Environmental Justice Mapping Tools and Their Cognitive Impact on Policy Decisions

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I. Introduction

The Environmental Protection Agency (EPA) defines environmental justice (EJ) as "the fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies" (EPA 2023b). Environmental justice became a central consideration of U.S. environmental legislation in 1994 with Executive Order 12898, which instructed federal agencies to collect environmental justice data and consider EJ in policy development. However, specific guidelines for the operationalization and enforcement of environmental justice in policy remain underdeveloped. Consequently, a significant policy consideration is determining how environmental justice can become a central priority in environmental legislation, especially when it is compared against other competing policy goals.

Under the federal partial preemption framework, states can develop individual environmental policies as long as their legislation aligns with the regulation standards set by the EPA. As a function of this framework, states like California and Maryland have developed EJ mapping technology to determine environmentally vulnerable populations by calculating cumulative impacts as measured by pollution burden and population characteristics. According to current scholarship, EJ mapping tools present the best existing policy framework for operationalizing environmental justice in policy (Lee 2020, Zrzavy et al. 2021). However, the body of environmental justice literature lacks an empirical analysis of this argument. I address this gap by evaluating whether interaction with EJ mapping tools produces a discernible impact on individuals' policy perspectives. I specifically examine how the visualization of information employed by EJ mapping tools impacts individuals' willingness to support policies that prioritize environmental justice over other environmental goals.

Federal and State Environmental Policy Background:

The term "environmental policy" entered U.S. federal and state policy landscapes in 1960 (Andrews 2018). The surfacing demand for environmental federal and state legislation at this time emerged due to the societal development of an "environmental consciousness." Major national events such as the consumption of Rachel Carson's *Silent Spring*, the fire in Ohio's Cuyahoga River, and substantial oil spills along the California coast inspired American citizens to reconsider their relationship with the environment (EPA 2023d). As U.S. citizens began to conceptualize the correlations between the environment and their health, public demand for environmental regulation materialized. In response to the national pressure for government action, President Richard Nixon created the National Environmental Policy Act (NEPA) in 1970, the first comprehensive federal framework for environmental policy (EPA 2023c). Although President Theodore Roosevelt passed multiple New Deal environmental policies—such as natural resources management and the national parks program—in the 1930s, NEPA created the first federal interdisciplinary and integrative approach to addressing environmental consequences at the national scale (Andrews 2018).

The National Environmental Policy Act orders all federal agencies to "assess the environmental effects of their proposed actions prior to making decisions" (EPA 2023c). NEPA specifically covers permitting decisions, federal land management, and the construction of publicly-owned facilities (i.e. highways) (EPA 2023c). NEPA constituted the first step toward reorganizing the federal agency structure to address environmental policy. This reorganization included the creation of the Environmental Protection Agency (EPA), whose initial responsibilities included monitoring environmental factors, creating environmental enforcement standards, and conducting environmental research (EPA 2023d). The establishment of both the

EPA and NEPA produced a legislative structure of environmental federalism, in which states are required to adjust their environmental policy according to federal thresholds and regulations (Andrews 2018). Additional federal legislation passed in the 1970s–such as the Clean Air Act, the Endangered Species Act, and the Resource Conservation and Recovery Act–contributed to a federal dominance in the environmental policy sphere (Koninsky & Woods 2022). Although the EPA sets regulatory standards for policy issues like air pollution, water contaminants, etc., it expects states to develop their own policy frameworks for meeting these standards (Andrews 2018). This relationship is defined as "partial preemption": states can construct their own policy if it aligns with "national goals" and "federal guidelines" (Koninsky & Woods 2022). Under the partial preemption framework, the implementation of environmental policy varies across states; some states struggle to meet mandated federal minimums while others pursue aggressive policies that significantly exceed the federal framework (Koninsky & Woods 2022).

California as a State Leader in Environmental Policy:

California is specifically identified as an "environmentalist" state, pursuing stringent legislation that transcends EPA requirements. For example, in 2002, California became the first state to pass legislation requiring "stricter vehicle standards" as a strategy for reducing greenhouse gas (GHG) emissions (Bedsworth 2013). In 2006, California passed the "California Global Warming Solutions Act" (AB 32), which required the state to reduce state GHG emissions to "1990 levels by 2020" (CARB 2023). AB 32 was the first piece of legislation that established a long-term mechanism for addressing climate change, making California a leader in climate change policy development (CARB 2023). Furthermore, California is unique in its local governments' administrative capacity to engage in environmental policy development and enforcement (Bedsworth 2013). California's legislative landmarks in environmental policy have inspired other states to follow suit. For example, thirteen states currently base their GHG emissions standards on California's regulatory framework (Koninsky & Woods 2022).

With a precedent for leadership in environmental policy development, California's innovative solutions to the escalating effects of climate change are often viewed under a national magnifying glass. As a result, California's environmental policy is impactful on a national scale. California policy development in areas such as environmental justice can affect state and federal policy frameworks, establishing them as an important unit of analysis.

Environmental Justice:

Environmental justice concerns the fair treatment of all individuals in the "development, implementation, and enforcement of environmental laws, regulations, and policies," (EPA 2023b). The federal government designated environmental justice as an important component of environmental legislation in 1994, when Executive Order 12898 was passed. EO 12898 instructed federal agencies to collect data on disproportionate environmental risks, develop policy frameworks for implementing environmental justice, and promote non-discriminatory policies in federal environmental legislation (Exec. Order No. 12898, 1994). This federal movement to address and correct environmental injustice was motivated by increasing evidence that low-income, minority populations in the United States disproportionately experience adverse environmental effects.

The concept of environmental racism entered public discourse in 1982 with the environmentally unjust case of Warren County. At the time, North Carolina intended to dump "120 million pounds of soil contaminated with polychlorinated biphenyls (PCBs)" into Warren

County, which contained the highest proportion of African Americans in the state (Mohai et al. 2009). Led by Benjamin Chavis, civil rights activists mobilized against the North Carolina state government. In their fight for justice, Chavis created the term “environmental racism,” which he defined as “racial discrimination in environmental policymaking, the enforcement of regulations and laws, the deliberate targeting of communities of color for toxic waste facilities, the official sanctioning of the life-threatening presence of poisons and pollutants in our communities, and the history of excluding people of color from leadership of the ecology movements” (Mohai et al. 2009). Environmental justice extends this definition to include ethnicity and class as populations disproportionately vulnerable to environmental burdens.

Robert Bullard, who is often coined as the “Father of Environmental Justice,” played a significant role in presenting the tangible intersection of race and class with environmental risk. In his book, *Dumping in Dixie,* Robert Bullard asserts, “In many instances, exclusionary zoning, discriminatory housing practices by rental agents, brokers, and lending institutions, and disparate facility sitting decisions have contributed to and maintained racially segregated residential areas of unequal quality” (8). Numerous studies validate the claim that high environmental burden intersects with race, ethnicity, and socioeconomic status. The U.S. General Accounting Office (GAO) initiated this research with its 1983 study on the correlation between hazardous waste facility locations and the racial and economic composition of surrounding communities (GAO 1983). This study found that three of the four evaluated waste facilities were located near communities with a majority African American population and a majority of inhabitants living below the established poverty level (GAO 1983). Later studies corroborate that race and class are correlated with both the location of hazardous waste facilities and exposure to air pollution (Mohai et al. 2009). For example, a 2008 study found that, on average, Black households making fifty to sixty thousand dollars annually live in more polluted areas than white households making under ten thousand (Downey & Hawkins, 2008). Furthermore, the body of environmental justice research finds that “vulnerable populations,” defined as predominantly minority and low-income, are exposed to health disparities generated by compounding social and environmental stressors (Morello-Frosh et al. 2011). These findings have produced federal and state legislation that address and mitigate environmental injustice.

EO 12898 is the main federal framework for implementing environmental justice in national policy. Although this order mandates that federal agencies assess environmental justice through data collection and integrate EJ into policy, it does not provide a distinct, replicable framework for agencies to follow. State governments have attempted to extend this framework in their own environmental justice policy initiatives. For example, California has produced extensive legislation on environmental justice including SB 115 (codifies the definition of environmental justice), SB 89 (created a public advisory committee for EJ), SB 32 (integrated risk assessment into regional and local land use planning), and SB 535 (mandates that 25 percent of California’s cap-and-trade revenues are distributed to disadvantaged communities) (Salazar and Chiu 2003, Lee 2020). To determine the vulnerable communities that should be targeted for these EJ policies, California, other states (i.e. Maryland, Michigan, and Illinois), and the federal government have turned to Environmental Justice mapping technology as a solution (Lee 2020).

Environmental Justice Mapping Tools:

Environmental justice mapping tools evaluate the cumulative impacts of environmental burdens through a calculated ranking system that identifies specific geographical areas to be disproportionately burdened compared to other evaluated locations (Lee 2020). The first EJ mapping tool created was the CalEnviroScreen 1.0, an interactive visual tool that identifies California's most environmentally burdened communities via the calculation of pollution burden and population characteristics (Delson 2013, Lee 2020). The CalEnviroScreen was created to aid decision-makers in their distribution of resources and to integrate community-based participatory research in the identification of environmentally burdened communities (Delson 2013, Murphy et al. 2018). A federal EJ mapping tool, the EJScreen, was released in 2016, followed by an influx of state EJ mapping tools released in the past 5 years (i.e. CO EJScreen, NC Community Mapping Screen, MD EJScreen, MI EjScreen, etc.) (EPA 2023a). Although these tools each maintain individual metrics for measuring pollution/environmental burden and population characteristics, they share the same central goal: to discern populations disproportionately affected by environmental hazards.

Although research claims that environmental justice mapping tools are the best investment in operationalizing environmental justice for policy, tangible evidence for this claim is absent (Coburn 2017, Driver et al. 2019, Lee 2020, Zrzavy et al. 2021). A theoretical explanation for how EJ mapping tools impact individuals' perceptions of environmental justice is also lacking. I address these gaps in my subsequent exploration of the relationship between the visual dissemination of environmental justice information and opinions on environmental policy. It is imperative to determine whether these tools have a discernible impact on perspective and, consequently, policy as a greater proportion of states allocate money and time to the development of EJ mapping technology.

This paper aims to answer the following question: Does the visualization of environmental injustice impact individuals' willingness to support policies that prioritize environmental justice? I theorize that EJ mapping tools visualize the cumulative impacts of climate change through a structural justice approach, operationalizing environmental justice and impacting individuals' perceptions of environmental justice relative to other priorities. Using a randomized control survey experiment, I evaluate the link between the visualization of environmental injustice, operationalized through interaction with the CalEnviroScreen, and policy perceptions. I analyze the results of the survey's findings and determine whether or not its outcomes support my proposed hypotheses. Finally, I discuss the limitations of this study and the conclusions that can be drawn from my findings.

II. Literature Review

This study is situated in two bodies of literature. The first is a subset of environmental justice policy research: cumulative impacts (CI) theory and its efficacy in constructing analytical environmental justice frameworks. Research on cumulative impacts points to environmental justice mapping tools as a compelling method for environmental justice risk assessment. I explore the differences in EJ mapping tools, techniques, and outcomes–an additional subset of the environmental justice scholarly debate. The second main body of literature investigates the cognitive impacts of visualization on attitudes and decision-making.

Cumulative Impacts Theory:

Cumulative impacts (CI) theory emerged in response to federal and state inability to comprehensively enforce environmental justice through existing approaches to environmental policy. The EPA defines cumulative impacts as "... the totality of exposures to combinations of chemical and non-chemical stressors and their effects on health, well-being, and quality of life outcomes" (2022). Although the term was initially referenced in the 1970 California

Environmental Quality Act, robust development of cumulative risk policy strategies did not occur until 2004 (EPA 2022). The existing literature argues that a cumulative impacts policy framework employs a "structural justice" evaluation of environmental burden in contrast to prior linear causal evaluations of environmental risk (Corburn 2017, Huang and London 2016).

The importance of cumulative risks as a function of environmental justice is validated throughout the literature. Solomon et al. (2016) argue that cumulative impacts analysis is driven by significant discrepancies in exposures to environmental hazards across populations, "biological" and "physiological" modifiers of environmental effects, and "extrinsic social vulnerability factors" that affect the extent of environmental harm. Barzyk et al. (2015) substantiate this claim, arguing that cumulative risk assessment–which integrates socioeconomic and environmental factors–has a higher efficacy rate for identifying the compounding effects of environmental vulnerability. The identification of the compounding relationship between social, physical, and environmental factors is crucial for the determination of allostatic load, which Solomon et al. (2016) define as "... the cumulative physiologic degradation that may result from chronic stress exposure and the accompanying long-term shift in homeostatic functions." EJ scholars agree that a CI analysis approach to environmental risk analysis provides the best appraisal of the pervasive disproportionate consequences of climate change (ie. higher allostatic load) that are reinforced by structural injustices (Corburn 2017, Payne-Sturges et al. 2021, Sadd et al. 2011). Although the literature consistently recognizes the importance of addressing cumulative impacts in effective environmental policy, there is disagreement over the best policy implementation framework.

One way that cumulative impacts theory is operationalized in federal and state policy is through cumulative risk assessments of environmental impacts. Cumulative risk assessments expand on conventional risk assessments by integrating "community-based participatory research," providing "population-based assessments," and considering non-chemical environmental stressors into its analysis of environmental risk (Barzyk et al. 2015). This approach represents a departure from the calibration of environmental risk derived from the analysis of an individual chemical factor or environmental hazard (Solomon et al. 2016). Although the EPA and its satellite research programs (ie. the Air, Climate, and Energy program, the Health and Environmental Risk Assessment program, the Sustainable and Healthy Communities program, etc.) have made commitments to integrating cumulative risk assessments into their respective research methodologies starting in 2016, these efforts remain significantly undeveloped (EPA 2022). The strongest existing federal operative for cumulative risk assessment is Executive Order 12898, which, as previously mentioned, instructed federal agencies to "consider" environmental justice in all proposed legislation that impacts "the quality of the human environment" (CEC 1997). This vague language has demonstrated the need for the redefinition of environmental justice and its associated adequate measurement methods over decades of federal environmental legislation.

Although amendments to this bill, such as the Fiscal Responsibility Act of 2023 and the introduction of "Environmental Impact Statements" have occurred, federal legislation that specifically identifies proper cumulative impact assessment steps and requires federal agencies to carry out these procedures does not exist (NEPA & EJ IWG 2016, NEPA 2023). To address this significant policy barrier, environmental justice scholars advocate for the development of regional and state initiatives that construct cumulative impact assessments (Murphy et al. 2018, Rickenbacker 2019, Solomon et al. 2016).

Solomon et al. (2016) outline six different types of cumulative impact assessment methods: biomonitoring, health risk assessment, ecological risk assessment, health impact assessment, burden of disease, and the mapping of cumulative impacts. Although each of these methodologies integrates multivariate analysis of environmental health effects, Solomon et al. (2016) argue that the mapping of cumulative impacts can unite the aforementioned separate forms of CI analysis. Payne-Sturges et al. (2021) and Scammell et al. (2014) both validate this claim, asserting that EJ mapping tools equip local, regional, and state governments with an effective mechanism for creating environmental policy solutions that target environmental justice based on CI analysis. However, the effectiveness of existing EJ mapping tools and the methods by which these tools can be integrated into future policy solutions is debated.

Environmental Justice Mapping Tools:

Prominent environmental justice scholar Charles Lee identifies EJ mapping tools as "a game changer in the making" (2020). There is consensus among the existing literature that cumulative impact mapping represents an instrumental shift toward restructuring the consideration of environmental justice in environmental policy (Corburn 2017, Lee 2020, Zrzavy et al. 2022). However, the evaluation of existing tools and the most effective mapping methodologies remain disputed within the literature.

There are multiple state and federal EJ mapping tools currently in use. The most notable and robust tools debated by scholars include the EJScreen (federal), the CalEnviroScreen (state), and the MD EJScreen (state) (Driver et al. 2019, Kuruppuarachchi et al. 2017, Lee 2020). Each of these tools operates under a baseline methodology that calculates cumulative risk for a specific population by multiplying environmental factors by demographic factors (Driver et al. 2019, Kuruppuarachchi et al. 2017). Although each system integrates environmental and social indicators of community health, they differ in the specific data subsets they utilize for these calculations (Driver et al. 2019).

The CalEnviroScreen and MD EJScreen both calculate risk by assigning percentile scores to an individual census tract's "population burden" and "pollution burden." These values are then combined to construct an overall environmental justice score, also measured by percentile rankings (Driver et al. 2019). In this case, population burden is measured by the identification of "sensitive populations" and "socioeconomic factors," and pollution burden is measured by pollution burden exposures and effects (Driver et al. 2019). Examples of the individual metrics used to calculate these categories include "diesel particulate emission" (pollution exposure), "impaired water bodies" (pollution effect), "low birth weight infants" (sensitive populations), and "poverty" (socioeconomic factors) (Kuruppuarachchi et al. 2017).

In contrast, the federal EJScreen tool measures environmental justice as the integrated calculation of environmental and demographic indicators (Kuruppuarachchi et al. 2017). Individual environmental indicators include "diesel particulate matter," "ozone," and "wastewater discharge" while demographic indicators are measured by low-income and minority population percentages (EPA 2023). Although the EJScreen, CalEnviroScreen, and MD EJScreen share ten environmental indicators, the CalEnviroScreen and MD EJScreen ultimately provide greater distinction in these metrics due to their smaller analytical scope (Driver et al. 2019). An additional important difference is the federal EJScreen's use of minority population characteristics to calculate socioeconomic vulnerability (Kuruppuarachchi et al. 2017). Under the federal EJScreen methodology, a demographic index is calculated by the combination of a census population's minority and socioeconomic percentages (Kuruppuarachchi et al. 2017). Unlike the MDScreen and CalEnviroScreen, the EJScreen uses race as a subset of social vulnerability.

The inclusion or exclusion of race in EJ mapping methodologies is widely debated. One school of thought argues that excluding race from environmental justice percentile calculations ensures that race is not a motivating factor for policy decisions that utilize mapping data (Lee 2020). Proponents of this argument assert that the exclusion of race allows EJ mapping tools to be more widely applicable across policy issues (Lee 2021, Liévanos 2018). However, the opposing argument attests that systematic racism is entrenched in environmental injustice, making race a critical measurement factor for the cumulative impacts of environmental burden (Liévanos 2018). The CalEnviroScreen 3.0 and 4.0, the most recent iterations of California technology, appeal to this argument by constructing a separate dataset of the recorded race and ethnicity of measured populations (Lee 2021). Although the tool still excludes race data from its calculations, the development of this separate dataset allows users to overlay race data with environmental justice percentile calculations. Despite disputes over methodological approaches to EJ mapping, the literature supports EJ mapping tools as the best operationalization of cumulative impacts theory.

Existing literature asserts that EJ mapping tools are the best analytical framework for addressing the cumulative impacts of climate change–including environmental justice (Lee 2021, Murphy et al. 2018). Mapping tools like the CalEnviroScreen and EJScreen facilitate the comparison of cumulative impacts across communities, progressing past traditional risk assessments rooted in the theoretical modeling of "well-characterized chemicals," (Murphy et al. 2018). This shift in structure visualizes environmentally burdened populations, which theoretically allows policymakers and stakeholders to make informed decisions about legislation that supports community health. Visualization is a crucial component of this technology because it identifies specific locations for environmental investments (ie. sustainable economic development, specific site clean-ups, etc.) (Murphy et al. 2018). Proponents of EJ mapping technology assert that these tools allow for concrete comparisons between low and high-burdened communities, affecting the allocation of resources from government agencies that utilize the technology (Lee 2021, Murphy et al. 2018). However, proof of a theoretical link between the use of EJ mapping tools and policy outcomes does not exist. Using a cognitive science framework, I will evaluate whether or not interaction with mapping tools significantly alters perceptions of environmental justice and consequently, policy decisions.

Cognitive Effects of Visualization:

The body of cognitive science research finds compelling evidence that the visualization of information has a direct impact on cognition (Eberhard 2021). Cognitive science scholars define visualization as "a visual representation of information or concepts designed to effectively communicate the content or message" (Eberhard 2021). Research finds that the visualization of information can positively impact decision-making efficiency if the visualization method and cognitive decision-making component are reasonably associated (Padilla et al. 2018, Vincent et al. 2018). What constitutes a reasonable association? Padilla et al. (2018) assert that "cognitive fit," or the matching of visualization to task, is strong when there are limited discrepancies between the visualized information and the information required for recall in a decision component. When visualization type and decision tasks are mismatched, the brain resorts to using the "working memory" to fill in the gaps, counteracting the benefits of introducing information through visual cues (Padilla et al. 2018).

Cognitive science scholars have also observed a correlation between the visualization of information and attitude change (Eberhard 2020). The literature specifically suggests that visual presentations of information can have a greater impact on attitude change than textual presentations of information (King Jr. et al 2019). However, an important mitigating factor of this relationship is prior user knowledge of the subject being visually introduced (Eberhard 2021, Padilla et al. 2018). Prior user knowledge of the subject that is visually displayed affects cognitive processing by conditioning how individuals interact with visual information (Eberhard 2021). This primarily manifests in two ways: individuals with a prior knowledge of the visually displayed information sustain increased interaction time with the stimulus; individuals with limited prior knowledge exhibit over-confidence in their post-interaction decisions. (Eberhard 2021, Padilla et al. 2018, Vincent et al. 2018). Both results can act as confounding variables for the relationship between visualization of information and decision-making efficiency, making it critical to subset these populations in research designs that evaluate this association. I address this confound in my research by implementing pre-treatment survey questions that measure prior knowledge of environmental justice.

Limited research exists on the cognitive impacts of the visualization of environmental justice using GIS technology (ie. Environmental Justice Mapping). Vincent et al. (2018) conducted a study evaluating the effect of interactive maps on spatial decision-making. They specifically analyzed the effect of the use of hazardous waste maps by “professional” and “citizen” stakeholders on environmental justice decisions. Using an experiment that randomly assigned map and decision complexity, Vincent et al. (2018) found that simpler visualization interfaces yielded greater decision effectiveness and security while decision complexity was not statistically significant. Although this study identifies the complexity of mapping visualization as an important mitigating factor for decision-making effectiveness, its analysis is based on a single-indicator visualization rather than a multivariate environmental justice analysis. An evaluation of the cognitive relationship between a cumulative impacts visualization of environmental justice and policy decisions does not exist–an opening that I explore. To determine whether EJ mapping tools significantly shift policy perspectives on environmental justice, as environmental scholars claim, I evaluate the impact of interaction with an EJ mapping tool on trade-off policy decisions.

III. Theory and Argument

According to existing scholarship, the analysis of cumulative impacts through EJ mapping technology is the best existing mechanism for creating information about environmental justice that can be used for policy development (Lee 2020, Murphy et al. 2018). The literature points to the visualization of information as an explanatory mechanism for a correlation between interaction with EJ mapping technology and policy change. However, there is no existing theory for how individuals' interactions with EJ mapping tools impact discernible policy change for environmental justice. The central goal of my research paper is to answer the following question: Does the visualization of environmental injustice impact individuals' willingness to support policies that prioritize environmental justice? I posit two hypotheses:

H1: Exposure to a visualization of the cumulative impacts of climate change increases the level of significance participants assign to environmental justice in trade-off policy decisions.

H2: Exposure to a visualization of the cumulative impacts of climate change increases the level of significance participants—with a prior knowledge of environmental justice concepts—assign environmental justice in trade-off policy decisions.

I theorize that EJ mapping tools shift individual perceptions of environmental justice through the visualization of cumulative impacts, which consequently affects how individuals rank environmental justice against other policy priorities. According to my theory, a shift in individuals' perceptions of environmental justice is linked to the likelihood of individuals' decisions to support policy options that prioritize environmental justice. This logic is situated in both environmental justice and cognitive science research.

Environmental justice scholarship asserts that cumulative impacts analysis is the ideal framework for identifying environmentally burdened communities and communicating the comprehensive risks that these communities experience (Corburn 2017, Lee 2020, Zrzavy et al. 2019). As such, using a cumulative impacts framework to highlight environmental injustice should provide individuals with a comprehensive, nuanced understanding. The theorized positive relationship between an increased understanding of environmental injustice and an increased probability of supporting policies that prioritize environmental justice is based on the assumption that people who know about environmental justice are more likely to care about it. This posited correlation is strengthened by cognitive science research, which finds a positive association between the visualization of information and two individual factors: decision-making efficiency and attitude change.

If the visualization of information positively impacts decision-making efficiency and attitude change, as cognitive science scholars suggest, then the visualization of environmental injustice should affect policy decisions involving EJ. The visualization of cumulative impacts will increase individuals' ability to conceptualize environmental justice in decisions, affecting their ranking of EJ against other policy priorities. Additionally, the visualization of cumulative impacts will provide knowledge of the specific populations experiencing environmental burden, enabling shifting attitudes towards environmental justice as a priority. However, the strength of the positive correlation theorized in H1 may be affected by prior knowledge of environmental justice. This mitigating factor is addressed in H2, which posits a positive correlation between the visualization of cumulative impacts and the subsequent significance assigned to environmental justice in policy decisions **only** for individuals with prior knowledge of EJ concepts.

Cognitive science literature indicates that prior knowledge of a subject can affect how individuals interact with information (Eberhard 2021). In the context of visually presented information, a pre-existing understanding of a subject can increase an individual's information interaction time (Eberhard 2021, Padilla et al. 2018, Vincent et al. 2018). Increased time interacting with visually presented information potentially indicates a more attentive consideration of the information presented, which could positively influence attitude change and decision efficiency. In the context of Hypothesis Two, I theorize that increased interaction with a visualization of cumulative impacts will produce a more nuanced understanding of environmental justice, making individuals more likely to support pro-environmental justice policies. This hypothesis subsets prior knowledge as a category of analysis, arguing that individuals with a prior framework of EJ will be more likely than individuals without a prior framework of EJ to have their policy attitudes impacted by the visualization of cumulative impacts.

IV. Research Methodology

My research design is a quantitative study designed to answer the following questions: Does the visualization of environmental injustice impact individuals' willingness to support policies that prioritize environmental justice? Does the visualization of environmental injustice have a greater impact on individuals' willingness to support policies that prioritize environmental justice for individuals with a pre-existing understanding of environmental justice? I evaluate these questions through a randomized survey experiment distributed to an undergraduate sample population, which serves as a proxy for state-level political and community actors involved in environmental policy decision-making.

Independent Variable:

My independent variable is the visualization of environmental justice. I operationalize this variable using the California EJ mapping tool, the CalEnviroScreen 4.0. The CalEnviroScreen 4.0 is an EJ mapping technology that visualizes environmental burden through a percentile ranking system calculated based on pollution burden and population characteristics. This tool is a digital interface that allows users to explore different metrics of environmental burden for individual census tracts in California. For each CA census tract, users of the CalEnviroScreen can examine the tract's overall percentile score of environmental burden, measured relative to the aggregated scores of all other census tracts. This score is presented on a scale from zero to one hundred, with zero representing low environmental burden and one hundred representing high environmental burden. This value is also visually represented using a color gradient of green to red: green constituting a low environmental burden and red constituting a high environmental burden.

In addition to the overall percentile score, users of the CalEnviroScreen can also view each census tract's overall pollution burden percentile, population characteristics percentile, eight "exposures" percentile scores, five "environmental effects" percentile scores, three "sensitive populations" percentile scores, and five "socioeconomic factors" scores. All of this information is immediately available to users when they click on a specific census tract. These scores appear in a pop-up window, which includes the census tract number and population count at the top followed by the twenty-one percentile scores broken down into the categories listed above.

Additionally, at the bottom of this pop-up window, there are two interactive pie charts: a race/ethnicity profile and an age profile of the selected census population.

In my randomized controlled survey experiment, the treatment group is presented with two CalEnviroScreen census tract maps while the control group has no interaction with the CalEnviroScreen. Instead, the control group receives textual information about environmental justice. Within this research design, visualization of environmental justice is measured by the interaction or non-interaction with the CalEnviroScreen 4.0.

Dependent Variable:

My dependent variable is the level of support individuals maintain for policies that prioritize environmental justice. How can individuals' support for policies that prioritize environmental justice be measured? I operationalize this variable by evaluating participants' responses to post-treatment survey questions that offer policy options, which respectively trade off environmental justice, GHG thresholds, and cost. Within this framework, environmental justice will be selectively prioritized in select policy options and deprioritized for GHG thresholds and cost efficiency in the alternatives. I evaluate an individual's level of support for pro-environmental justice policies by analyzing the number of pro-environmental justice policy alternatives each survey respondent selects. According to this research design, a participant who chooses the two policies that prioritize environmental justice out of the four policy options would have the highest level of support for pro-environmental justice policy. Accordingly, a participant who chooses zero of the policies that prioritize environmental justice would have the lowest level of support for pro-environmental justice policy.

Prior knowledge of environmental justice is a potential mitigator for the level of support individuals possess for policies that prioritize environmental justice. To account for this relationship, I measure survey respondents' pre-existing knowledge of environmental justice with two pre-treatment questions. A specific mechanism by which prior EJ knowledge mitigates the dependent variable is the researched proportional relationship between prior subject knowledge and increased interaction with visualization. I account for this mechanism by analyzing the time survey respondents spent viewing treatment material against their pre-treatment responses. This analysis is specifically relevant to Hypothesis Two, which posits a positive relationship between the visualization of information and perception change specifically for individuals with a pre-existing comprehension of environmental justice. I expect individuals in the treatment group who possess prior knowledge of environmental justice to spend increased interaction time with the treatment materials, producing a stronger correlation between visualization and policy selectivity for environmental justice.

V. Survey Design:

I evaluate the impact of the visualization of information about environmental justice on environmental justice policy preferences through a randomized survey research experiment. In this experiment, the treatment group is introduced to environmental justice information through interaction with the CalEnviroScreen 4.0 while the control group receives textual information about environmental justice. The control and treatment groups then both receive two survey questions that instruct respondents to choose between policy options that respectively trade off environmental justice, GHG emissions, and cost efficiency. The survey additionally includes two pre-treatment questions that evaluate the respondent's baseline knowledge of environmental justice.

Figure 1: Survey Pre-Treatment Questions

Do you agree or disagree with the following statement: "Climate change in the United States disproportionately affects communities with a higher percentage of low-income and minority citizens."

- Agree
- Disagree
- Unsure

Do you agree or disagree with the following statement: "Environmental hazards such as high pollution and contaminated drinking water are more likely to occur in low-income, minority communities."

- Agree
- Disagree
- Unsure

The objective of the pre-treatment questions is to evaluate each participant's baseline understanding of environmental justice. Environmental justice aims to correct environmental injustice, which is characterized by the existence of communities with a higher percentage of low-income and minority populations who disproportionately experience a high environmental burden. The pre-treatment questions determine whether the respondents understand this basic tenet of environmental justice. Although both questions are similar in nature, the second question includes specific environmental effects that low-income, minority communities are more likely to experience. This specificity is intended to determine whether respondents have a nuanced understanding of the specific burdens disproportionately experienced by low-income, minority populations. Additionally, the rephrasing of question two addresses the potential proclivity for respondents to answer the pre-treatment questions arbitrarily.

Treatment and Control:

Both the treatment and control groups are provided with a written explanation of the CalEnviroScreen 4.0 percentile scoring and the following information they will interact with. Since both groups are exposed to information about the same two census tracts and their CalEnviroScreen percentile scores, a baseline description of these tracts including their racial and ethnic breakdown is provided.

Figure 2: Explanation of CalEnviroScreen Percentile Scores and Census Tracts

> You will now receive information about two census tracts and their respective CalEnviroScreen 4.0 percentile scores, which is calculated as the combination of pollution burden and population characteristics (average of sensitive populations and socioeconomic factors) for each census tract.
>
> The first census tract is 607700390, which captures a portion of Stockton City located in San Joaquin County, CA. In this census tract 70% of the population identify as Hispanic, 29% identify as White, and 1% identify as Other. Census Tract 6013304005 is a bordering census tract that captures a portion of Discovery Bay located in Contra Costa County, CA. In this census tract 60% of the population identify as White, 22% identify as Hispanic, 8% identify as African American, 6% identify as Asian American, and 4% identify as Other.

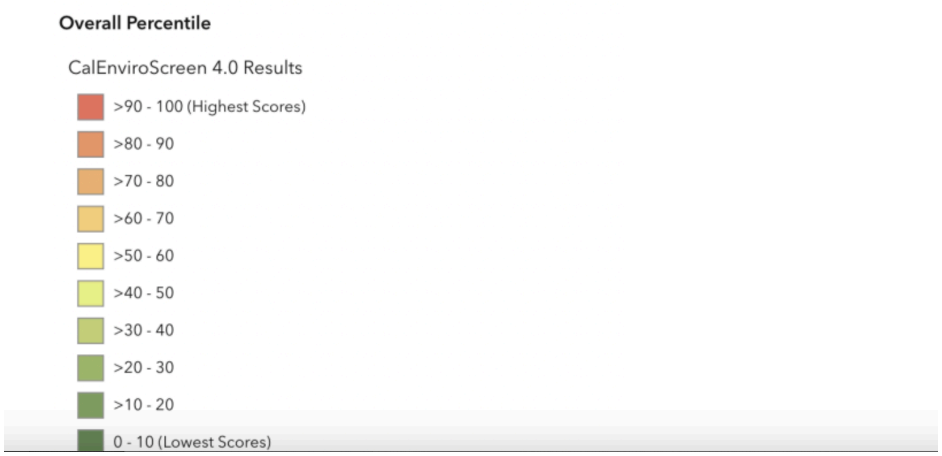
Given that hypotheses one and two both aim to test the visualization versus textual presentation of information, the treatment and control groups are both presented with the

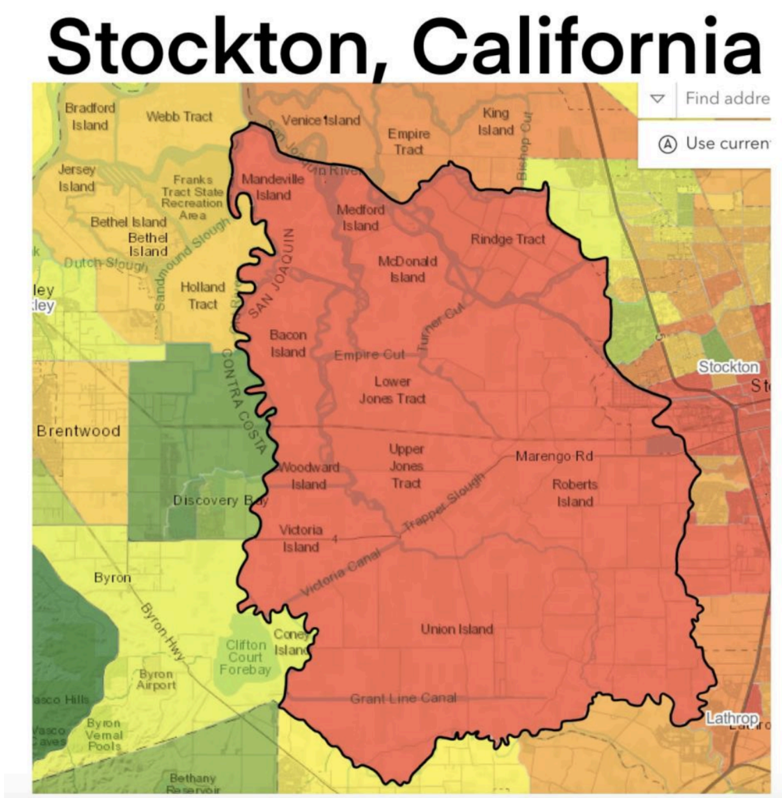
CalEnviroScreen environmental burden score for census tract 607700390, Stockton, and census tract 6013304005, Discovery Bay. However, the treatment group is presented with this information visually while the control group is presented with the score through a textual explanation. The above pre-treatment explanation ensures that both respondent groups are familiar with the CalEnviroScreen 4.0 scoring metrics and the racial breakdowns of each census tract, which are not visually displayed in the treatment materials.

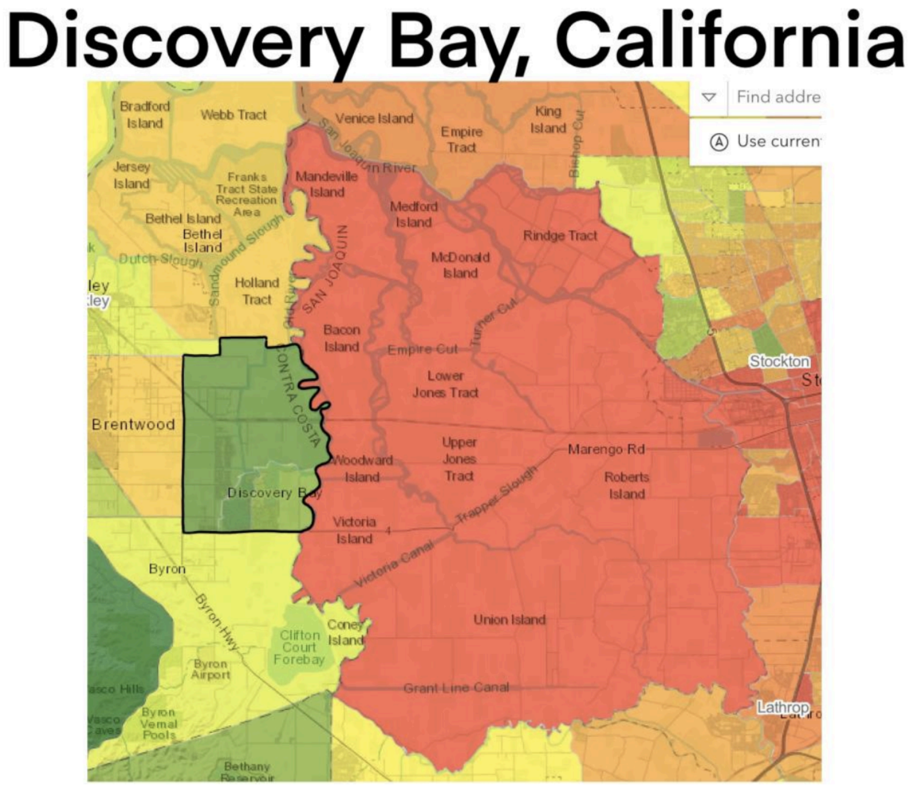
The treatment group is provided with two CalEnviroScreen census tract maps: census tract 6077003900 (Stockton, a city located in San Joaquin County) and census tract 6013304005 (Discovery Bay, a city located in Contra Costa County). The selected Stockton census tract has a CalEnviroScreen environmental burden percentile score of 93, a pollution burden percentile score of 88, and a population characteristics percentile score of 89: indicating a high environmental burden and a high percentage of low-income and minority citizens. Conversely, the Discovery Bay census tract has a CalEnviroScreen environmental burden percentile score of 16, a pollution burden percentile score of 28, and a population characteristics percentile score of 14: indicating a low environmental burden and low percentage of low-income, minority citizens. The treatment group is introduced to an image of the CalEnviroScreen 4.0 percentile scoring scale and two images captured from the CalEnviroScreen 4.0: a map of census tract 6077003900 (Stockton) relative to its nearby census tracts and a map of census tract 6013304005 (Discovery Bay) relative to its nearby census tracts. I selected these two census tracts because despite bordering each other, they display extreme ends of the CalEnviroScreen environmental burden spectrum. Although separated below, the scale and maps are all displayed on the same slide within the survey format.

Figure 3: Treatment Group Survey Material

The following screenshots were captured from the CalEnviroScreen 4.0, a program that maps each California census tract according to their CalEnviroScreen percentile score, which is calculated as the combination of pollution burden and population characteristics.. This is indicated by the scale below:







The control group does not interact with the CalEnviroScreen material. Instead, the control group receives a written explanation of the environmental burden as measured by the CalEnviroScreen 4.0 percentile score of both census tract 6077003900 (Stockton) and census tract 6013304005 (Discovery Bay).

Figure 4: Control Group Survey Material

Census Tract 6077003900 (Stockton) experiences 93% more environmental burden relative to all other census tracts in California. This census tract is specifically 88% more susceptible to pollution burden than all other California census tracts and 99% more vulnerable to groundwater threats.

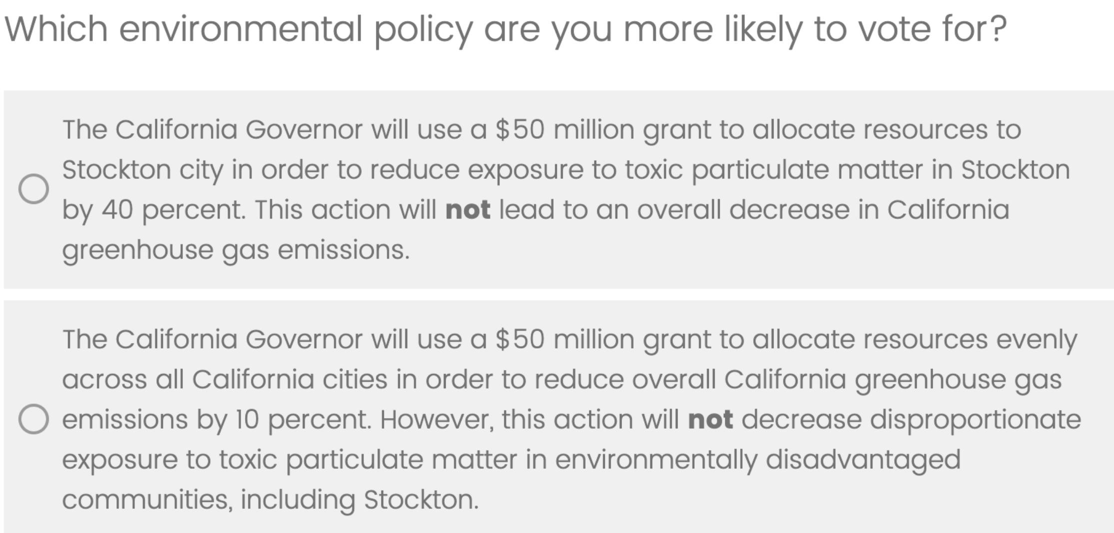
The bordering census tract, 6013304005 (Discovery Bay) experiences 16% more environmental burden relative to all other census tracts in California. This census tract is specifically 28% more susceptible to pollution burden than all other CA census tracts and 0% more vulnerable to groundwater threats.

I specifically chose to include metrics about pollution burden and groundwater threats in the textual presentation of information because these indicators should theoretically be similar for bordering census tracts. The fact that these indicators are drastically different indicates that the disproportionate environmental burden is associated with the proportion of low-income, minority citizens in each census tract, metrics that were introduced in the pre-treatment explanation.

Post-Treatment Questions:

The post-treatment questions aim to evaluate the survey participants' preferences about environmental justice, specifically how they rank environmental justice against other policy preferences. The post-treatment questions trade off environmental justice for overall emissions thresholds and cost respectively. These questions are introduced on the same screen within the survey design.

Figure 5: Post-Treatment Question 1 (State vs. Stockton)



Which environmental policy are you more likely to vote for?

- The California Governor will use a $50 million grant to allocate resources to Stockton city in order to reduce exposure to toxic particulate matter in Stockton by 40 percent. This action will **not** lead to an overall decrease in California greenhouse gas emissions.
- The California Governor will use a $50 million grant to allocate resources evenly across all California cities in order to reduce overall California greenhouse gas emissions by 10 percent. However, this action will **not** decrease disproportionate exposure to toxic particulate matter in environmentally disadvantaged communities, including Stockton.

This post-treatment survey question keeps policy costs constant, but varies the GHG emission impact on vulnerable populations versus the state as a whole. Policy A directly benefits environmental conditions in a singular environmentally burdened city, Stockton. However, this option does not affect California state emissions overall. In contrast, Policy B improves California's statewide emissions but does not address the disproportionate pollution exposure experienced by environmentally burdened cities. Respondents who choose Policy A prioritize the allocation of resources to an environmentally burdened community over statewide emissions, indicating a stronger significance ranking of environmental justice in policy.

Figure 6: Post-Treatment Question 2 (More vs. Less Funding):

Which environmental policy are you more likely to vote for?

- ○ The California Governor will allocate \$50 million to reduce carbon dioxide emissions statewide and another \$50 million to bring additional reductions to ten environmentally burdened cities.
- ○ The California Governor will allocate \$50 million to reduce carbon dioxide emissions statewide.

This post-treatment survey question keeps the rate of GHG emissions constant, but varies the associated policy cost. Furthermore, the cost increase in Policy A is associated with resource allocation to environmentally burdened communities. Policy A ultimately demands a greater payoff in exchange for the policy option that better prioritizes environmental justice. Respondents who choose Policy A prioritize environmental justice at a higher significance threshold by choosing to support the aid of more environmentally burdened communities at the expense of a higher cost.

Demographic Questions:

After completing the post-treatment questions, participants are asked to complete a series of optional demographic questions. These demographic questions include political ideology, political party affiliation, gender identity, and racial/ethnic identity.

Figure 7: Survey Demographic Questions:

The following are demographic questions. If you would prefer to not answer these questions, click continue.

How would you describe your political ideology?

- Very Liberal
- Liberal
- Neutral
- Conservative
- Very Conservative

If you are registered to vote under a specific party, identify the party below:

- Democrat
- Republican
- Green Party
- Independent
- Other

Please specify your gender identity.

- ○ Male
- ○ Female
- ○ Non-binary
- ○ Other

Please specify your ethnicity

- ○ White/Caucasian
- ○ African-American
- ○ Latino or Hispanic
- ○ Asian American or Pacific Islander
- ○ Native American
- ○ Native Hawaiian
- ○ Middle Eastern or North African
- ○ Two or More
- ○ Other/Unknown

The demographic questions are used to account for potential confounding effects on the relationship between the treatment and the post-treatment questions. For example, an individual who identifies as "Very Liberal" could be predisposed to assign a higher level of significance to environmental justice than an individual who identifies as "Very Conservative." This potential confounding variable and others are controlled for using a linear regression that predicts the effect of the treatment on the post-treatment responses while holding all other variables constant.

Survey Validity Measures:

Using the Qualtrics randomization software, I coded the survey so that it would randomly generate either the control or treatment block each time a new survey was initiated. Additionally, I ensured that the presentation of each policy option as well as their respective answers were randomized to limit “order bias,” or the cognitive tendency to choose an answer based on its positionality in a list. The survey was distributed online with zero contact with the survey participants. The method of sample selection and survey distribution is detailed below.

Sample Population:

The survey sample population was selected from four UCSD undergraduate classes: USP 100 (Introduction to Urban Planning), USP 143 (The US Health Care System), USP 125 (The Design of Social Research), and POLI 127 (Politics of Development). There are 61 students enrolled in USP 100, 245 students enrolled in USP 143, 29 students enrolled in USP 125, and 145 students enrolled in POLI 127 respectively. Therefore a total of 480 students were offered the opportunity to participate in the survey. To comply with UCSD Institutional Review Board standards, no incentives were provided to students in exchange for survey completion. Consequently, the final survey sample population was much smaller than 480.

I selected classes from the Urban Planning and Political Science departments because the undergraduate students from these departments presumably have a working understanding of public policy. Additionally, classes such as POLI 127 and USP 143 attract a wide variety of majors, expanding the scope of students reached. I chose undergraduate students as my sample population of choice because they have a relatively high education level and could be feasibly recruited for the survey (through distribution in undergraduate classes) in the limited designated time frame.

Although I expect the participants to have a similar educational baseline, the extent of these students' knowledge about environmental justice will be dependent on their individual interests and respective course experience. This variance is relatively representative of gaps in knowledge across environmental policy actors due to curriculum, research experience, past careers, etc. Although the experimental sample is not an exact proxy for state political and community actors involved in environmental policy decisions, the variety in knowledge across recruited undergraduate students and their baseline education level provides a feasible representative sample for the subgroups.

VI. Analysis & Results

Out of the 480 students offered the survey, 39 students completed the survey. My original target response rate was 60 participants, however, due to time constraints, I was only able to collect 39 participants: an eight percent response rate. Within this sample population, the treatment group comprised of 18 individuals and the control group comprised of 21 individuals. The demographic breakdown of the sample population is visualized below:

Table 1: Demographic Breakdown of Treatment and Control Groups

Demographic Categories	**Control**		**Treatment**	
Political Ideology				
Very Liberal	6	(15%)	8	(20%)
Liberal	8	(20%)	7	(18%)

Neutral	4	(10%)	1	(3%)
Conservative	1	(3%)	2	(5%)
Very Conservative	1	(3%)	0	(0%)
No Answer	1	(3%)	0	(0%)
Political Party				
Democrat	13	(33%)	15	(38%)
Republican	1	(3%)	0	(0%)
Green Party	0	(0%)	0	(0%)
Independent	1	(3%)	2	(5%)
Other	3	(8%)	1	(3%)
No Answer	1	(3%)	2	(5%)
Gender				
Male	4	(10%)	5	(13%)
Female	15	(38%)	13	(33%)
Non-Binary	1	(3%)	0	(0%)
Other	0	(0%)	0	(0%)
No Answer	1	(3%)	0	(0%)
Ethnicity				
White/Caucasian	6	(15%)	6	(15%)
African-American	2	(5%)	0	(0%)
Latino or Hispanic	4	(10%)	5	(13%)
Asian American or Pacific Islander	2	(5%)	4	(10%)

Native American	0	(0%)	0	(0%)
Native Hawaiian	0	(0%)	0	(0%)
Middle Eastern or North African	1	(3%)	0	(0%)
Two or More	4	(10%)	3	(8%)
Other/Unknown	1	(3%)	0	(0%)
No Answer	1	(3%)	0	(0%)

To ensure the absence of statistically significant differences across demographic categories between the treatment and control group, I calculated the difference in means for each demographic variable. The difference in means for Political Ideology, Political Party, Gender, and Race/Ethnicity are not statistically significant, as indicated by the p-values listed in the table below (Table 2). This result suggests that the randomization for the treatment and control groups across demographic categories was successful.

Table 2: Demographic Variables Balance Table

	Political Ideology	Political Party	Gender	Race/Ethnicity
Treatment	2.05	1.79	1.76	3.71
Control	1.83	1.56	1.72	3.39
p-value	0.537	0.629	0.821	0.710

Hypothesis One (H1):

Hypothesis One posits that exposure to a visualization of the cumulative impacts of climate change increases the level of significance participants assign to environmental justice in trade-off policy decisions. In order to evaluate the correlation between the treatment (visualization) and the significance ranking of environmental justice–as measured by the post-treatment questions–I first conducted a difference in means tests for both post-treatment questions respectively.

Post-treatment Question One (State vs. Stockton) offers two policy options: the first policy option (coded as zero) allocates funding evenly across California to address state GHG emissions while not impacting Stockton whereas the second option (coded as one) allocates funding to reduce emissions in Stockton without addressing overall state GHG emissions. For post-treatment Question One (State vs. Stockton), the treatment group evenly selected the two policy options. Within the eighteen members of the treatment group, nine selected the Stockton policy option and nine selected the State policy option. Conversely, the control group appeared to prefer the Stockton policy option over the State policy option. Within the twenty-one members of the control group, fifteen selected the Stockton policy option and six selected the State policy option. This contradicts H1's assumption that individuals who interact with visualization (treatment) are more likely to prioritize environmental justice over other policy options. In post-treatment Question One, the Stockton policy option ultimately designates environmental justice as a higher priority than overall state GHG emissions. Therefore H1 predicts that the treatment group is more likely than the control group to select the Stockton policy option, which the survey results contradict. However, the difference in means test for the effect of treatment on post-treatment Question One suggests that the correlation is not statistically significant.

Graph 1: State vs. Stockton Difference in Means

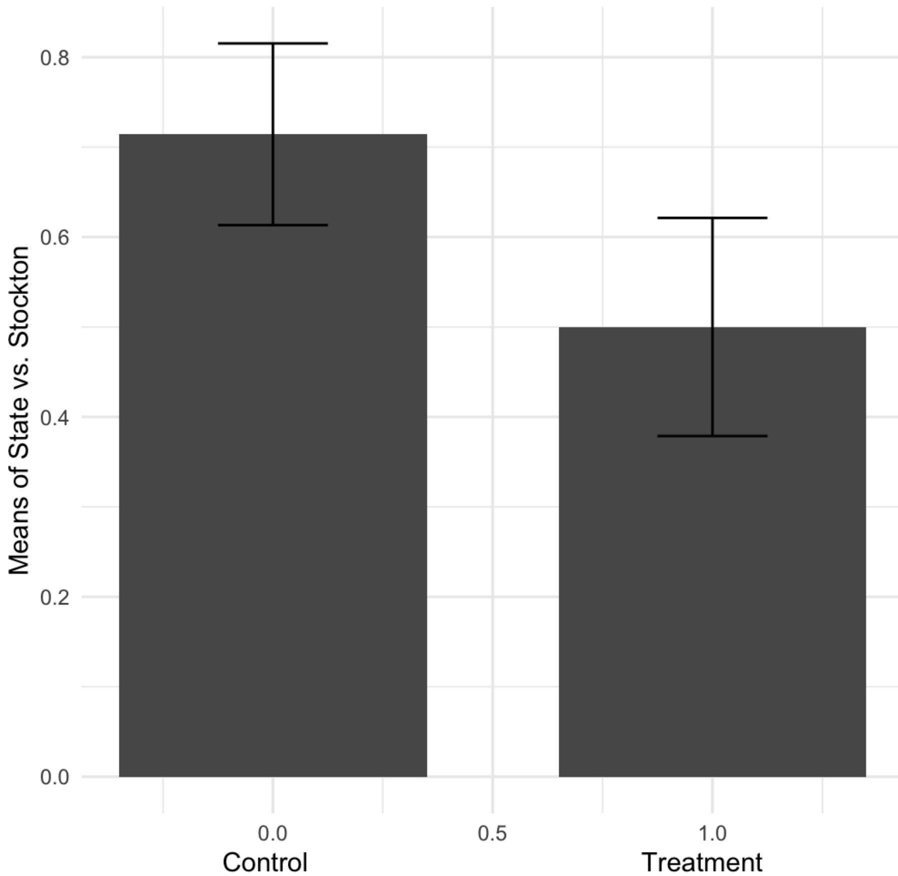


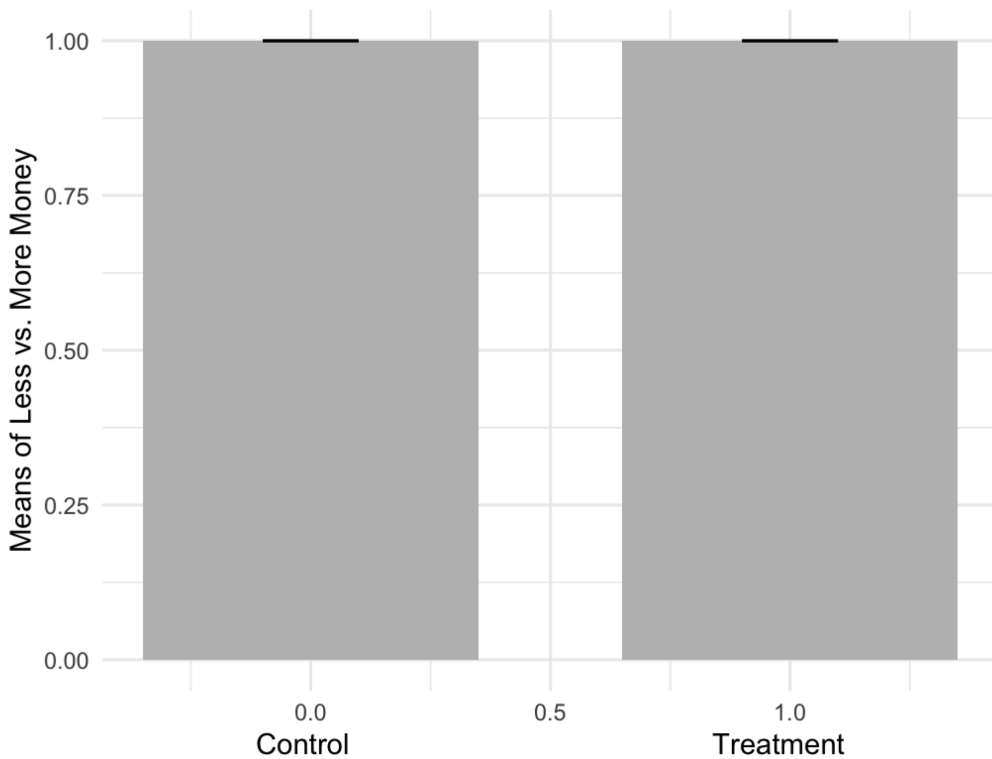
Table 2: Welch Two-Sample T-Test for State vs. Stockton

Statistic	**Value**
t-value	1.358
Degrees of Freedom (df)	34.6
p-value	0.184
Confidence-Interval	[-0.106, 0.535]
Mean in Control group	0.714
Mean in Treatment group	0.500

The mean of the control group (0.714) is higher than the mean of the treatment group (0.50). However, the p-value and Confidence-Interval both indicate that this difference in means falls short of statistical significance. The p-value is 0.184, meaning that we cannot reject the null hypothesis, as 0.184 is greater than the conventional alpha level of 0.05. This p-value indicates that we could have observed a difference in means this large in 18 out of 100 experimental trials, even in the true population means did not differ. Additionally, the confidence interval value set includes 0, further proving that the difference in means is not statistically significant.

Post-Treatment Question Two evaluates the ranking of environmental justice against cost. Post-treatment Question Two (less vs. more money) offers two policy options: the first option (coded as zero) only allocates $50 million to reduce GHG emissions statewide while the second option (coded as one) allocates $50 million to reduce GHG emissions statewide and an additional $50 million to reduce GHG emissions in ten environmentally burdened cities. For post-treatment Question Two, all participants in the treatment group selected policy option two, which allocates additional funding to environmentally burdened cities. H1 predicts that individuals exposed to visualization (treatment) will have a stronger significance ranking of environmental justice, which this result aligns with. However, all individuals in the control group also selected policy option two, indicating a ceiling effect. A ceiling effect occurs when the sample population's answers cluster towards the upper limit of the scale used for analysis– in this case one. The existence of a ceiling effect for post-treatment Question Two limits variance and maximizes skew, indicating that the effect of treatment on post-treatment Question Two is moot. Due to an absence of difference between the means of the control and treatment groups, I was unable to produce a Welch Two-Sample Test for post-treatment Question Two. The ceiling effect–and subsequent absence of a difference in means– is visualized in the error-bar plot below.

Graph 2: Less vs. More Money Difference in Means



Due to the ceiling effect in post-treatment Question Two response, my subsequent analysis of the relationship between visualization and EJ significance ranking focuses on the correlation between treatment and post-treatment Question One (State vs. Stockton). To further analyze the impact of treatment on response variation for post-treatment Question One, I ran an ordinary least squares (OLS) linear regression for the treatment's effect on State vs. Stockton policy selection.

Model Specification 1:

$\hat{Y} = \beta_0 + \beta_1 X + \in$

Within this formal model, $\hat{Y}$ represents the predicted value of the dependent variable (post-treatment Question One), β_0 represents the predicted value of post-treatment Question One when treatment is equal to zero, β_1 represents the slope of the regression line, X represents the independent variable (Treatment/Control) and ϵ represents residual effect not accounted for by the regression model. The effect of treatment on post-treatment Question One produced the following residuals:

Table 3: Regression Analysis of State vs. Stockton

	Model 1
Treatment	-0.215 (0.157)
Num. Obs.	39
Adjusted R_2	0.023
F	1.874

Significance Codes: ***p<0.001, **p<0.01, *p<0.05, .p<0.1

The Treatment coefficient, -0.215, suggests a decrease in selection for the Stockton option with treatment. This outcome is opposite of H1's expected trajectory: an increase in selection for the Stockton option when exposed to treatment. However, this correlation is not statistically significant because the p-value is 0.179, which is greater than the conventional alpha level of 0.05. This is driven by the large standard error for the treatment variable, indicating a significant degree of uncertainty in the estimate of the treatment's effect on post-treatment question one. This standard error value is most likely strongly influenced by the small sample size. Although the results of this regression are not statistically significant, the negative correlation between the treatment and the selection of the Stockton policy option is intriguing. With no statistically significant conclusion, this regression model suggests that we cannot conclusively support or reject the null hypothesis, that visualization positively impacts individuals' significance ranking of environmental justice.

I ran an additional OLS linear regression for the treatment's impact on State vs. Stockton policy selection, holding all other measured demographic variables constant.

Model Specification 2:

Predicted State vs. Stockton = $\beta_0 + \beta_1$ *x Treatment*+ β_2 *x Political Ideology* + β_3 *x Political Party* + β_4 *x Gender* + β_5 *x Race/Ethnicity* + ϵ

In this model, *Predicted State vs. Stockton* represents the predicted value of the dependent variable, post-treatment Question Qne. B_0 represents the intercept of the model, which is the expected value of post-treatment Question One when all independent variables (ie. Treatment and demographic variables) are equal to zero. The individual β x Demographic factors (ie. β_2 *x Political Ideology*) represent the coefficient of each demographic factor, indicating the expected change in post-treatment Question One for a one-unit change in each respective demographic variable category, when all other variables are held constant. The ϵ value represents the residual effect not accounted for by the regression model. The effect of treatment on post-treatment Question One when demographic variables are held constant produced the following residuals:

Table 4: Regression Analysis of State vs. Stockton, with demographic variables

	Model 1
Treatment	-0.200 (0.168)
Political Ideology	-0.093

	(0.103)
Political Party	-0.045 (0.065)
Gender	0.209 (0.170)
Race/Ethnicity	-0.015 (0.034)
Num.Obs.	39
Adjusted R_2	-0.025
F	0.8237

Significance Codes: ***p<0.001, **p<0.01, *p<0.05, .p<0.1

Holding all demographic variables constant, the effect of the treatment on the expected value of State vs. Stockton is -0.200–indicating a decrease in the probability of selecting the "Stockton" policy option for individuals exposed to the treatment. This corroborates the correlation of the first linear regression, which tested the effect of treatment on State vs. Stockton without holding demographic variables constant. However, this observed effect is not statistically significant because the p-value is 0.241, which is greater than the 0.05 significance level. All of the individual indicators for the demographic variables are also statistically insignificant at the 0.05 significance level, as indicated by the estimated p-values (Table 2) for each respective category. Overall, this regression suggests that there is no statistically significant effect of treatment or demographic indicators on respondents' State vs. Stockton policy selection. Similar to the first linear regression, this model suggests that exposure to visualization produces a decrease in the probability of individuals to rank environmental justice above other policy priorities (overall state GHG emissions in this case). However, as previously stated, this observation is not statistically significant, meaning that there is no conclusive evidence to support H1.

I originally planned to run an additional regression analysis on the relationship between treatment and post-treatment Question Two (Less vs. More Money), and incorporate the results into the evaluation of H1. However, as previously mentioned, pre-treatment Question Two (Less vs. More Money) experienced a ceiling effect: all survey participants within both treatment and control groups selected policy option two, allocating “More Money” to aid environmentally burdened cities. As a result, there is no observable change across treatment and control for post-treatment Question Two. Consequently, my evaluation of visualization’s impact on the “significance ranking” of environmental justice in trade-off policy decisions is restricted to the analysis of the relationship between treatment and post-treatment Question One (State vs. Stockton). In the limitations section I explore the likely explanation of the observed ceiling effect: a young, undergraduate student sample population.

Hypothesis Two (H2):

Hypothesis Two posits that exposure to a visualization of the cumulative impacts of climate change increases the level of significance participants—**with a prior knowledge of environmental justice concepts**—assign environmental justice in trade-off policy decisions. Hypothesis Two builds on Hypothesis One by subsetting “prior knowledge of environmental justice” as a category of analysis. The survey design measures “prior knowledge of environmental justice” with the two pre-treatment questions: statements that prompt respondents to select “agree,” “disagree,” or “unsure” for two statements about environmental justice. The selection of “agree” to both statements indicates a nuanced understanding of environmental justice.

I originally planned to evaluate the effect of prior knowledge of environmental justice on EJ significance ranking by performing a linear regression of the effect of "prior knowledge" on the post-treatment questions. This linear regression would discern whether prior knowledge of environmental justice impacted individuals' likeliness to select policy options that prioritize environmental justice. Additionally, subsetting prior knowledge as a separate category of analysis would allow me to determine whether a relationship between prior knowledge and treatment-interaction time exists. Cognitive science scholars argue that prior knowledge can increase participants' interaction-time with visualization, stimulating greater attitude change and decision efficiency (Eberhard 2021, Padilla et al. 2018, Vincent et al. 2018). I planned to evaluate this relationship by analyzing prior knowledge against the duration of survey participants' interaction with treatment for the treatment group.

However, I was unable to perform these analyses because all 39 survey participants answered "agree" to both pre-treatment questions, indicating that the entire sample size had a nuanced "prior knowledge of environmental justice," according to the survey design's definition. Similar to post-treatment Question Two, a ceiling effect is observed for both pre-treatment queesitons. All respondents indicate prior knowledge, restricting my ability to determine if a correlation between prior knowledge and environmental justice significance ranking exists. Due to this observed consistency across all respondents, I am unable to subset "prior environmental justice knowledge" as a separate category of analysis. Accordingly, I cannot reach a definitive conclusion on whether H2 is statistically supported. However, the uniformity in pre-treatment response selections for all survey participants prompts interesting observations about my sample population, which I will further explore in my "Limitations and Discussion" section.

VII. Limitations & Discussion

Multiple limitations arise from the allocated funding and time frame of this study, which should be explored in future research.

The largest limitation of this study is the time frame and the resulting small sample population size. My initial projected minimum sample size was sixty survey participants; however, due to an extended approval period for the distribution of my survey experiment, I did not have adequate time to recruit participants. Despite distributing the survey to an aggregate of 480 students, only 39 students participated. I believe that an incentive structure (ie. one extra credit point for completion of the survey) or the release of the survey earlier in Winter Quarter—as I had originally planned—would have increased participation. A larger sample population size would address the large sampling variability present in my analysis, potentially producing a statistically significant result.

An additional limitation of my observed sample population is its limitation to undergraduate UCSD students. Although the selection of UCSD students for my sample population is intended to serve as a proxy for state environmental and community actors, there are inherent limitations in restricting the sampling to undergraduate students. For example, the average age of undergraduate students may have influenced the observed response to post-treatment Question Two. Younger individuals are typically more progressive with government spending preferences, which could explain why the entire sampled population chose the policy option that allocated additional funding to environmentally burdened cities in post-treatment Question Two (Less vs. More Money). The sample population's identity as undergraduate students may have also influenced the ceiling effect observed for both pre-treatment questions, which evaluated prior knowledge of environmental justice. Relatively recent advancements in environmental science education in universities (specifically at UCSD) could explain the sample population's understanding of environmental knowledge, which was observed across all demographics (ie. Conservative and Liberal). Obtaining a larger sample size with greater variance in population type would provide a stronger evaluation of the effect of visualization on environmental justice significance ranking. Future research could replicate this survey or a survey with similar motivating ideology at a larger scale.

This study was also limited in its presentation of the visual information disseminated by environmental justice mapping tools. Although both H1 and H2 tested only the visualization of information, future research design could include a treatment that facilitates digital interaction with visual information. For example, an alternate treatment program could include facilitating active interaction with EJ mapping tools, where participants can click on and manipulate the map features. This could provide insight on whether or not the design of EJ mapping tools facilitates attitude change and policy preferences, contributing to the nascent body of research on whether or not EJ mapping tools should be prioritized as a policy strategy for distributing information about environmental justice. Additional research is needed to examine EJ mapping tools' impact on policy and attitude change, especially as a greater proportion of states allocate funding towards these "technological solutions."

VIII. Conclusion

Environmental justice and, by extension, environmental injustice are considerable challenges that have altered and continue to shape the U.S. policy landscape. The disproportionate distribution of environmental burden to low-income communities and communities of color is a significant issue that future environmental policy needs to prioritize.

Although the U.S. federal government identified environmental justice as an important policy criterion in 1994, specific guidelines for the operationalization and enforcement of environmental justice in policy remain underdeveloped. Existing literature argues that the generation and distribution of Environmental Justice mapping tools like the CalEnviroScreen provide a pathway for creating policy that targets environmental justice (Corburn 2017, Lee 2020, Zrzavy et al. 2019). However, the existing body of research lacks empirical evidence to support this claim. My thesis attempted to address this gap by evaluating whether or not the visualization of information employed by EJ mapping tools has a discernible impact on the significance ranking of environmental justice against other environmental policy priorities. I constructed two hypotheses:

H1: Exposure to a visualization of the cumulative impacts of climate change increases the level of significance participants assign to environmental justice in trade-off policy decisions

H2: Exposure to a visualization of the cumulative impacts of climate change increases the level of significance participants—with a prior knowledge of environmental justice concepts—assign environmental justice in trade-off policy decisions.

I evaluated these hypotheses through a randomized survey experiment distributed to UCSD undergraduate students. My randomized survey experiment yielded statistically insignificant results for the effect of treatment (visualization) on environmental justice significance ranking. Accordingly, I cannot reject the null hypothesis that exposure to visual information has no effect on individuals' probability to rank environmental justice higher than other policy priorities. Despite the lack of conclusive evidence, the available data suggests a moderate negative correlation between treatment and environmental justice significance ranking, as measured by the relationship between treatment and post-treatment policy Question One

(Stockton vs. State). This indicates that the opposite of H1 could be true, that textual organization of information has a greater effect than the visual organization of information on environmental justice significance ranking. However, this observed result could also be a product of random chance along or of factors unaccounted for in the model. The ceiling effect for post-treatment Question Two in the context of H1 is also notable. All survey participants selected the policy option that allocated additional funding to environmentally burdened cities, regardless of whether they were in the treatment or the control condition. This indicates potential generational differences in willingness to spend tax-dollar money on social and environmental policy, with the younger generation willing to pay more.

I am also unable to conclusively support or reject H2: that exposure to the visualization of cumulative impacts for the subsetted category of individuals with prior environmental justice knowledge increases the level of significance the individuals assign to environmental justice in trade-off policy decisions. I was unable to perform analysis on H2 because my entire sample population indicated prior knowledge of environmental justice, as measured by the pre-treatment questions. This consistency across the sample population could indicate the consistency of environmental knowledge across UCSD undergraduate students and/or a ceiling effect for the pre-treatment questions. Despite negatively impacting my ability to test H2, this result and its implications about the progression of environmental science education is notable.

Although my randomized survey experiment produced statistically insignificant results, it remains the first recorded empirical study on the relationship between the visualization of cumulative impacts and individuals' willingness to support environmental policy that prioritizes environmental justice. If the survey were re-distributed to a larger sample from a more varied population, it could produce insight into whether or not visualization is a causal mechanism for policy preference and attitude change in environmental policy decisions. Furthermore, my analysis provided intriguing descriptive observations about the opinions of undergraduate students on environmental justice policy. The ceiling effect observed in both the pre-treatment questions and post-treatment Question Two potentially indicate generational differences in access to environmental education and willingness to increase fiscal contributions for policies that address environmental justice. These observations should be further explored to understand whether or not generational differences serve as a mitigating variable on the relationship between information distribution style and policy preferences for environmental justice.

This study serves as the first step for evaluating the relationship between the visualization of information and policy preference within the environmental policy sphere. Further extensions of this research should be pursued in order to determine whether environmental justice mapping tools have a discernable impact on policy preference, as the existing literature claims. The widespread allocation of state funding for the development of EJ mapping programs makes it imperative to understand if these tools significantly alter preferences and by extension reprioritize environmental justice in environmental policy.

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