Evaluating the Partisan Fairness of the Concept Maps Proposed by New Mexico's Citizen Redistricting Committee

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Abstract

This report evaluates the concept maps proposed by New Mexico's Citizen Redistricting Committee for the state's Congressional, House, Senate and Public Education Commission districts. I evaluate each proposed map using various metrics of partisan fairness that are commonly used to evaluate redistricting plans. This includes an evaluation of each concept map's expected partisan outcome, average district compactness, efficiency gap, mean-median difference, and partisan asymmetry. I compare each map's performance on these metrics to the performance of an ensemble of 1,000 alternative maps drawn using a computer-automated redistricting algorithm. The algorithm is instructed to build districts that are equally-populated, contiguous, compact, adhere to county boundaries, and establish districts required by the Voting Rights Act. Given that the algorithm uses only partisan-neutral criteria, the ensemble maps provide a baseline set of expectation for the types of partisan outcomes that one should expect under non-partisan redistricting. Using the computer-draw plans as a baseline, I test whether each of the proposed maps exhibit significant partisan bias. Ultimately, I find that all of the proposed concept maps tend to conform with expectations.

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Introduction

I have been asked to evaluate the partisan fairness of each of the proposed concept maps produced by New Mexico's Citizen's Redistricting Committee (CRC). I received three distinct concept maps for the state's Congressional districts (referred to as Concepts A, E, and H), three distinct concept maps for the state's Public Education Commission (referred to as Concepts A, C, and E), three distinct concept maps for the state's Senate districts (referred to as Concepts A1, C, and C1), and three distinct concept maps for the state's House districts (referred to as Concepts E1, I, and J).[1] Each of these concept maps are displayed as figures in the appendix for reference.[2]

The goal of this report is to evaluate each of the maps with respect to a set of objective metrics commonly used by political scientists for assessing the partisan fairness of redistricting plans. These metrics include the expected partisan outcome, average district compactness, efficiency gap, mean-median difference, and partisan asymmetry.Each metric uses a different approach to measuring the extent to which a map advantages one party over another. Together, they can provide insight into how the maps ultimately translate votes into seats and bias representation.

The benefit of using objective metrics for evaluating redistricting plans is that they provide precise and transparent values for describing an abstract concept like partisan fairness. These metrics have the advantage of being easy to define, compute, and apply uniformly across redistricting plans. This is certainly an important feature for distinguishing one plan from another.

However, measuring partisan fairness is not easy. Just like any precise measure of an abstract concept, the metrics used in this report are unlikely to capture the full extent to which a plan is fair or unfair. Sometimes these metrics inadvertently measure concepts other than fairness itself.[3] And sometimes the measures will disagree with each other on what a fair plan looks like. Therefore, it is important to accept some degree of uncertainty in applying

[1] I received the maps for Congress, Public Education Commission, and state Senate on October 18, 2021 and I received the maps for the state House on October 21, 2021. The maps were sent to me by Research & Polling as Census block assignment files, which I subsequently merged with 2021 precincts.

[2] Figure A.1 presents the maps for Congress, Figure A.3 presents the maps for Public Education Commission, Figure A.5 presents the maps for the state Senate, and Figure A.7 presents the maps for the state House.

[3] Using measures of district compactness to identify unfairly drawn districts, for example, can lead one

such a precise measurement to an abstract concept like partisan fairness.

One major challenge with evaluating partisan fairness in redistricting plans is developing expectations for just *how fair* a plan should be. It is likely unreasonable to expect a plan that is perfectly fair to both parties. Even the most partisan-neutral map-makers can produce unfair outcomes without intending to do so. And if that is the case, then we should consider unfairness as a natural product of a neutral redistricting process. And we must account for these natural and random variations in fairness when establishing expectations for just how fair a plan ought to be.

Therefore, when evaluating the concept maps produced by the CRC, I first establish a baseline set of expectations regarding the types of partisan bias that might arise simply by chance alone. I do this by summarizing the outcomes produced by thousands of alternative redistricting plans that have been randomly generated by a computer algorithm. These computer-generated outcomes help to characterize the natural variation in fairness that one should expect in a neutral redistricting process. And with this baseline expectation, one should be able to distinguish between the partisan bias that is designed intentionally and the partisan bias that is a natural product of redistricting.

I proceed as follows. First, I discuss the partisan composition of the each of the concept maps proposed by the CRC. Then I describe the metrics of partisan fairness used to evaluate the maps. Then I describe the computer algorithm used to generate the computer ensemble. And, ultimately, I compare the scores of the concept maps to the scores generated by the computer ensemble to test whether each of the concept maps are unexpectedly unfair.

Evaluating the partisan composition of each of the concept plans.

In order to evaluate the partisan composition of the districts in each of the proposed redistricting plans, I rely on election data collected and sent to me by Research & Polling. The election data consists of votes cast for all major-party candidates across all contested

to falsely attribute oddly-shaped districts to gerrymandering when they are instead the result of boundaries conforming to a state's geographic features, like winding rivers and coastal regions.

Table 1: Votes Cast for Major Party Candidates in All Statewide Contests in New Mexcico from 2012 to 2020

Democrat	Republican	Percent Democrat
13,268,194	10,895,844	54.9

statewide elections in New Mexico from 2012 to 2020. These votes have been tabulated at the precinct-level for each election and merged to the most recent 2021 precinct boundaries. The 2021 precincts are the building blocks of each concept map proposed by the CRC, so the votes can then be aggregated to the level of each district in the map.

Unfortunately, no single contest in a given election is able to capture the full extent of partisanship in a specific district. Therefore, to assess district partisanship, I aggregate total votes cast for Democratic candidates and total votes cast for Republican candidates across all statewide contests for every election going back to 2012. By aggregating votes across a number of contests and elections, I am attempting to capture the consistent partisanship that underlies the vote rather than the election-specific or contest-specific variables that might temporarily swing partisanship in one-direction or another.

Table 1 displays the sum total of these votes for the entire state. New Mexico voters cast a total of 13.3 million votes for Democratic candidates and 10.9 million votes for Republican candidates in statewide contests from 2012 to 2020. Using these totals, we can estimate the partisan composition of the state overall. Dividing the Democratic votes by the total votes cast for Democrats and Republicans, we see that Democrats make up 54.9% of the two-party vote.

We can make the same calculation for every district in each concept plan. By aggregating the precinct-level votes to each district, I compute the Democratic share of the two-party vote in every district across every concept plan. This measure provides an indicator for the partisan composition of each district.

I then tabulate the number of districts that fall within various important intervals of Democratic vote share. The tabulations are displayed in Table 2. Every column of the table counts the number of districts that fall within the intervals defined in the first column on the left. Each of the twelve columns to the right of the intervals correspond with each of the

Table 2: Partisan Composition of All Proposed Plans

	Congress			Public Ed.			State Senate			State House		
Percent Dem	A	E	H	A	C	E	A1	C	C1	E1	I1	J
0% to 49.9%	1	1	0	3	3	3	14	15	15	23	26	26
50% to 100%	2	2	3	7	7	7	28	27	27	47	44	44
45% to 45.9%	1	0	0	0	0	0	2	2	2	1	3	3
46% to 46.9%	0	1	0	0	0	0	1	0	1	2	1	1
47% to 47.9%	0	0	0	1	1	0	0	1	0	0	3	3
48% to 48.9%	0	0	0	0	0	1	1	1	2	1	1	1
49% to 49.9%	0	0	0	0	0	0	1	1	1	1	2	2
50% to 50.9%	0	0	0	1	1	1	3	1	1	3	0	0
51% to 51.9%	0	0	0	1	1	1	1	0	0	4	4	4
52% to 52.9%	0	0	1	1	0	1	0	1	2	3	3	3
53% to 53.9%	0	0	0	0	1	0	2	1	2	1	2	2
54% to 54.9%	0	0	1	0	0	0	1	4	1	2	0	0
45% to 49.9%	1	1	0	1	1	1	5	5	6	5	10	10
50% to 54.9%	0	0	2	3	3	3	7	7	6	13	9	9

twelve concept plans proposed by the CRC.

The first row of the table tabulates the number of districts that fall below 49.99% Democrat. And the second row of the table tabulates the number of districts that fall above 50% Democrat. Hence, the first two rows display the expected number of Democrats and Republicans that will result from each map.

One common characteristic of each map is that they all produce Democratic supermajorities. In fact, many of the plans produce nearly twice the number of Democratic seats as they do Republican seats. Thus, Democrats can expect to receive a larger share of the seats than their share of the vote, which is under 55%.

This table also reveals a few important distinctions between the concept maps for each set of districts. For example, Congress Concept Map H produces Democratic districts for all three seats in Congress, whereas the other two concepts produce only two Democratic districts. The difference is just one seat, but it represents a third of the New Mexico Congressional delegation.

Another distinction that stands out is that House Concept Map E1 produces 3 additional Democratic districts compared to the alternative Maps I1 and J. Both Maps I1 and J produce

44 Democratic districts. And map E1 produces 47. However, an important caveat is that Maps E1 and J are nearly identical maps, with only small differences between them.

On the other hand, there is little distinction in terms of the partisan composition between the maps for Public Education Commission and State Senate.

In addition to partisan seats, the table also reveals tabulations for the number of competitive districts in each plan. These tallies are displayed in 1-point intervals as well as 5-point intervals. Notably, all concept maps produce similar numbers of competitive districts. And most tend to lean Democrat.

Measuring partisan fairness

While the partisan composition of each plan provides some insight into its partisan features, is not a complete picture. To better understand the partisan fairness of the plans, I have been asked to assess each plan according to a set metrics commonly leveraged for evaluating partisan fairness. The metrics include the expected number of Democratic seats, expected number of competitive seats, the average district compactness, efficiency gap, mean-median difference, and partisan asymmetry. The following provides a brief overview describing each of these six metrics.

Expected Number of Democratic Districts: To determine the expected number of Democratic districts for each plan, I first compute the Democratic share of the two-party vote in each district. I then compute the number of districts where the Democratic share of the two-party vote exceeds 50%. This value is computed for each plan and represents the number of districts that Democrats are expected to win.

Expected Number of Competitive Districts: I define a district to be competitive if its Democratic share of the two-party vote is between 45% and 55%. While I've defined these intervals arbitrarily, districts where candidates win by less than a ten point margin are conventionally accepted as being somewhat vulnerable.

Average Polsby-Popper Score: The Polsby-Popper score is a measure of district compactness. It is calculated by comparing the area of a district to the area of a circle that has a circumference equal to the perimeter of the district. Higher scores indicate more compact districts. Lower scores indicate less compact districts. Oddly-shaped districts with winding perimeters will approach a low score of 0 according to this metric. Redistricting plans with a lower average Polsby-Popper score might imply a high degree of partisanship in the design. This assumes map-makers must deviate from designing compact shapes in order to bias their maps toward a particular party.

Efficiency Gap: The Efficiency Gap is a measure of how a plan disadvantages a party by wasting its votes (Stephanopoulos and McGhee, 2015). It does this by quantifying the number of wasted votes cast for each party, where a wasted vote is defined as any vote cast for a party that does not contribute to that party's victory in a given district. This includes every vote cast for the losing party. And it also includes every vote cast for the winning party in excess of the majority vote required to win. To compute the Efficiency Gap, one simply takes the difference between the number of wasted votes cast for Republicans and the number of wasted votes cast for Democrats and presents the net wasted Republican votes as a fraction of the total votes cast for both parties. Therefore, redistricting plans with larger positive values imply that the plan is more biased against Republicans (it wastes a larger fraction of the Republican votes). And redistricting plans with smaller negative values imply that the plan is biased against Democrats (it wastes a larger fraction of the Democratic vote).

Mean - Median: Just as the name suggests, the Mean-Median difference is calculated as the difference between the average Democratic vote share across the districts (the mean) and the Democratic vote share in the median district (the median). It attempts to measure the extent to which the average voter is represented by the median district (McDonald and Best, 2015). Positive values indicate that Democrats are underrepresented, whereas negative values indicate that Democrats are over-represented. Hence, higher values imply that a map is biased to favor Republicans and lower values imply that a map is biased to favor Democrats. So if the average Democratic vote share across the districts is .55 and the Democratic vote share in the median district is .60, the mean-median difference is $-.05$, implying that the redistricting plan over-represents

Democrats by 5 percentage points in the median district. On the other hand, if the Democratic vote share in the median district is .50, then the mean-median difference is +.05, implying that the redistricting plan over-represents Republicans by 5 percentage points in the median district. A measure of zero indicates that the median district and the average voter are aligned. Zero implies that the redistricting plan is unbiased.

Partisan Asymmetry: Partisan asymmetry is a measure of the extent to which parties are rewarded differently when receiving an identical share of the vote. In redistricting plans that are perfectly symmetric, both parties should expect the same reward in seat share for obtaining the same share of the vote. One way to measure asymmetry is "partisan bias." This is a special case of partisan asymmetry, looking at a hypothetical event where Democrats and Republicans are tied with 50% of the vote. According to the metric, a plan would reward each party with 50% of the seats if that plan were perfectly symmetric. Therefore asymmetry refers to the extent to which a party's seat share would deviate from 50% .King (1989) Higher positive values indicate greater asymmetry in favor of Democrats and lower negative values indicate greater asymmetry in favor of Republicans. For example, if a redistricting plan were expected to give Democrats 55% of the seats with only 50% of the vote, then the plan would be giving Democrats a 5 percentage point seat advantage in tossup elections. In this instance, the partisan asymmetry metric would be calculated as $.55 - .50 = .05$ indicating bias in favor of Democrats. However, if a redistricting plan were expected to give Democrats 45% of the seats with 50% of the vote, then *Republicans* would have a 5 percentage point seat advantage in tossup elections. In this instance, the partisan bias metric would be calculated as $.45 - .50 = -.05$, indicating bias in favor of Republicans.[4]

In addition to computing these six metrics for every Concept plan, I also compute the metrics for every map in the Computer-generated ensemble. Given that there are 6 metrics

[4] In order to determine what the Democratic seat share would be in a hypothetically tied election, Democratic vote share in each district is adjusted uniformly by the same amount that would be required to adjust average Democratic vote share across districts to .50. For instance, if the average Democratic vote share across the districts in New Mexico is .55, then every district would have its vote share reduced by .05 and the number of Democratic seats would be calculated as the number of districts where Democrats have a majority of this adjusted vote share.

and 1,000 ensemble plans generated separately for Congress, PEC, state Senate, and state House, this provides 24,000 distinct measurements of partisan fairness to be used as a baseline comparison for the proposed concept maps.

In the next section I provide a brief overview of the algorithm I used to draw the ensemble maps.

The computer-automated redistricting algorithm

Before evaluating each of the Concept maps on the 6 metrics discussed above, it is important to set a range of expectations for the type of unfairness that might result naturally in the maps, by chance alone. To establish this expectation, I use an ensemble of 1000 alternative redistricting maps, generated by a computer-automated redistricting algorithm, for Congress, PEC, state Senate, and state House. The algorithm has been instructed to build districts that are equally-populated, contiguous, compact and adhere to county boundaries. And for the state Senate and House maps, it has been instructed to search for districts required by the Voting Rights Act. To do this, the algorithm follows a series of steps, which I describe below.

Take the algorithm I use for the state Senate as an example. There are 42 districts in the Senate. The concept plans for the Senate have been designed to produce 42 contiguous districts that are roughly equally-populated, with a maximum population deviation of no more than 10% of the target population (the target population is defined as the total population divided by 42). The plans are required to be roughly compact, containing geographically-concentrated populations. They are to adhere to administrative boundaries. And they are to adhere to standards established by the Voting Rights Act.

Therefore, the goal of the algorithm is to design 1000 distinct Senate maps with 42 districts that comply with these same redistricting principles. The only difference would be that the algorithm is guaranteed to leave all other considerations for how to build districts up to chance. As a result, it produces an ensemble of maps that reflect the possible outcomes of a redistricting process that considers basic principles for redistricting, and nothing else. Partisanship is completely ignored in the design of the ensemble plans - which is ideal for fair redistricting.

For each redistricting plan generated for the Senate, the algorithm follows these six steps:

Step 1: Create a base map with 42 contiguous districts. To create a set of randomly generated maps for the Senate, the algorithm begins by randomly selecting 42 different precincts across the state. These 42 precincts become the "seeds" from which 42 contiguous districts will grow. Each precinct is now a district. The algorithm grows the districts in population by repeatedly adding to each district a randomly selected neighboring precinct that has not yet been assigned to another district. It stops when all precincts have been assigned to a district. The result is a map of 42 contiguous districts generated at random. However the districts are not necessarily equally-populated or compact in shape.

Step 2: Amend the base map so that the districts are equally populated. The districts generated in Step 1 may not be equally populated. Therefore, the algorithm proceeds to revise the map so that the maximum deviation in population between the districts is less than 10% of the target population.[5] It begins by computing the maximum population deviation of the base map. If it is less than 10%, it selects a district at random – but aims for districts that deviate the most from the target population – and merges it with one of its neighboring districts. Then the algorithm searches for ways to split the merged districts back into two contiguous districts, choosing the split that minimizes the districts' deviation from the target population.[6] Once a split is performed, the original two districts have been recombined into two districts that are distinct from their original form and the map is altered slightly. It does this repeatedly until the maximum population deviation between any two districts is less than 10% of the target population.

Step 3: Make 1000 random alterations to the map. To ensure that the map is a uniquely random map, the algorithm proceeds by selecting districts at random and

[5]For Congress I use the standard of designing districts with no more than 1% maximum population deviation. For all other maps, I use the standard of 10%.

[6]This merge-split method follow similar approaches adopted by Chen and Stephanopoulos (2020), DeFord, Duchin and Solomon (2019), and Carter et al. (2019). It uses a version of Prim's algorithm to find a Minimum Spanning Tree (MST) that connects the adjacent precincts within each county within each district. The result of cutting the MST creates two contiguous districts that conform with county boundaries.

proposing a merge-split for those districts. It executes a merge-split if the resulting map has a maximum population deviation less than the 10% threshold. And it stops after 1000 merge-splits have been executed. The resulting map is randomly-generated, contiguous, and equally-populated. But it is not necessarily compact.

Step 4: Make 1000 attempts to improve district compactness. Although the districts that result from Step 3 are mostly compact, the algorithm makes additional attempts to improve the compactness of the districts. It does this by repeatedly proposing 1000 merge-splits and executing the ones that improve the overall compactness of the districts – where compactness is defined by the degree of precinct dispersion in the districts. This alters the maps so that the districts contain precincts that are closer to the district center.

Step 5: Make 1000 attempts to improve Native representation in the Northwest. Given that VRA considerations are in important part of designing maps in the Senate, the algorithm makes 1000 attempts to create three VRA districts (Districts 3, 4, and 22) in the Northwest part of the state. VRA Districts are defined as having a non-Hispanic Native voting-age population of 60% of the total voting-age population. The algorithm targets the districts in the Northwest with the largest Native populations and performs merge-splits in those districts only if it improves the Native representation. The algorithm stops after it has made 1000 attempts to improve Native representation.

Step 6: Make 1000 attempts to improve Hispanic representation in the Southeast. Lastly the algorithm makes 1000 attempts to create three VRA districts (Districts 32 and 41) in the Southeast part of the state. VRA Districts are defined in this region as having a Hispanic voting-age population of 55% of the total voting-age population. The algorithm targets the districts in the Southeast with the largest Hispanic populations and performs merge-splits in those districts only if it improves the Hispanic representation. The algorithm stops after it has made 1000 attempts to improve Hispanic representation.

Step 7: Repeat steps 1-6 1,000 times. After Step 6 is executed, a single redistricting plan with 42 contiguous, equally-populated, roughly compact districts that attempts to comply with the VRA has been randomly generated. The algorithm then repeats steps 1 through 6 1,000 times to establish an ensemble of 1,000 computer generate maps for Senate.

I repeat this process to generate 1,000 ensemble maps for Congress, the Public Education Commission, state Senate, and state House. Figures A.2, A.4, A.6, and A.8 plot three different examples from each of the ensembles.

In the next section, I present the results of those tests for Congress, the PEC, the state Senate, and the State House.

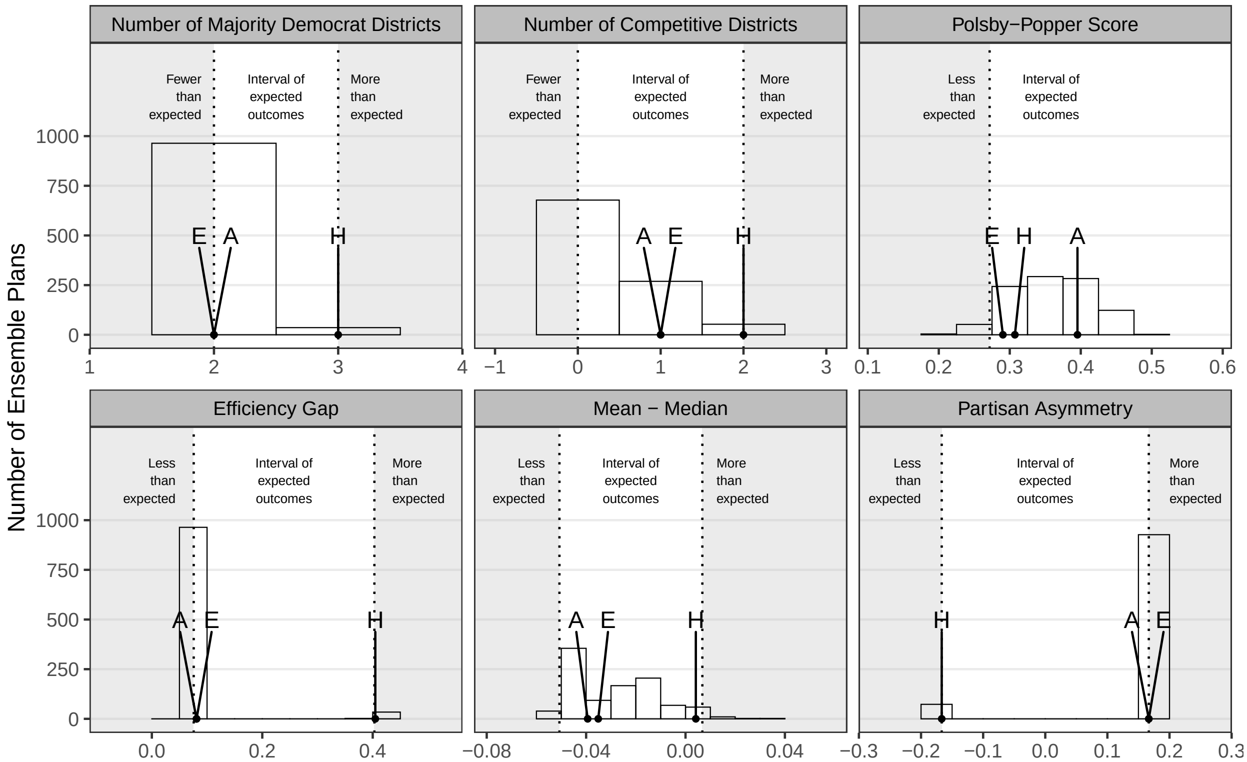
Results

For all 1,000 ensemble maps, I measure the number of majority-Democratic Districts, number of Competitive Districts, the Polsby-Popper Score, the Efficiency Gap, the Mean-Median difference, and Partisan asymmetry. I then take the range of the middle 95% of those scores to create an interval of expected outcomes for the Concept plans. Concept plans that score outside of that range are plans that are unexpectedly unfair, since they correspond with less than 5% of the of the ensemble maps. This provides a test of fairness that can be applied to all of the Concept maps.

The results for the concept maps for Congress are plotted in the Figure 1. For each of the six measures, scores of the three concept plans are arranged as points along the x-axis and their names listed above each point. The distribution of scores for the 1,000 corresponding ensemble maps are displayed in histograms in the background of each plot. The height of the histogram bar reflects the number of ensemble plans that scored values contained within the range of each bar. 95% of the computer-generated ensemble maps produced outcomes within the white region and 5% of the maps produced outcomes in the shaded region. This develops a range of outcomes that we can expect to occur under non-partisan redistricting and establishes a baseline for determining whether a concept map is significantly unfair.

As the figure displays, each of the concept maps for Congress fall within expected ranges

Figure 1: Results for Congress

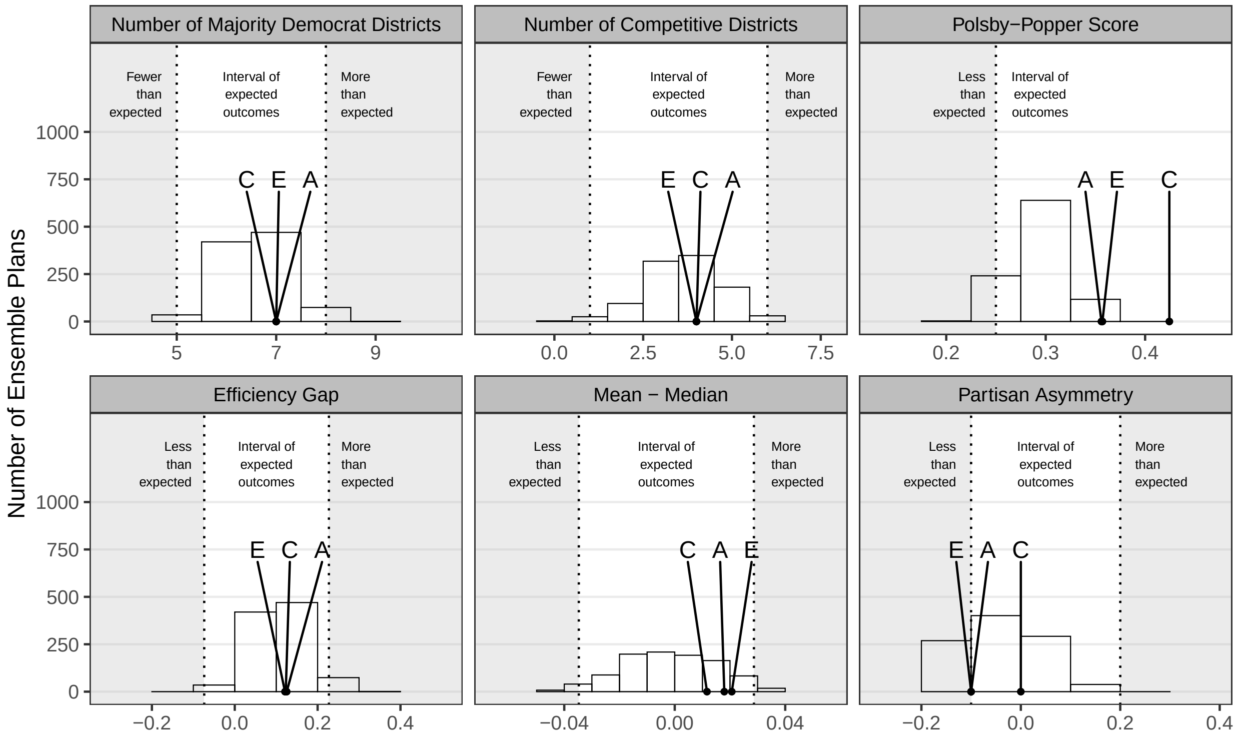


for all six measures. Maps A and E tend produce similar scores to each other, whereas Map H is distinct from the other two. Map H produces more Democratic districts than the others but its partisan symmetry favors Republicans. Map H has a higher Efficiency Gap that favors Democrats while maps A and E have a more extreme Mean-Median score that favors Democrats. None of the Concept maps for Congress produce scores that are unexpected.

The results for the concept maps for Public Education Commission are plotted in Figure 2. Just like the plans for Congress, no plan scores outside the expected range. Not only do the plans seem to agree with each other, but they also conform very well with the ensemble plans. They produce similar numbers of Democratic seats and competitive seats. They are also more compact than most of the ensemble plans. If anything is unusual, it is that plans E and A produce partisan symmetry scores that lean more Republican than the bulk of ensemble plans.

The results for the concept maps for state Senate are plotted in Figure 3. Again the concept maps tend to fall within expected ranges on each of the metrics. They produce

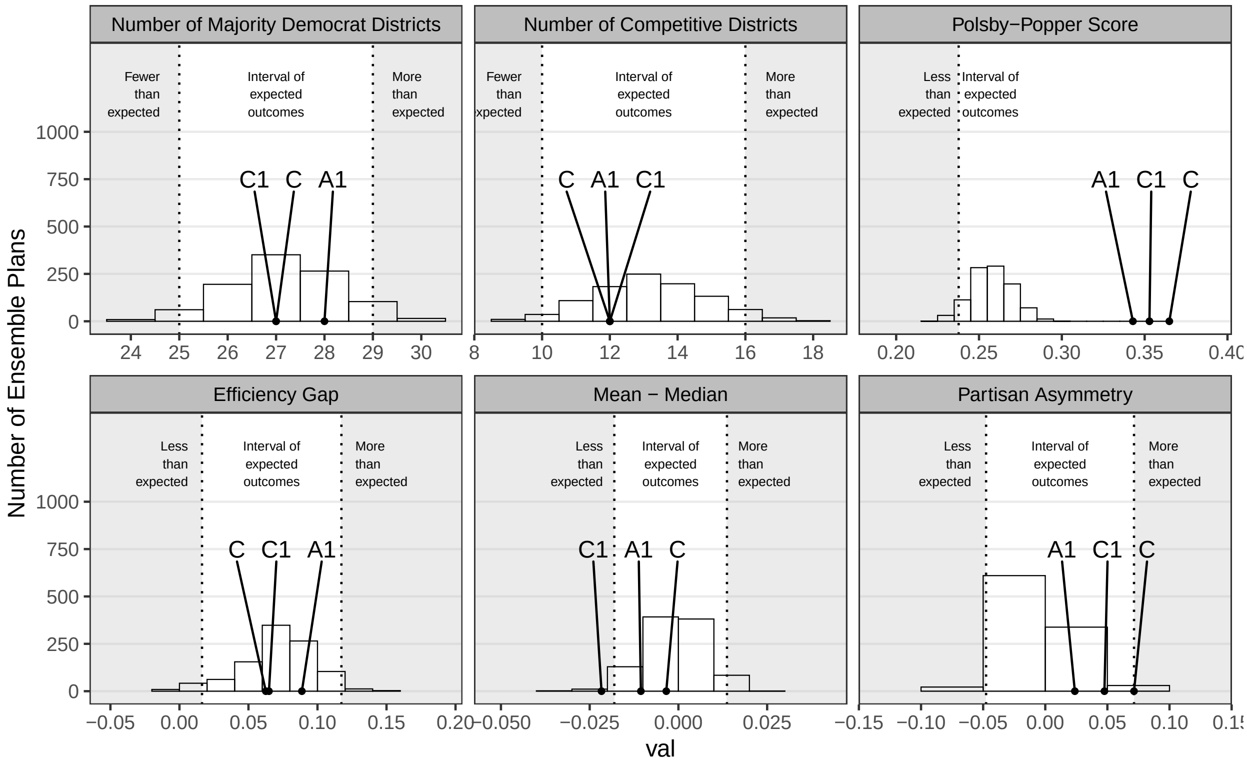
Figure 2: Results for Public Education Commission



similar numbers of Democratic seats and competitive seats. They are also more compact than all of the ensemble plans. The only outcome in the shaded region is Senate plan C1 on the mean-median score. According to that measure, it has an unusually strong Democratic bias. However, it is well within the expected range for other measures, producing a similar number of Democratic seats as the Ensemble plans.

Lastly, the results for the concept maps for the House are plotted in Figure 4. Once again, each of the Concept plans for the House fall within expected ranges. None exhibit extreme partisan unfairness and they correspond with the middle 95% of the ensemble plans. They produce similar numbers of Democratic districts and competitive districts, produce compact district scores, and produce similar partisan fairness scores. If anything stands out, is that plan E1 tends to produce more Democratic districts than the bulk of ensemble plans – although it is within the range of expectation.

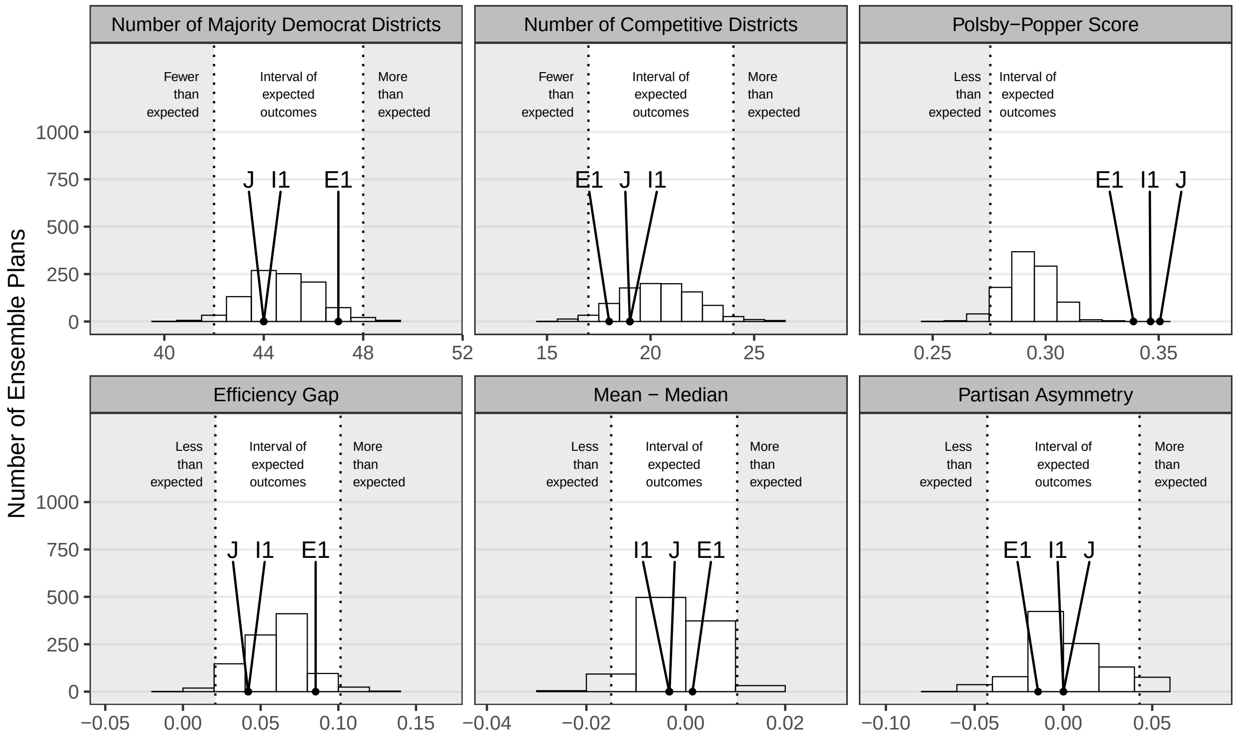
Figure 3: Results for State Senate



Conclusion

In this report I have evaluated each of the Concept maps proposed by the Citizen's Redistricting Committee with respect to 6 different metrics of partisan fairness, capturing each plan's expected partisan outcome, average district compactness, efficiency gap, mean-median difference, and partisan symmetry. I have also evaluated a computer-generated ensemble of 1,000 alternative plans using the same metrics of partisan fairness. In comparing the concept maps to the computer-generated ensemble maps, I find little evidence to suggest that the maps are unexpectedly unfair. Other than a minor exception, the concept maps fall within expected ranges of partisan fairness.

Figure 4: Results for State House



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Appendix

Figure A.1: Concept Maps for Congressional Districts

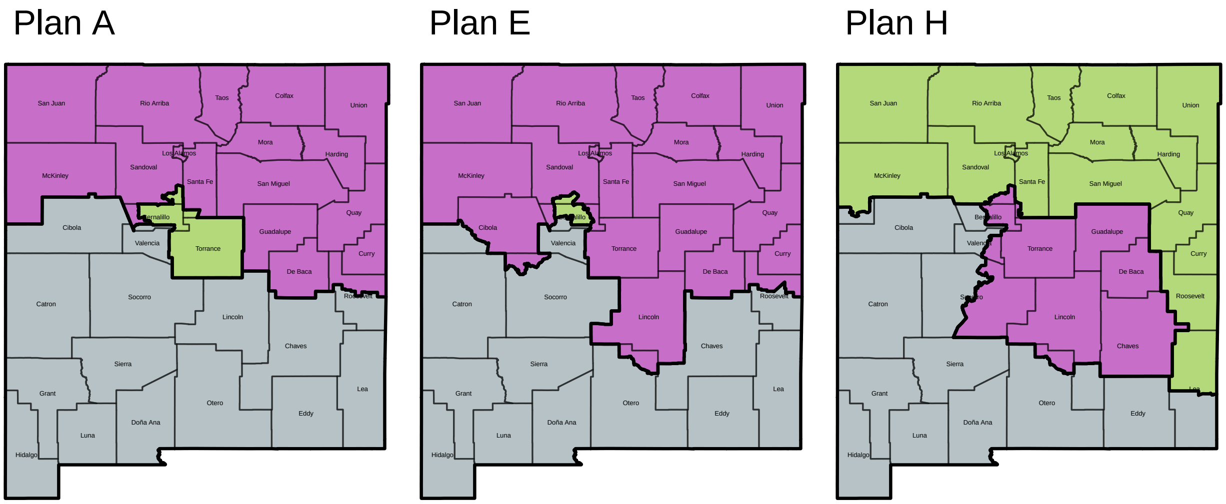

Figure A.2: Three Computer-Generated Ensemble Maps for Congressional Districts

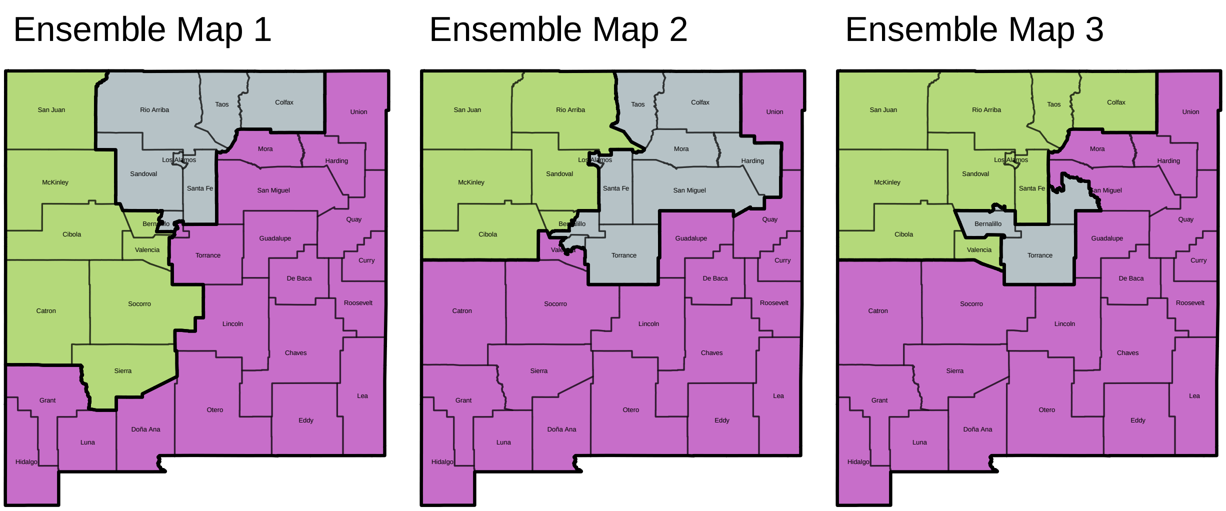

Figure A.3: Concept Maps for Public Ed. Commission Districts

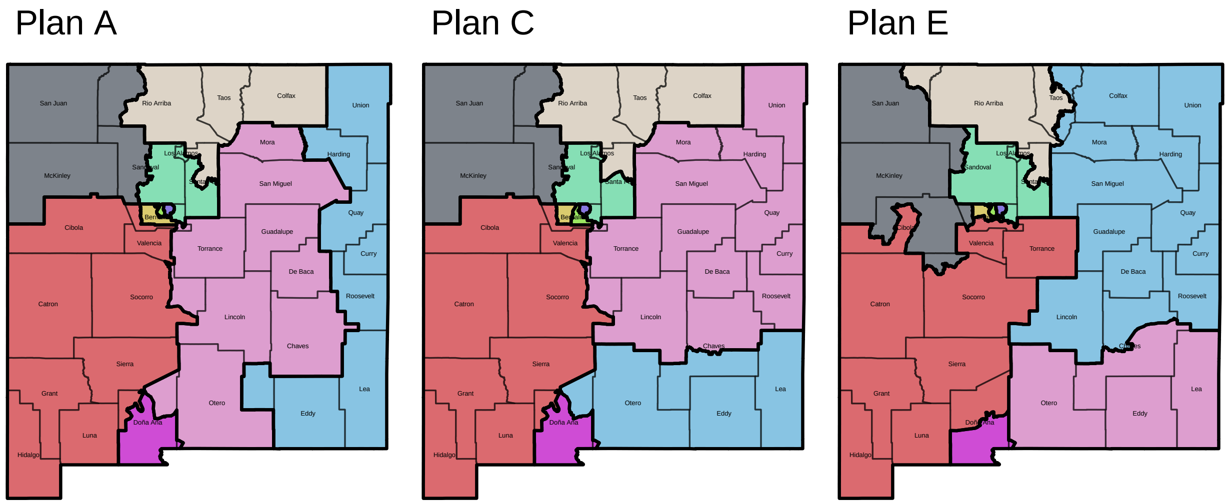

Figure A.4: Three Computer-Generated Ensemble Maps for Public Ed. Commission Districts

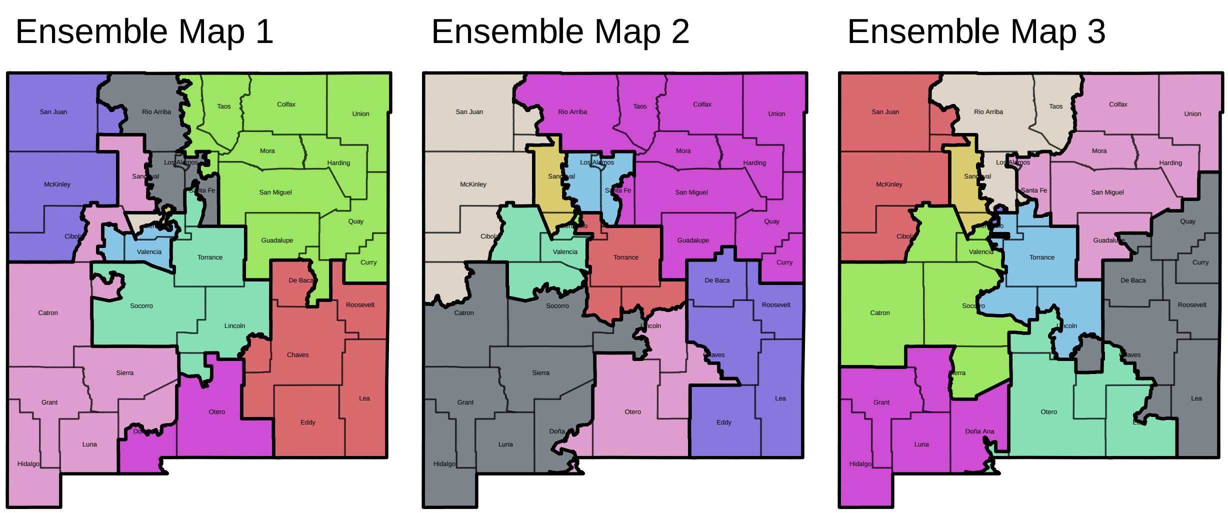

Figure A.5: Concept Maps for State Senate

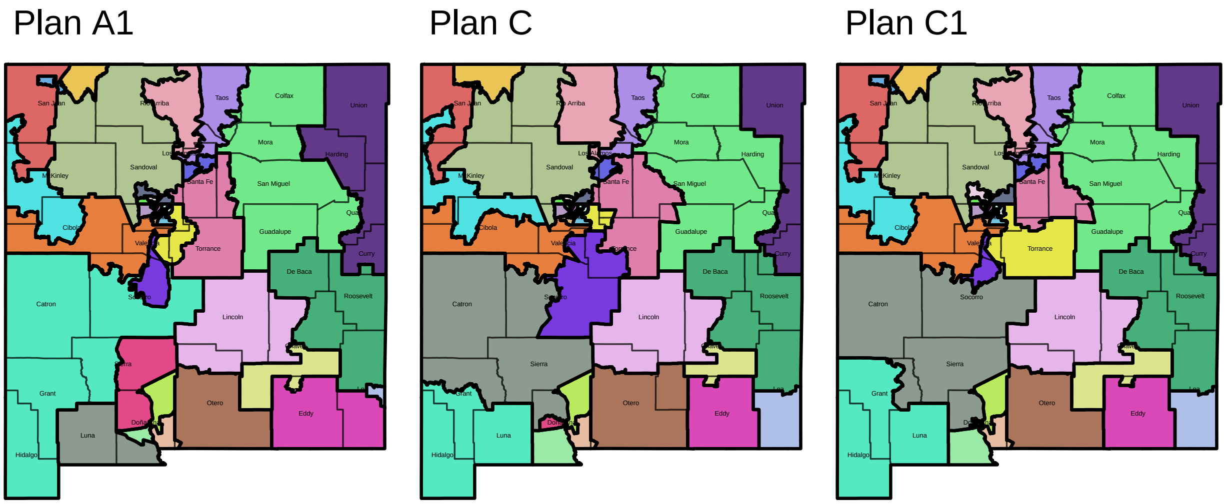

Figure A.6: Three Computer-Generated Ensemble Maps for State Senate

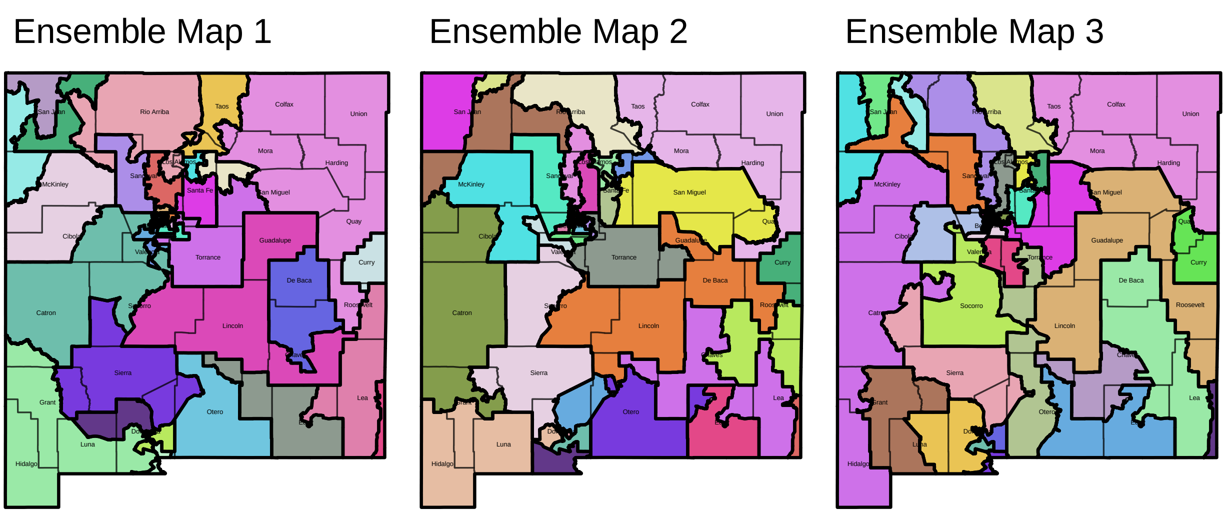

Figure A.7: Concept Maps for State House

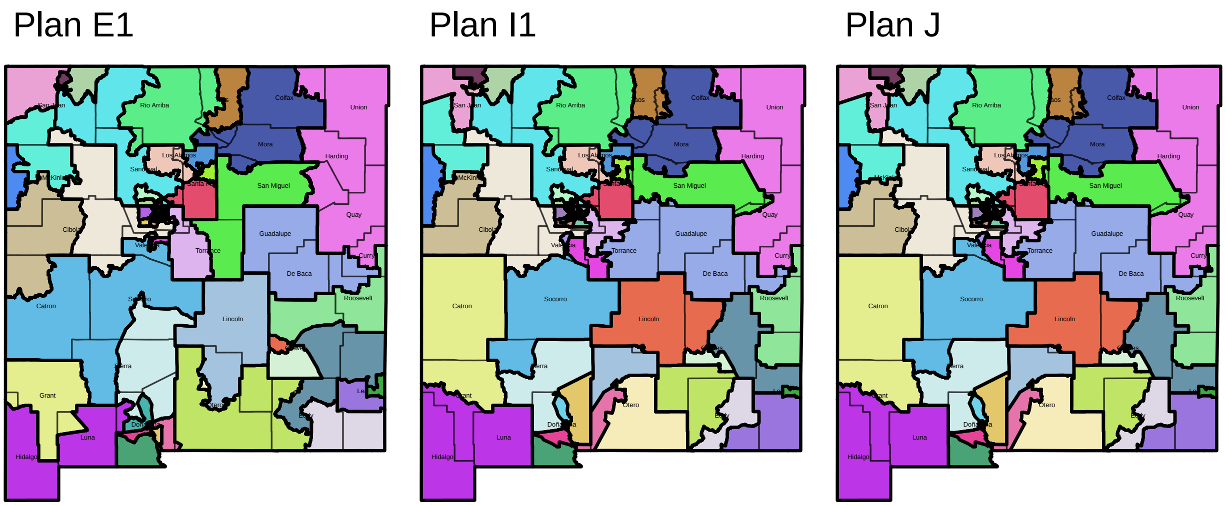

Figure A.8: Three Computer-Generated Ensemble Maps for State House