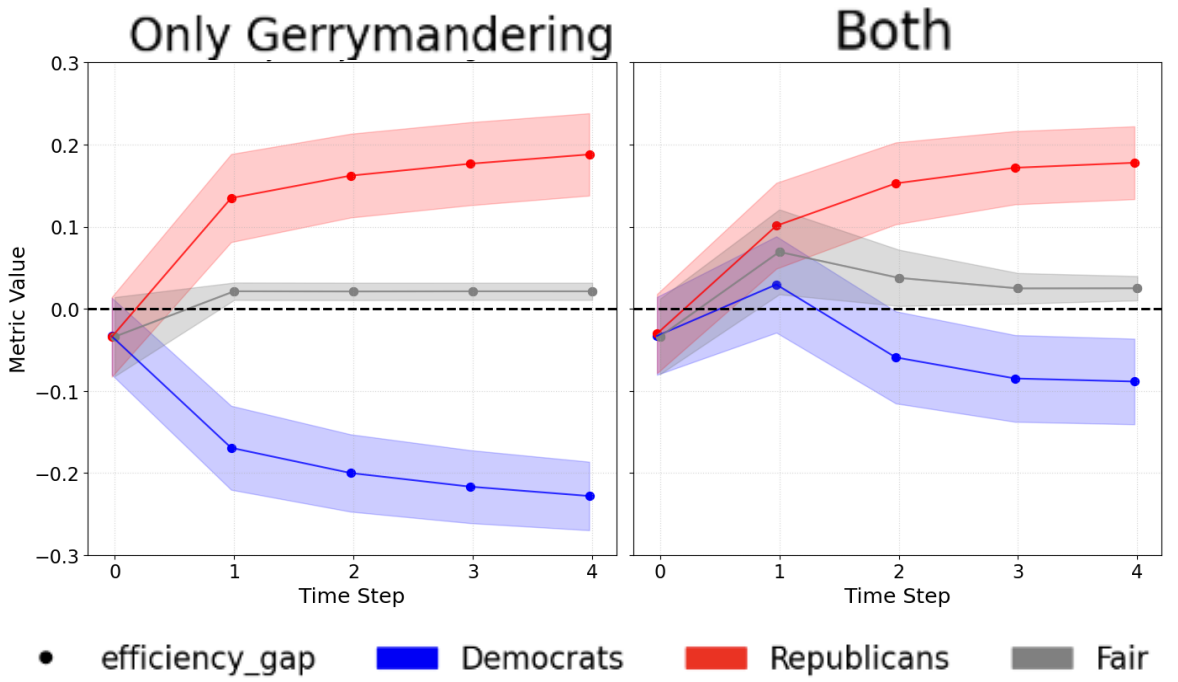
Testing Role of Political Geography – Results

Efficiency Gap during simulation **MI (fabricated)**



- Democrats become **unable** to gerrymander

Efficiency Gap during simulation **PA (fabricated)**



- Democrats become **able** to gerrymander

Main Conclusions

Baseline Experiments:
- Democrats typically disadvantaged
- However: in 3 of 4 states, both parties can gerrymander
- PA is an exception → due to political geography

Testing Role of Political Geography:
- Party with highly clustered voter base (one or two clusters) are unable to attain gerrymandered map

Redistricting Reform Experiments:
- Effective only if process is free from partisan interference
- Reform success depends on state-specific political geography

Limitations

- Control mechanism not realistic
- Utility function payoffs somewhat arbitrary
- Only 4 states modeled

Relevance

- Rucho v. Common Cause (2019) → Legalized partisan gerrymandering
- Polarization persists → Partisan segregation
  - Sorting happens across states

→ Important to determine the effects of "unintentional gerrymandering"

Research Questions

M-RQ:

- How do **gerrymandering** and **geographical partisan sorting** combined affect the partisan bias of electoral maps?

S-RQs:

- (*S-RQ1–3):* How does the presence of **geographical self-sorting/gerrymandering/combination** affect the fairness of electoral maps?

- (*S-RQ4):* How do **different spatial voter distributions** influence the outcomes observed in *S-RQ1–3*?

- (*S-RQ5–6)* How does promoting **competitive/compact** districts affect the fairness of electoral maps?

Model Description – Parameters

Parameter	Symbol	Type	Range	Description
`max_iters`	$T_{\max}$	Int	≥ 1	Maximum number of simulation steps.
`npop`	N	Int	≥ 100	Total number of agents.
`tolerance`	T	Float	$[0, 1]$	Happiness threshold of agents.
`beta`	β	Float	$[0.0, 100.0]$	Degree of randomness in agent decisions.
`ensemble_size`	E_S	Int	≥ 1	Number of redistricting maps generated.
`epsilon`	ϵ	Float	$[0.0, 1.0]$	Max population deviation from ideal district size (fraction).
`sigma`	σ	Float	$[0.0, 1.0]$	Std. dev. of noise added during redistricting optimization.
`n_moving_options`	M_O	Int	≥ 1	Number of alternative precincts considered for relocation.
`distance_decay`	D_D	Float	$[0.0, 1.0]$	Influence decay factor on utility of potential moving spot based on relocation distance.
`capacity_mul`	C_M	Float	$[0.9, 2.0]$	Multiplier adjusting county population capacity.

Model Description – Outputs

- **Avg. Competitiveness:**

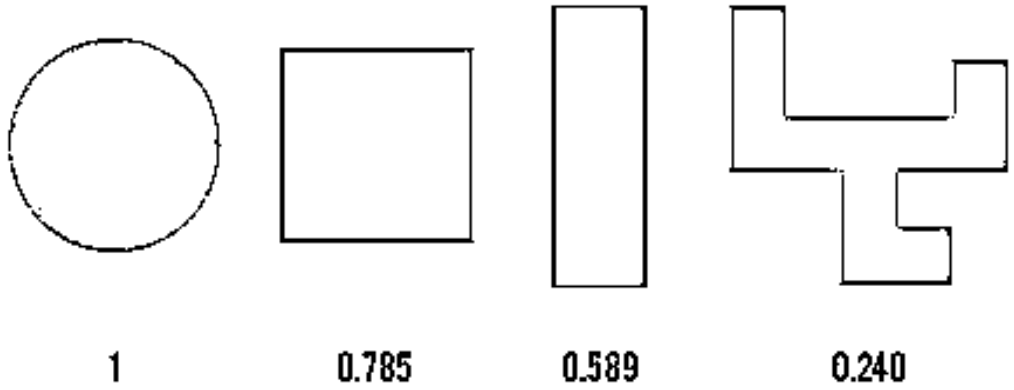
$$\text{Competitiveness Score} = 1 - \frac{|D - R|}{N}$$

- Range: 0 (least) to 1 (most) competitive district
- Averaged over all districts

Model Description – Outputs

- **Avg. Compactness:**

$$\text{Polsby-Popper} = \frac{4\pi A}{P^2}$$



- Where: A = Area; P = Perimeter Length

- Range: 0 (least) to 1 (most) compact district
- Averaged over all districts

Global Sensitivity Analysis – Set-Up

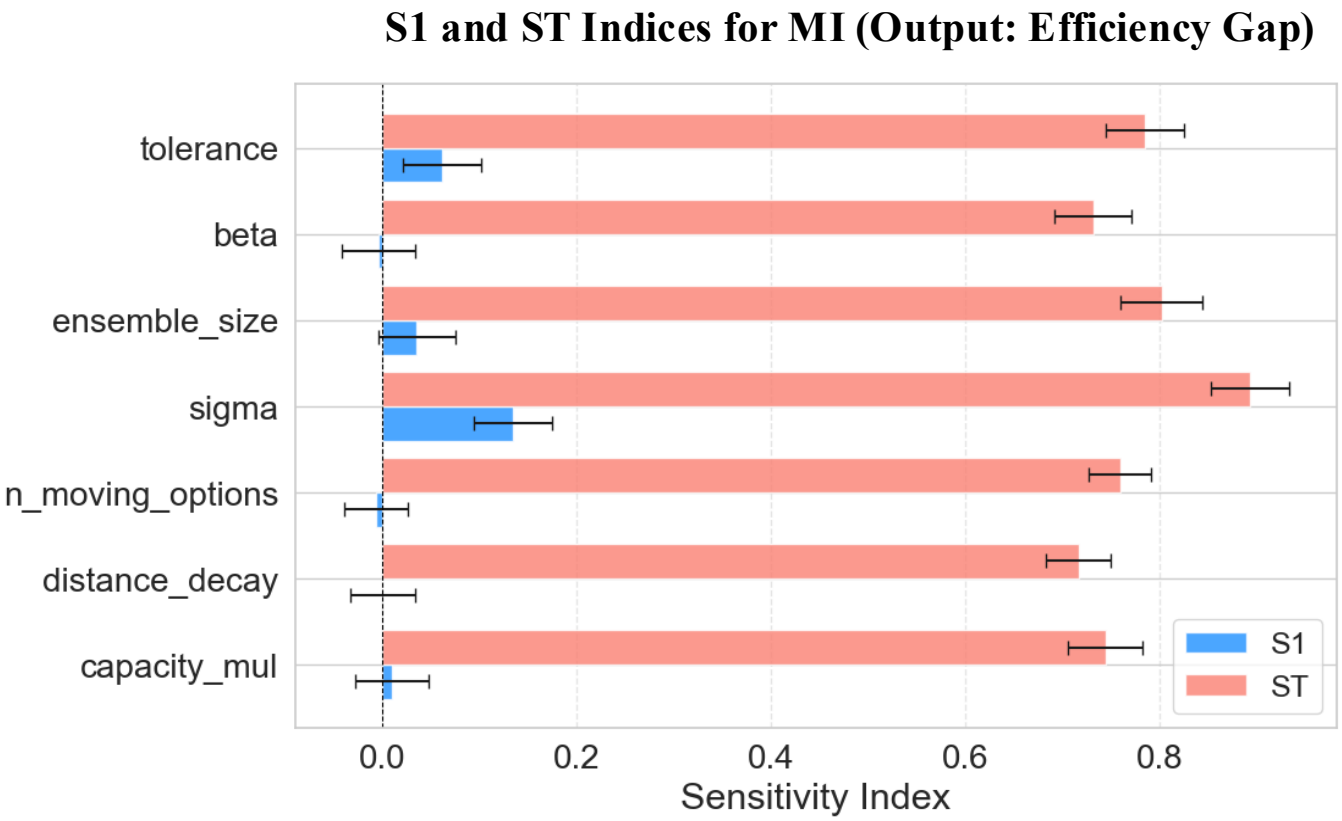
- **Sobol' Indices**
  - Ranks parameter influence and detects interaction effects
  - S1 = main, S2 = interactions, ST = total
  - Saltelli sampling (+65k sims)

Outputs: Efficiency Gap, Avg. Compactness, Avg. Competitiveness

Global Sensitivity Analysis – Results

- Top drivers: Tolerance, Sigma, Ensemble Size
- Strong interaction effects (ST ≫ S1)

- Only Tolerance affects competitiveness (S1=ST)
- No impact on compactness



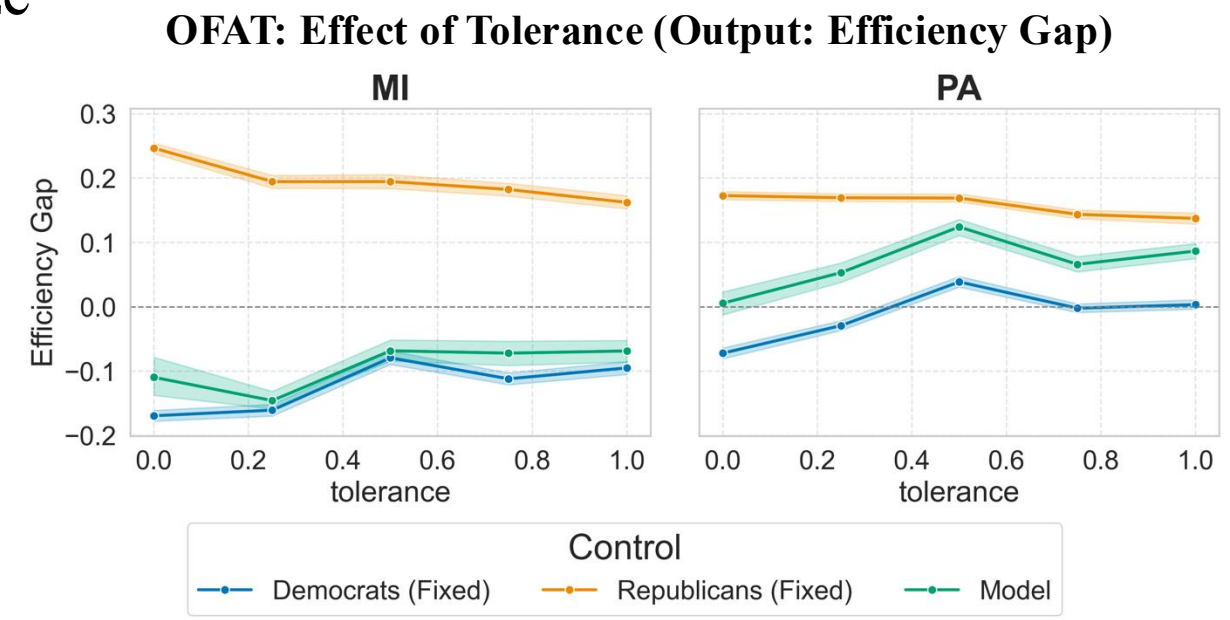
Local Sensitivity Analysis – Set-Up

- **One-Factor-at-a-Time:** Vary one, hold others fixed
- **Outputs**: Efficiency Gap, Avg. Compactness, Avg. Competitiveness

Local Sensitivity Analysis – Results

- Top drivers: Tolerance, Sigma, Ensemble Size
- ↑ sigma → weaker gerrymandering
- ↑ ensemble size → stronger gerrymandering
- ↑ tolerance → weaker gerrymandering

- Only Tolerance affects competitiveness
- No parameter affects compactness



Sensitivity Analysis – Results

Output: Efficiency Gap

- **Sobol' Indices (Global)**
  - Most impactful parameters: *Tolerance, Ensemble Size, Sigma*
  - Most output variance explained by interaction effects

- **One-Factor-at-a-Time (Local)**
  - Reaffirmed global results

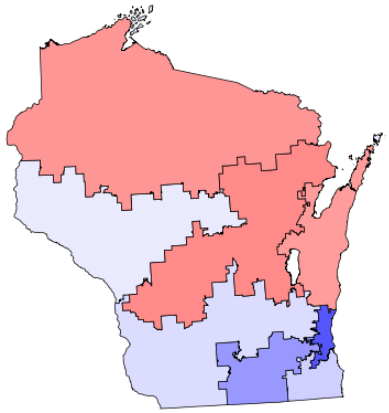
→ Model behaved as expected

Baseline Experiments – Results

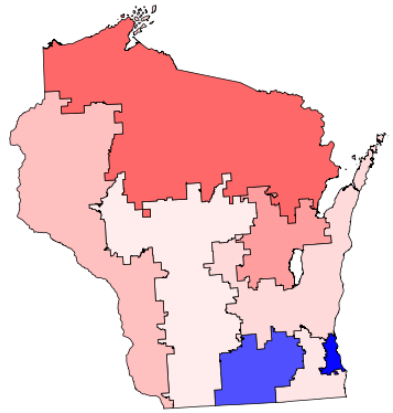
Gerrymandering Strategies:

- Republicans: *Pack* Dem voters (concentrate in few districts)
- Democrats: *Crack* Dem voters (spread across many districts)

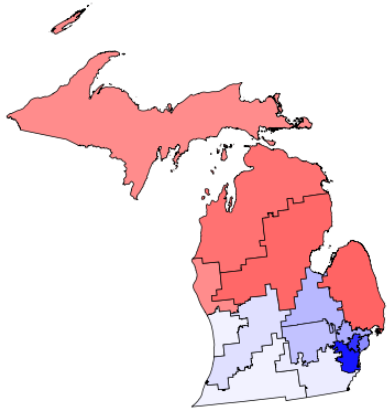
WI (Dem)
EG: -0.10 | COMPET: 0.66 | COMPACT: 0.13



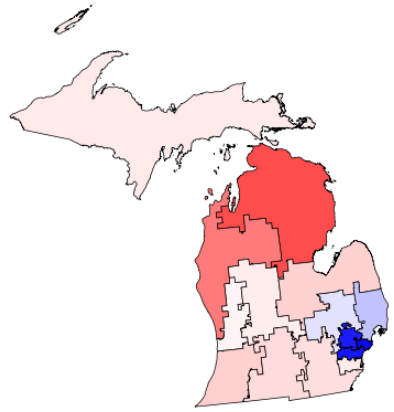
WI (Rep)
EG: 0.26 | COMPET: 0.60 | COMPACT: 0.15

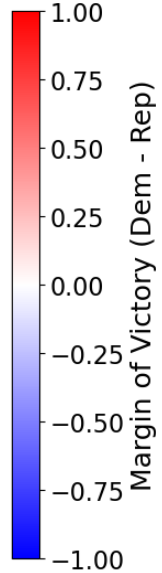


MI (Dem)
EG: -0.14 | COMPET: 0.61 | COMPACT: 0.17



MI (Rep)
EG: 0.22 | COMPET: 0.63 | COMPACT: 0.16





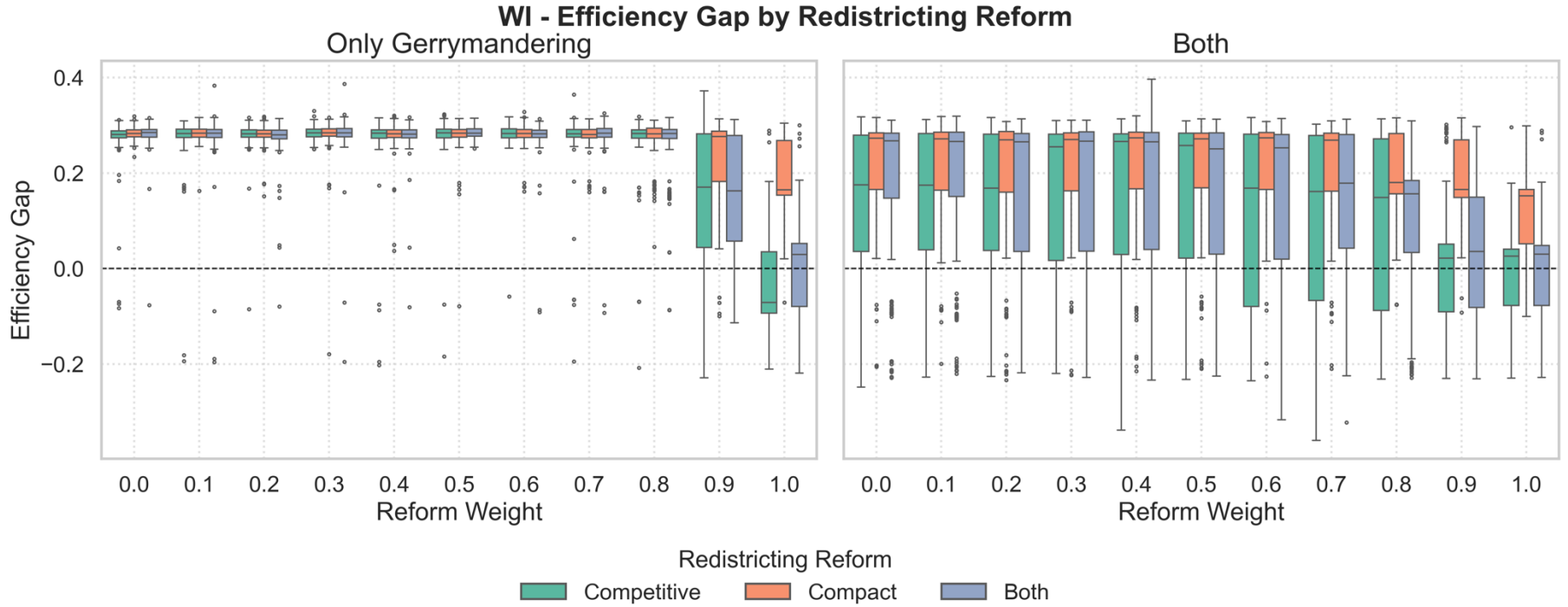
Redistricting Reform Experiments – Set-Up

- New objective function: includes reforms

$$\mathcal{O}(x) = \begin{cases} w_1 \cdot \text{Reform}(x) + w_2 \cdot \text{Gerrymandering}_P(x) + \varepsilon, & \text{if } P = R \vee D \\ \text{Reform}(x) + \varepsilon, & \text{if } P = T \end{cases}$$

- Reform weights (w1, w2=1-w1) incremented from 0 to 1
- 250 simulations per weight value
- Used baseline parameter values

Redistricting Reform Experiments – Results



- **High weights** needed for fairness gains
- Reforms improve **only targeted criteria**
- **State-specific effects:**

→ Least effective in PA (due to voter geography)

Future Work

- Model different forms of segregation
- Explore alternative reform criteria
- Model gerrymandering at multiple levels