# Uneven Ground: Spatial Patterns in California School District Funding


## Abstract

School funding disparities are often linked to demographic and socioeconomic differences, but less is known about whether funding varies systematically across space beyond these predictors. Using district-level per-pupil expenditure data from California, we examine whether school funding exhibits significant geographic clustering and whether such clustering persists after accounting for student demographics. We apply Global and Local Moran's I statistics to assess spatial autocorrelation and identify precise geographical clusters across the state, finding modest but statistically significant spatial dependence in funding levels. Although demographic and need-based variables account for some variation in per-pupil expenditure, substantial spatial clustering remains unexplained. These results suggest that funding patterns reflect geographically structured variation beyond observable demographic traits, highlighting spatial context as an important dimension of California's educational landscape.

## Introduction

The United States public school system claims a “commitment to providing every child in every community access to a highly effective education” (The Public Education Promise, 2023). However, historical inequalities have created barriers to equal and accessible education for students of diverse backgrounds, leading to systematic inequalities within education that persist despite safeguards. US Legislation such as the No Child Left Behind Act (2001), later renamed the Every Student Succeeds Act (ESSA), has historically required schools to meet national education accountability standards (Noltemeyer, 2012). Nevertheless, expenditures across U.S. public school districts remain unequal, and the relationship between spending and educational outcome has been explored across various studies. One such investigation finds that district test scores are related to expenditures of schools and districts in Alabama (Ferguson & Ladd, 1996). We seek to expand on this research by exploring the spatial distribution of per-pupil expenditure within California school districts and consider how these patterns relate to education’s promise as “the great equalizer.”

## Methods

This project describes the spatial variation of per-pupil expenditure (PPE) across California’s educational districts. We utilize 2023-2024 data from the California Department of Education (California Department of Education, 2018) and the California State Geoportal (California State Geoportal, 2020) to examine whether high-PPE and low-PPE districts form significant spatial clusters, whether these clusters differ in their demographic composition and if they persist after demographic adjustment. Of the 938 districts in the statewide boundary file, 891 had complete PPE data and are included in our analysis. All demographic and expenditure data was self-reported by each school district from the 2023-2024 fiscal year. PPE values above $100,000 were deemed outliers due to misreporting and excluded.

To examine whether PPE is at all clustered throughout California, we conducted a Global Moran’s I test. Global Moran’s I measures spatial autocorrelation by examining how similar feature values are distributed across a geographic area (ESRI, n.d.). This statistical method compares each district's PPE to the statewide mean, determining whether neighboring districts’ PPEs are more alike than would be expected under random chance. It calculates a test statistic by summing the cross products of deviations from the mean across all pairs of adjacent districts and standardizing by the overall variance and total number of “neighbors.” We use rook contiguity spatial weights to define “neighbors” as districts which share a common edge (CRAN, 2024). The Global Moran’s I test then assesses statistical significance through a permutation test: PPE values are shuffled across districts to generate a null distribution of Moran’s I, and the observed statistic is compared to this distribution to generate a p-value.

To identify the localized clusters driving this spatial dependence, we conducted a Local Moran’s I test. Unlike Global Moran’s I which provides a summary measure of spatial autocorrelation, Local Moran’s I locates the specific districts that form statistically significant PPE clusters. It uses the same standardization and spatial weights framework as the global test, multiplying each district’s deviation from the statewide mean by the weighted average deviation of its neighbors to generate 891 statistics. The p-value for each district’s Moran’s I is similarly determined through a permutation test (ESRI, n.d.). Utilizing results from this local Moran’s I, we classified districts with $p < 0.05$ and a PPE above the statewide median as “High PPE”, and districts with $p < 0.05$ and a PPE below the statewide median as “Low PPE.” The districts with $p > 0.05$ were labelled “Not Significant.”

After understanding how districts were clustered based on PPE, we explored these results further by accounting for the percentage of Black and Hispanic students in each educational district, fitting a highly simplified linear model to isolate the portion of PPE variation associated with these two demographic variables. Then we conducted a Local Moran's I test on the residuals of this simplified linear model to again understand where High-PPE and Low-PPE clusters were but this time adjusted for the demographics of that district.

We extended our analysis by incorporating additional Local Control Funding Formula (LCFF) high-need indicators: the percentages of socioeconomically disadvantaged, English-Learner, homeless, and foster youth students in each district (Learning Policy Institute, 2025). Because California's supplemental and concentration grants are allocated based on these categories, we fit a simple linear model regressing PPE on all four need-based measures. Again we utilized a Local Moran's I test on the residuals of this linear model. Together, these steps allow us to assess whether spatial clustering in PPE persists after accounting for key demographic and need-based funding factors.

Results

Our Global Moran's I result for PPE is weakly positive and statistically significant ($I = 0.065$, $p < 0.001$), indicating that funding levels exhibit a modest but non-random spatial dependence across the state of California. The Local Moran's I test showed the existence of 33 High PPE clusters, 25 low PPE clusters, and 824 non-significant districts. Together, these results convey that California's school funding landscape contains geographically concentrated, non-random pockets of over and under investment.

Our Local Moran's I test on the residuals of our first linear model that accounted for certain demographic variables – specifically the percentage of Black and Hispanic students within a district – revealed that 22 High-PPE clusters and 32 Low-PPE clusters remain after demographic adjustment (Figure 1). Compared to the 33 High-PPE and 25 Low-PPE clusters which existed before, this represents a reduction of 11 high-spending clusters and an increase of 7 low-spending clusters. The reduction in High-PPE clusters reflects a pattern in our dataset: districts with lower percentages of Black and Hispanic students tended to have higher PPE, and even a minimal model captured this broad correlation. As a result, some districts that initially appeared to be unusually high-spending no longer stood out once the portion of PPE that co-varies with racial composition was removed. In contrast, the increase in Low-PPE clusters identified districts whose spending falls below what would be expected given their demographic makeup. This illuminates pockets of underinvestment that remained after adjusting for these two variables and may be explained by other predictors that were previously masked by the strong race effect. These results are descriptive rather than causal, and the simplicity of the model limits the range of factors that can be adjusted for. However, the residual clustering provides evidence that spatially structured influences beyond racial composition contribute to variation in school funding.

Our second linear model, which regressed PPE on high-need indicators only explained a modest share of the variation in PPE. A Local Moran's I test on the high-needs residuals revealed that 31 high-PPE clusters and 30 low-PPE clusters remain after adjusting for these need-based variables. These clusters represent districts whose PPE is higher or lower than what is typical for districts with similar need profiles (Figure 2). As with our prior models, this analysis is descriptive rather than causal, and our simplified linear model cannot fully capture the complexity of educational finance. Nonetheless, we found a persistence of spatial clustering in the residuals after controlling for need-based variables, showing that geographically structured factors beyond student need continue to influence where funding is higher or lower than expected.

Overall, our results show that while PPE is clustered across California, observable demographic traits within districts cannot explain away these geographic patterns. We aim to visualize these findings through our Shiny application (Figures 3-5). The app displays choropleth maps highlighting the geographical distributions of PPE, socioeconomic disadvantage, predominant race, and locale type across California school districts, and summarizes our spatial analysis, including our further explorations of racial, socioeconomic, and locale predictor variables.

## Conclusion

The fact that present-day race and socioeconomic composition do not explain all observed funding clusters should not be interpreted as evidence that disparities have vanished. Our analysis instead suggests that spatial variation in PPE is shaped by multiple influences. Some clusters reflect contemporary demographic patterns, while others persist even after accounting for these factors, indicating that additional structural processes may contribute to geographic differences in funding. Our descriptive, exploratory approach does not allow us to identify their specific origins.

Despite these limitations, the persistence of low-PPE clusters is meaningful. It suggests that some groups of students may face resource environments that differ systematically from those of demographically similar districts elsewhere in the state. Although these clusters represent a minority of districts, they encompass thousands of students whose educational opportunities may be shaped by patterns outside of their control. This underscores the importance of examining school funding not only through contemporary measures of need but also through a broader lens that considers how structural and historical factors may influence the geography of educational investment.

Our study is exploratory rather than causal, but it clearly establishes that geographically patterned differences in PPE exist and that many of these differences remain after demographic adjustment. These findings point to the value of further research into the institutional, fiscal, and historical mechanisms that continue to shape school funding across California.

## Future Work

A key limitation of our exploratory analysis is its reliance on district-level PPE data, which are too coarse to capture the full extent of resource variation across California's schools. Many districts contain substantial internal disparities: individual schools may differ dramatically in demographics, local revenue support, or access to need-based programs. District averages smooth over these differences, potentially obscuring pockets of underfunding that exist within otherwise well-resourced districts.

Our project's constraints point toward several valuable directions for future research. One of these is to investigate the institutional factors that may drive persistent low-PPE clusters, including variation in local tax bases, district size, governance structures, and administrative capacity. Another promising direction is to examine historical determinants of district boundaries and funding trajectories, particularly in regions where low-PPE residual clusters remain significant after demographic adjustment. Incorporating information on past boundary changes, redevelopment patterns, or historic segregation and redlining could help clarify why geographically concentrated underfunding continues in some areas. Future work could also leverage improved school-level fiscal data to evaluate how resources vary not only across districts but within them, offering a more precise understanding of how spatial inequities shape students' educational opportunities.

Appendix

**Figure 1. Race Residual PPE Spatial Clusters**

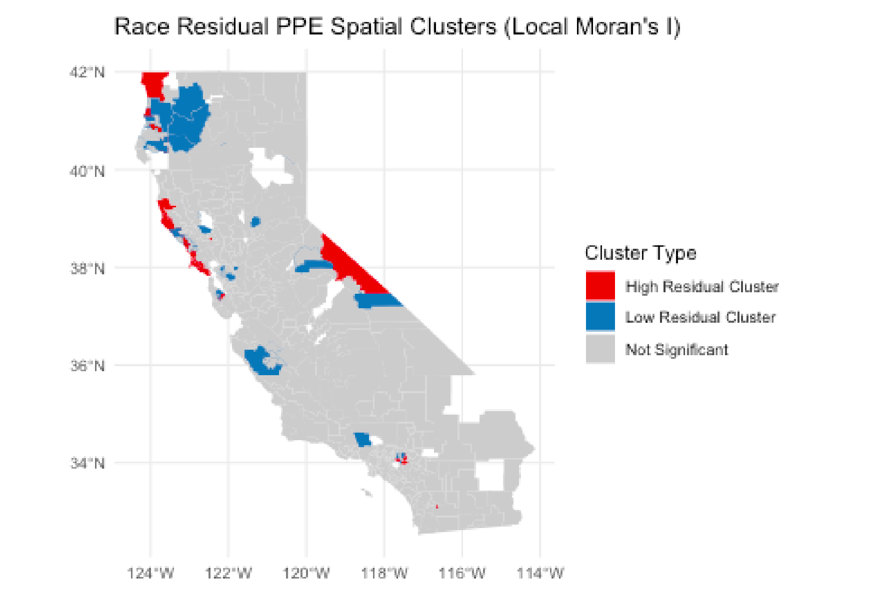
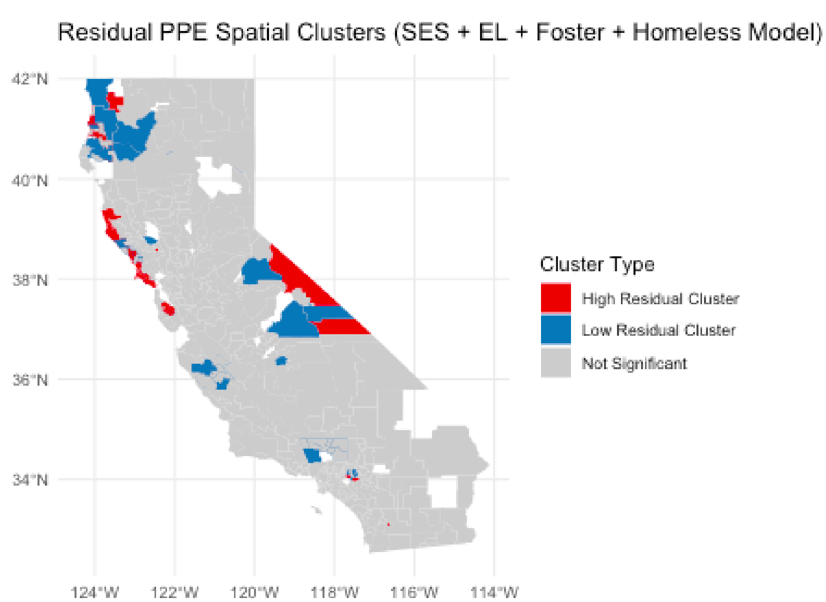


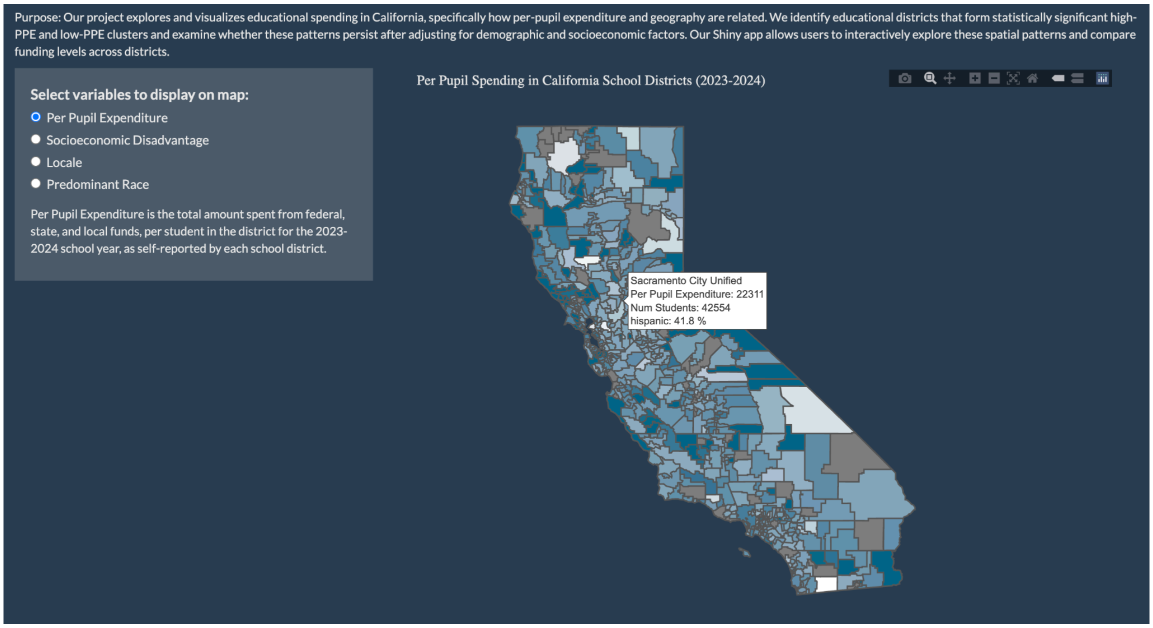

**Figure 2. LCFF Residual PPE Spatial Clusters**




**Shiny App Overview**

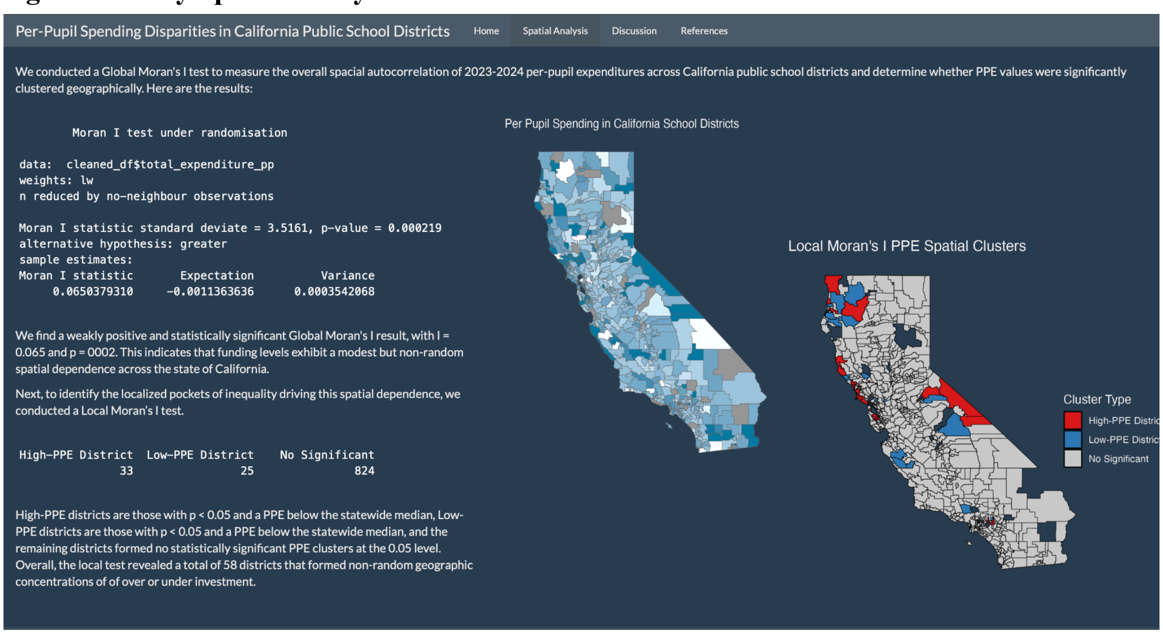
The visualization tab uses Plotly with ggplot2 to generate interactive maps, allowing users to hover over districts to view details such as district name, per-pupil expenditure, enrollment, and other variables of interest. Users can toggle between Per Pupil Expenditure, Socioeconomic Disadvantage, Locale, and Predominant Race variables to display on our map visualizations.

**Figure 3. Shiny Home Tab**




The second tab discusses the findings of the spatial analysis. These results are described in the results section. It also includes plots and visualizations to present our conclusions.

**Figure 4. Shiny Spatial Analysis Tab Main**




Within the spatial analysis tab, three subtabs for racial composition, socioeconomic disadvantage, and locale type explain and visually present our further explorations of the race, LCFF, and locale predictors.

## Figure 5. Shiny Spatial Analysis: Racial Composition Subtab


## Figure 6. Shiny Spatial Analysis: Socioeconomic Disadvantage Subtab

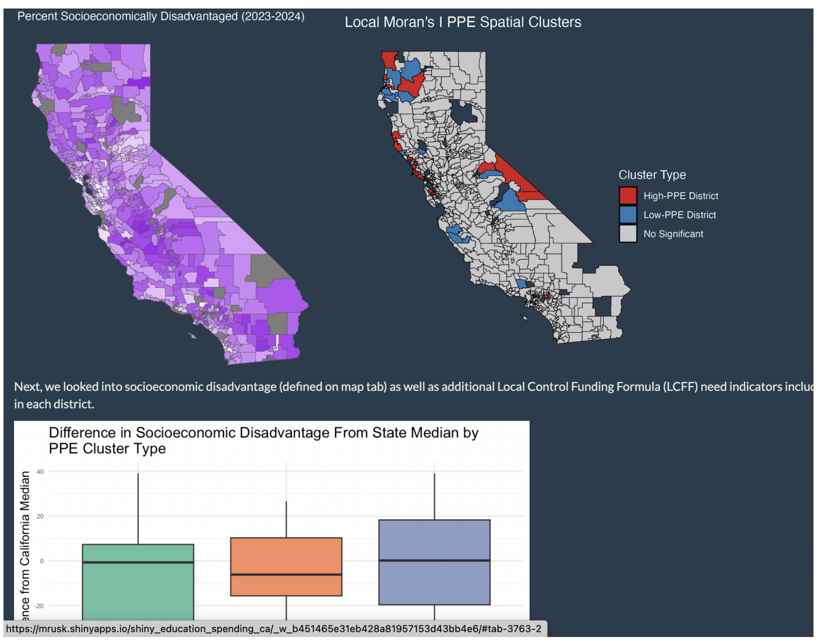


**Figure 7. Shiny Spatial Analysis: Locale Type Subtab (I)**

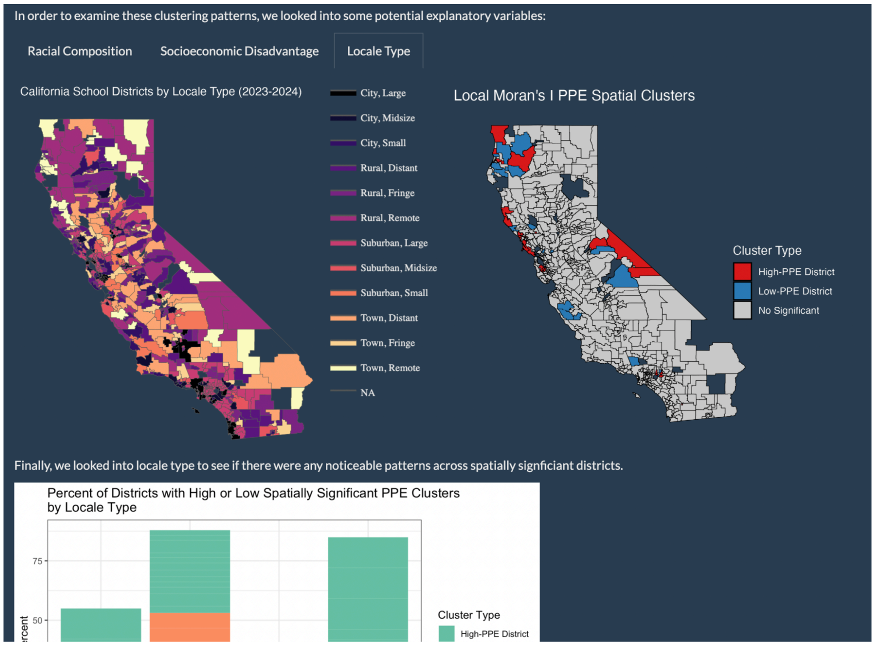
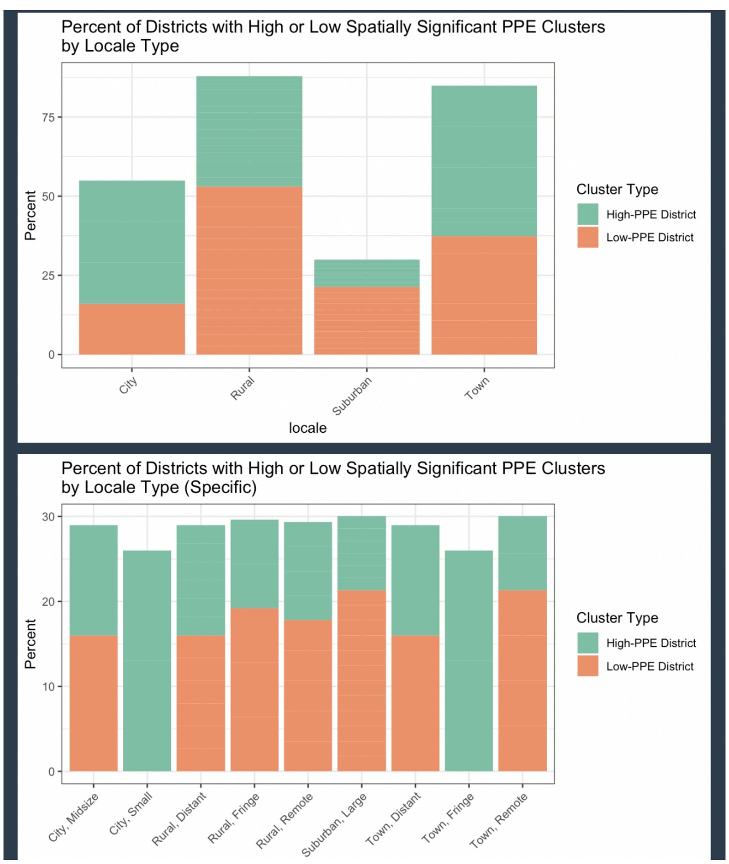



**Figure 8. Shiny Spatial Analysis: Locale Type Subtab (II)**



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