ECONOMIC ANALYSIS OF GROUNDWATER USE PATTERNS AND ENVIRONMENTAL JUSTICE CONSIDERATIONS

by

Zoey Reed-Spitzer

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As members of the Master's Committee, we certify that we have read the thesis prepared by: Zoey Reed-Spitzer
titled: Economic Analysis of Groundwater Use Patterns and Environmental Justice Considerations

and recommend that it be accepted as fulfilling the thesis requirement for the Master's Degree.

Bonnie G Colby
Bonnie G Colby (Jun 12, 2024 12:57 PDT)
Bonnie G Colby — Date: Jun 12, 2024

George Frisvold
George Frisvold (Jun 26, 2024 09:47 PDT)
George Frisvold — Date: Jun 26, 2024

Jeffrey Michler — Date: Jun 12, 2024

Final approval and acceptance of this thesis is contingent upon the candidate's submission of the final copies of the thesis to the Graduate College.

I hereby certify that I have read this thesis prepared under my direction and recommend that it be accepted as fulfilling the Master's requirement.

Bonnie G Colby
Bonnie G Colby (Jun 12, 2024 12:57 PDT)
Bonnie G Colby — Date: Jun 12, 2024
Thesis Committee Chair
Agricultural & Resource Economics

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Abstract

Groundwater is threatened in the Southwestern United States and world-wide. Hydrologic, economic and environmental factors contribute to both groundwater quantity and quality outcomes. These outcomes impact those living in regions that rely primarily on groundwater to satisfy their water demand. This thesis explores two broad questions: 1) Are climate, economic and regulatory patterns reflected in depth to water levels? 2) Do environmental burdens relating to groundwater have disproportional negative impacts on racial and ethnic minorities, low-income households, or less educated individuals? Depth to water data is more widely attainable than groundwater extraction data due to political and legal factors. We find modeling factors that directly relate to groundwater extraction (planted acreage, groundwater regulation status, recharge, climate factors, etc.) does explain variation in depth to water levels over time at the sub-basin level. These results can inform groundwater policy in areas where groundwater extraction is unavailable. Additionally, racial and ethnic minorities, low-income households, and less educated individuals are found to be associated with higher environmental burden prevalence. This disproportional exposure highlights disadvantaged communities in the Colorado River Basin and adjacent service areas, suggesting that further efforts towards environmental justice throughout groundwater management decisions are needed.

Chapter 1: Introduction

1.1 Groundwater Level Data and their Use in Economic Analysis

Disruptions in groundwater supply threaten Arizona due to regional drought and groundwater use exceeding natural recharge. From 2010 to 2020, population and housing units have increased by 11.9% and 8.9%, respectively, and agricultural production continues to grow (United States Census Bureau, 2021; Arizona Department of Agriculture, n.d.). The state has made regulatory and structural decisions to keep up with the rise in water demand including designating Active Management Areas (AMAs) and Irrigation Non-expansion Areas (INAs), constructing artificial recharge sites, and outsourcing water supply through projects like the Central Arizona Project (CAP). However, policy surrounding groundwater in Arizona only exists in part of the state, while outside of these regulated areas no monitoring and reporting standards regarding groundwater extraction exist. Additionally, roughly fifty percent of irrigated agriculture occurs outside groundwater regulated areas (McGreal and Eden, 2021). Knowing which economic and climate aspects provide insight to groundwater level changes can help inform policy decisions in areas that lack explicit groundwater use data in Arizona, and in other rural areas worldwide.

Precipitation, temperature, and groundwater pumping have been used to study changes in groundwater levels. However, political, legal, and technical factors inhibit the requirements and accuracy for reporting groundwater use in areas outside of Arizona's regulated areas (AMAs and INAs); thus, pumping data is not available in much of rural Arizona. Alternatively, groundwater level data, known as depth to water (DTW), is more widely attainable. This study examines the usefulness of groundwater level data in understanding linkages between groundwater conditions and economic, demographic, and climate factors.

1.2 Arizona's Groundwater Scarcity Mitigation Efforts

Established in 1980 were the first four AMAs, Prescott, Phoenix, Pinal, Tucson (later a fraction split into Santa Cruz), along with the two INAs, Joseph City and Douglas (now an AMA as of 2022). The Harqhahala INA was established the following year, and the Hualapai Valley INA was created in 2022. All designated areas fit the criteria for establishing stricter water management plans since they heavily rely on groundwater and were the culprit of 70% of Arizona's groundwater overdraft (Arizona Department of Water Resources, n.d.b; Water

Resources Research Center, 2007). Municipal, industrial, and agricultural water users within an AMA zone are required to attain permits to pump groundwater, conserve its use, and report annual withdrawals to the Arizona Department of Water Resources (Arizona Department of Water Resources, 2016). Those within INA zones must install measuring devices on all nonexempt wells (wells that pump water greater than or equal to 35 gallons per minute or irrigates more than 2 acres of land), file a notice when modifying or digging a new well, and report groundwater withdrawals annually (Arizona Department of Water Resources, 2022).

Arizona does not use economic incentives such as fees to promote less groundwater use. Those that withdraw groundwater within AMA zones are required to pay only a nominal fee. In 2023, fees differ by AMA and range from $2.00 (Pinal AMA) to $3.50 (Tucson AMA) per acre foot pumped (ADWR, 2022b). These fees are low and likely have little influence on the quantities pumped. There are lower barriers to pump groundwater in unregulated areas. Miscellaneous nominal fees are charged to particular wells outside of AMAs, but they are also very low.

By 2005, all existing AMAs had artificial groundwater recharge sites, a popular method for using human intervention to improve groundwater conditions. There are two types of artificial recharge: surface and subsurface level, with the latter being more costly in terms of development and upkeep. Both methods share the goal to increase water level in a particular aquifer. There are artificial recharge sites throughout Arizona including outside of AMAs and INAs (Water Resources Research Center, 2007).

The Central Arizona Project was authorized in 1968 and designated to transport 1.5 million acre-feet (MAF) of water from the Colorado River to central and southern portions of Arizona’s most populated areas. This outsourced supply provides water for 80% of the state’s population, easing groundwater dependencies and overdraft (Central Arizona Project, n.d.).

Compared to large municipal areas, rural communities in Arizona are disproportionately affected by threats to their groundwater as they have limited options to adapt and little regulation in place to monitor and protect underground flows. Understanding the economic, demographic, climatic, and regulatory factors that influence groundwater conditions is important for rural community resilience and sustainable water management planning.

1.3 Study Area

This paper uses hydrological definitions from the Arizona Department of Water Resources (ADWR). A basin is designated based on an area's topography, land use, and hydrology features, regarding an underground body of water. Some basins in Arizona have multiple related bodies of groundwater, each of which are broken up into smaller geographical areas called sub-basins (Arizona Department of Water Resources, n.d.). Some basins are not separated into sub-basins, thus are sub-basins themselves. This paper refers to all study areas as sub-basins. Sub-basin boundaries are set by ADWR (Arizona Department of Water Resources, n.d.c). Eight groundwater regulated and six unregulated sub-basins are included in the study area. All the sub-basins in this study are majority groundwater dependent, have active agriculture, and have similar topography, climate, and economic activity. A detailed description of each individual sub-basin can be found in Appendix A1 and a visualization of each is shown below in Figure 1.

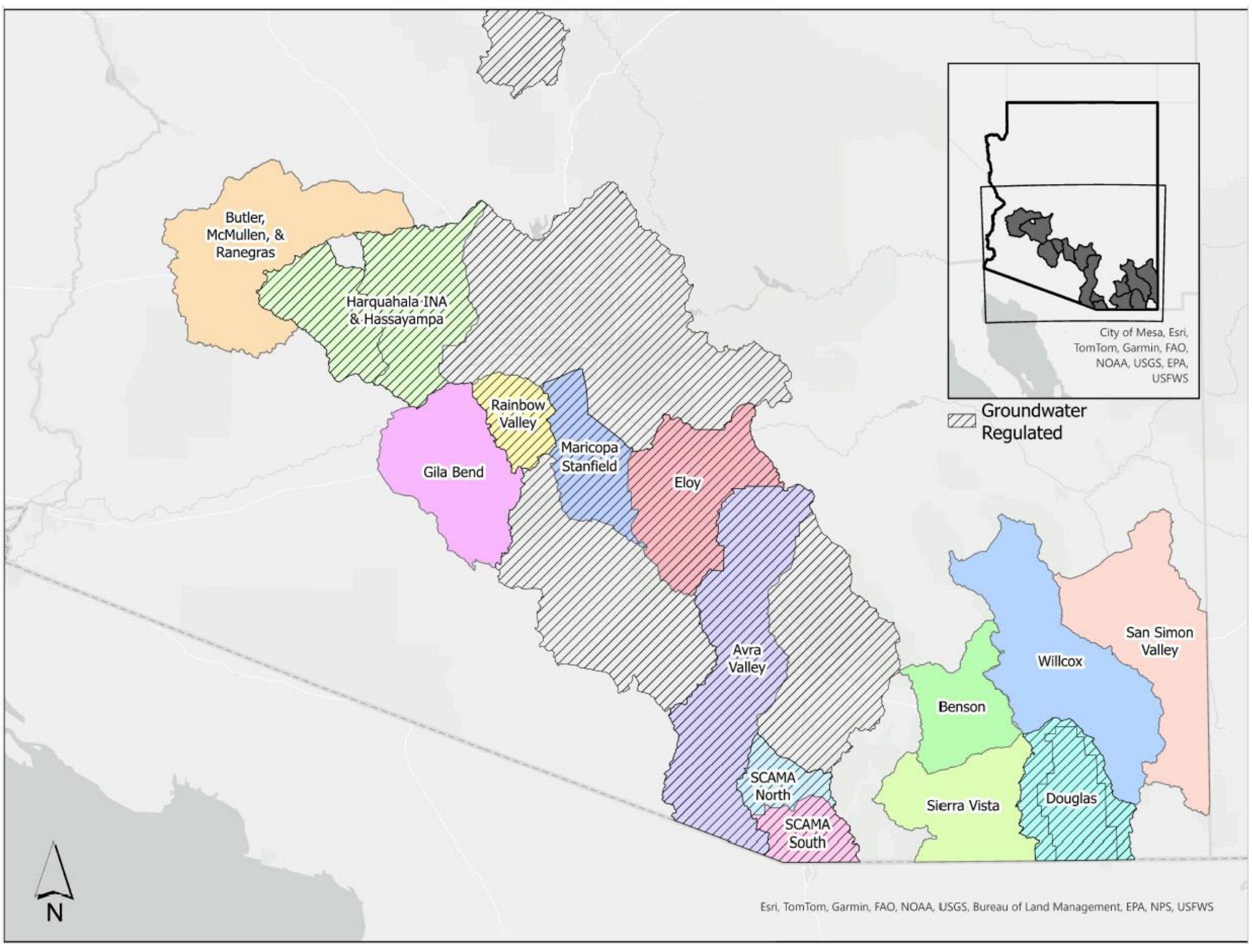

Figure 1. Sub-basins in Study Area

1.4 Key Findings

Results find unregulated groundwater sub-basins have the largest, positive, economically significant relationship with DTW, indicating sub-basins without regulation in place are also those whose groundwater levels decrease over time. As expected, planted acreage in unregulated sub-basins and groundwater levels move in opposite directions throughout the study period. Temperature and precipitation correlate with groundwater levels the way they are expected: higher temperatures and lower precipitation correlate positively with DTW. Increases in housing units likely occurs in sub-basins whose groundwater levels are decreasing. No clear relationship is seen between per capita income and groundwater levels over time in any models. Lastly, active recharge projects are likely to occur in areas where groundwater levels increase over time once unobserved heterogeneity is controlled for.

1.5 Social and Environmental Justice Considerations in the Larger Colorado River Basin

While analyzing economic, climate, and regulatory signals in groundwater levels can help provide policy insight for communities facing groundwater scarcity risk, understanding which groups are most vulnerable provides further detail on where to aim such investments in environmental amenities and infrastructure. Chapter 7 provides further discussion and presents econometric models to investigate relationships between disadvantaged communities and environmental burdens regarding groundwater allocation, quality, and access.

Results show ethnic and racial minorities, compared to mostly White non-Hispanic populations, are positively correlated with four different environmental burdens (lack of green space, households with incomplete plumbing, leaky underground storage tanks (USTs), and air pollution). Populations without a high school degree have positive correlations with each environmental burden. Areas with a higher mean income correlate positively with greener areas and air pollution, and negatively with leaky USTs and households with incomplete plumbing. Population density has the largest positive relationship with each of the four environmental burdens.

Chapter 2: Literature Review

Past studies analyze influences of precipitation, temperature, and groundwater pumping on changes in groundwater levels (Shin et al., 2020; Li et al., 2020; etc.). On a national, international, and global scale, water databases are found to be inconsistent regarding measuring and defining indicators of groundwater conditions. There is a general lack of official statistics nationally in many countries and across the globe (Dantas et al., 2021). Groundwater level data is more attainable than groundwater pumping data and has a consistent definition and measurement.

Prominent evidence suggests that water use is price inelastic in both the agricultural and municipal sectors (Foster et al., 2015; Hendricks et al., 2012; Alhassan et al., 2020; Sukcharoen et al., 2020; O’Donnell et al., 2018). In contrast, Bruno et. al. (2023) find increases in groundwater extraction prices led farmers in California to significantly decrease groundwater use. Moreover, an important factor to include in an analysis of agricultural water demand is well yield (the maximum capacity of a well) to avoid skewing the calculated elasticities (Mieno et al., 2021).

With strong evidence pointing to price inelastic municipal water demand, some studies focus on efforts to curb water use in municipal areas through other policy decisions besides targeting price. O’Donnell and Berrens (2018) break down the effects of different rebate programs in Clovis, New Mexico, a small municipal town. The authors find water saving toilet rebates are more effective than efficient washing machine or landscape rebates in decreasing water use (O’Donnell et al., 2018). In further regard to policy decisions other than increasing water prices, water use has been found to have decreased over time in large urban cities where population has increased, decoupling a commonly found positive relationship between the number of people and water use level. This finding suggests water management decisions being made in municipalities are working to improve groundwater conditions (Lee et al., 2022).

There is a social cost to using water. The cost for water as an input for agricultural output has been modeled more recently to include environmental externalities while maximizing social welfare. Accounting for environmental externalities in establishing the price that farmers pay for water decreases individual farm profits while increasing social welfare (Bierkens et. al., 2024). Bierkens et. al. (2024) proceed to test their model by setting parameters for the amount of groundwater pumped as well as hydrological features relating to groundwater levels (i.e. recharge, surface water characteristics, etc.) that likely occur in a semi-arid region. Results show the model that accounts for environmental externalities while maximizing social welfare leads to higher projected groundwater levels over time compared to alternative scenarios. Also modeling the value and demand for groundwater, Strand (2010) emphasizes that the cost to pump groundwater should be greater than its marginal cost when profit is maximized to account for the externalities presented when pumping.

Some studies use various groundwater use estimation methods including hydrologic and demand-based modeling, remote sensing estimation with field-level evapotranspiration, water table fluctuation models, land cover estimation, and electricity use as a proxy for groundwater pumping (Brookfield et. al., 2024; Alam et. al., 2023; Martindill et. al., 2021; Burlig et. al., 2021; Wang et. al., 2020; Hurr and Litke, 1989). However, the usefulness of these methods requires different levels of data of which availability varies by region, and rural areas are no exception to data challenges that make these estimation efforts particularly challenging (Brookfield et. al., 2024). This study takes a different approach by using regression analysis to analyze changes in groundwater levels. This method incorporates factors that directly relate to groundwater use to determine whether there is a relationship between them and DTW changes over time, while exploring whether this approach is useful when faced with groundwater use estimation challenges.

There is much to say about changes in groundwater conditions in large municipalities and agricultural districts; however, little research can be found on this topic in small rural communities due to the lack of pumping data. This study aims to add to the sparse literature by looking at rural areas in Arizona. Preliminary work finds significant statistical relationships between groundwater levels and economic, demographic, climatic, and regulatory factors in portions of Arizona’s Santa Cruz and San Pedro watersheds. This project will refine and extend this work into other rural regions of Arizona over the period 2010 – 2021.

Chapter 3: Theoretical Model

Irrigated agriculture is the dominant water use in the state of Arizona, especially in the study areas included in this thesis. Of all water supplied in Arizona, 74% is used by irrigated agriculture (ADWR, n.d.a). In 2015, 4,400 million gallons per day were used for irrigated agriculture in Arizona, of which 42.9% came from groundwater sources (Pullen, 2023). To understand groundwater use behavior at the sub-basin level, one must first elaborate on the profit-maximization decisions of individual farmers. The theoretical model discussed in the next section follows discussion in Griffin (2005).

3.1 Individual Producer Profit-Maximization Model

First, the assumption is made that an individual farm in the study area is profit maximizing. To produce output, y, a specified level of groundwater, w, is required as an input with the assumption that any-nonzero amount of water makes a profit. The farm likely has other fixed and variable inputs used in production of y. Fixed variables can include land, buildings, and equipment. Variable inputs include seed types and fertilizer. Altogether, the individual farm's production function is as follows.

$$y = f(w, x_1, x_2, \dots x_i \dots, x_n) \forall i \in N$$

Where different levels of inputs are chosen simultaneously to both maximize profit and minimize costs, the former guarantees the latter.

When analyzing the relationship between groundwater, as an input, and output, ceteris paribus, economic theory informs that a rational farmer chooses a level of groundwater to use where the marginal product ($y' = \frac{\partial f}{\partial w}$) is greater than or equal to zero. To visualize, the production function for an individual farm in Figure 2 shows that a profit maximizing farm ultimately chooses to use groundwater at w^* to achieve a profit maximizing level of output, y^*.

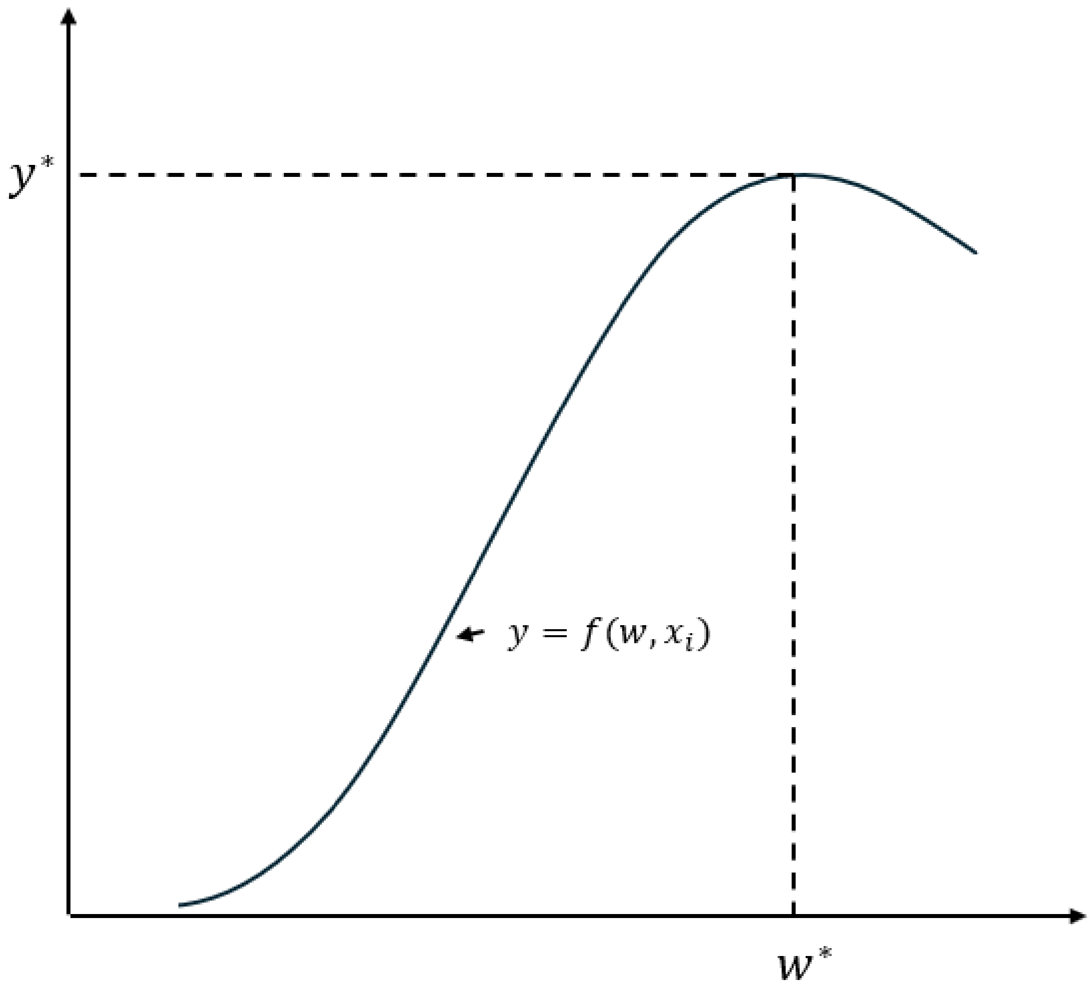

Figure 2. Individual Farmer's Production Function with Water Input, Ceteris Paribus

We assume the farm's output, y, sells for a constant per unit price, p_y. The firm also purchases x_i inputs for the constant per unit cost of p_{x_i}. The price for pumping groundwater is not necessarily constant. Like Griffin (2005), the cost of water, denoted $c(w)$, is assumed to increase as more water is used. Thus, it follows that

$$\frac{\partial C}{\partial w} > 0$$

However, if the firm pays one price for water, p_w, then $c(w) = p_w w$.

Accounting for the price received for the farm's output and costs for inputs, the profit maximization function is as follows:

$$\max\ \pi = p_y f(w, x_i) - c(w) - \sum p_{x_i} x_i$$

Where p_y is the output price, x_i are inputs excluding water, and p_{x_i} are the prices for each non water input. Each input must be maximized to achieve maximum profit, π. To do this, first order conditions (FOC) are set where the first derivative of the profit function is taken with respect to each input, w and x_i. Thus, the FOC are as follows.

$$\frac{\partial \pi}{\partial w} = \frac{\partial\left[p_y f(w, x_i) - c(w) - \sum p_{x_i} x_i\right]}{\partial w}$$

and

$$\frac{\partial \pi}{\partial x_i} = \frac{\partial\left[p_y f(w, x_i) - c(w) - \sum p_{x_i} x_i\right]}{\partial x_i}$$

Where setting each equation to zero and simplifying equates to

$$\frac{\partial \pi}{\partial w} = p_y f_w - c'(w) = 0$$

And

$$\frac{\partial \pi}{\partial x_i} = p_y f_{x_i} - p_{x_i} = 0$$

Therefore, solving for both w and x_i yields the optimal input values w^* and x_i^*.

Observe that

$$\frac{c'(w)}{f_w} = \frac{p_{x_i}}{f_{x_i}}$$

This occurs only when profit is maximized. From here, one can rearrange to find the technical rate of substitution,

$$\frac{f_{x_i}}{f_w} = \frac{p_{x_i}}{c'(w)}$$

Which equals the ratio of input prices and marginal cost of water.

Furthermore, when rearranging the FOC equation for w, and plugging in the optimal value for w, w^*, one can obtain the following.

$$p_y f_w = c'(w^*)$$

This shows the marginal product of water is equal to its marginal cost, only when profit is maximized. Hence,

$$MVP_w = MC_w.$$

This relationship holds true for all inputs in a profit-maximizing farm's production function.

The profit-maximizing model only results in a socially optimal quantity of groundwater use if the price that farmers pay per unit of water includes the full social costs of their groundwater use. Bierkens et. al. (2024) develop a model that identifies the conditions for maximizing social welfare, instead of maximizing farmer profit. They find that including environmental externalities in the water price used in the model decreases farm water use, increases social welfare and decreases individual farm profits. The following section discusses the consequences of failure to incorporate full social costs in the price of water, neglecting to account for environmental externalities.

3.2 Optimal Groundwater Use to Maximize Social Welfare

Maximizing social welfare entails accounting for non-water inputs, water as an input, prices for water and other inputs and the social and environmental externalities of extracting that water. This section follows Bierkens et. al. (2024) to develop a conceptual model that identifies optimal groundwater use to maximize social welfare in a groundwater sub-basin. Such models can better inform drivers for groundwater demand. Maximizing social welfare is important to consider when groundwater withdrawals exceed natural recharge, increasing groundwater depletion and leading to environmental externalities. Groundwater withdrawal externalities include limiting water availability for other water users, negative impacts on nearby streams and wetlands, and reducing aquifer storage capacity (Bierkens et. al., 2024).

To account for environmental externalities, one must include these externalities in the overall social cost of groundwater withdrawal. Recall the cost for water as an input in the individual farm profit function, $c(w) = p_w w$. Adding the environmental externalities, we get the following cost equation.

$$c_e(w) = p_w w + \tau w$$

Where $c_e(w)$ is the cost for water including environmental externalities from withdrawal and τ represents the externality cost. While τ generally will be a function, τ (w), in this illustrative conceptual model it is treated as a constant monetary amount. See Bierkens et. al. (2024) for more sophisticated models of externalities related to water use that account for interactions between τ and various hydrologic factors.

The equation above can be simplified to the following:

$$c_e(w) = w(p_w + \tau)$$

Now that the cost for water has been redefined to include externalities, we can construct a simple social welfare maximization equation. Maximizing social welfare means to maximize total Social Net Benefits (SNB) related to agricultural groundwater pumping in a sub-basin . SNB maximization considers individual farm profit functions, with water users paying a price per unit that reflects the environmental externalities. The social welfare maximization equation below is simplified to apply to decisions in a single time period. See Bierkens et. al. (2024) for examples of dynamic models.

The SNB maximization problem for water users in a sub-basin in a particular year is as follows, given there are i inputs for each of the j water using entities:

$$\text{SNB} = \sum p_{y_j} f(w_j, x_{ij}) - \sum \left[C_e(w_j) + p_{x_{ij}} \right]$$

Where $i = 1 \rightarrow N \; and \; j = 1 \rightarrow M$. Maximizing each input for each water using entity to achieve maximized social welfare, we compute the following FOC’s.

$$\frac{\partial \text{SNB}}{\partial w_j} = p_{y_j} f_{w_j} - c_e'(w_j) = 0$$

And

$$\frac{\partial \text{SNB}}{\partial x_{ij}} = p_{y_j} f_{x_{ij}} - p_{x_{ij}} = 0$$

Where

$$c_e'(w_j) = p_{w_j} + \tau$$

Solving for w_j^* and x_{ij}^* yields the optimal values for water and all other inputs. When rearranging the FOC equation for w_j and plugging in the optimal value, we find the following.

$$p_{y_j} f_{w_j^*} = p_{w_j^*} + \tau$$

This optimality condition, the marginal product of water is equal to its social marginal cost, provides for maximizing SNB. When environmental externalities are not included into the price that farmers pay for water use, farm profits are larger, SNB are smaller and groundwater extraction will be larger, compared to the case in which the environmental externalities are incorporated into water prices.

Arizona does not attempt to charge water users for the negative environmental externalities that come from pumping groundwater. Only nominal fees are charged to water users inside AMAs and those with specific wells statewide (these wells pertain to recharge and non-irrigation personal benefit) to fund groundwater administration and conservation programs (ADWR, 2022b). All groundwater users, statewide, do pay for pumping costs through paying for electricity or other energy sources used to pump groundwater. These pumping costs are often cheaper than costs for using renewable alternatives to groundwater (ADWR, 2022c). Those using groundwater for irrigation outside of AMAs are not required to pay fees beyond the electricity costs to pump.

3.3 Drivers of Sub-basin Water Demand

Understanding drivers of sub-basin water demand can help build a conceptual model that investigates whether groundwater level changes reflect signals of these drivers over time.

3.3.1 Agricultural Water Demand

The demand for irrigation water in agriculture is driven by water prices, input prices, expected crop choice, and environmental characteristics, as described in Schoengold (2006). Also a driver of agricultural water demand is whether water extraction or agricultural expansion regulations are in place. This section discusses the elements that pertain to individual farm water demand, which will be incorporated into a sub-basin aggregate demand function.

The cost of water is directly related to prices or fees charged per unit of water pumped plus the energy cost it takes to pump it from the ground (Alam et. al., 2023; Martindill et. al., 2021; Burlig et. al., 2021; Wang et. al., 2020; Hurr and Litke, 1989). In most regions of the world, groundwater users pay for the energy used to pump groundwater but there are no additional costs charged to reflect externalities associated with groundwater pumping. Energy prices can vary over space and time, depending on the energy provider in specific areas as well as other factors. There can be high barriers to obtain this private data, however, trend controls can be incorporated into the analysis to control for changes in energy prices over time in each sub-basin and is discussed further in Chapter 5. The same is true for other input prices that may be time dependent only, but the same in each sub-basin, such as alfalfa seed prices, which can be controlled for by using year fixed effects.

Expected crop choice varies both spatially and over time. Farmers can also choose to fallow their land, which requires significantly less water, if any at all. Common crops grown in the study area include alfalfa, cotton, and tree crops, which are relatively water intensive. The amount of planted acreage, regardless of crop choice, can be a major driver for water demand. Thus, a measure for land area can indicate groundwater irrigation intensity in each sub-basin over time.

Environmental factors, such as temperature and precipitation, can alter irrigation patterns. Hotter temperatures increase evapotranspiration, causing plants to require more water. Less precipitation also requires more water to be irrigated to meet each crop's water demand. Both scenarios often move together (i.e. hotter years on average have less precipitation on average) and incentivize more groundwater pumping in the study area. In this study, average yearly temperature and precipitation in each sub-basin are accounted for.

Groundwater regulation and irrigation non-expansion requirements can change groundwater demand over time. Limits on agricultural expansion can lessen water demand and alter farmers' crop choice decisions. Best management practices implementation can also allow farmers to increase their water use efficiency. This study accounts for whether regulation is in place in a sub-basin. This study also accounts for the relationship between regulation and the amount of irrigated acreage planted.

3.3.2 Municipal Water Demand

Although a significantly smaller proportion of total sub-basin water demand, municipal water needs are still relevant to this study. Residential, commercial, and industrial water demand is found to be highly price inelastic, so the effect of water cost on municipal water users is not considered in the theoretical model (Foster et al., 2015; Hendricks et al., 2012; Alhassan et al., 2020; Sukcharoen et al., 2020; O'Donnell et al., 2018). However, the amount of water used may be driven by how many people demand it, and their ability to make choices on how to use it (through investing in water efficient appliances or water-intensive landscaping). Therefore, the number of households in each sub-basin as well as per capita income is incorporated.

Increases in new housing in a sub-basin can be indicative of expected water demand and the adoption of new, more water efficient appliances. Sub-basins with increases in per capita income can provide insight into water use behavior by indicating greater ability to choose how to use groundwater water (i.e. landscaping choices, installing pools, etc.). Both aspects are further elaborated in Chapter 5.

3.4 Sub-basin Water Demand Model

A conceptual model for water demand at the sub-basin level is now defined since drivers of this demand have been examined. Water demand (w_{it}) in each sub-basin i and time t is described as a function of planted acreage ($Plant_{it}$), temperature ($Temp_{it}$) and precipitation ($Precip_{it}$), number of households ($House_{it}$), income ($PerCapInc_{it}$), and regulation status ($Unreg_i$) shown below.

$$w_{it} = f(Plant_{it}, Temp_{it}, Precip_{it}, House_{it}, PerCapInc_{it}, Unreg_i)$$

This model guides the econometric analysis in Chapter 5.

Chapter 4: Data

4.1 DTW

The dependent variable is DTW as a measure for groundwater level. DTW measures the distance from the ground surface to the top of the water table in a particular well. Measures for each well in the sub-basins of interest are found on the ADWR Wells 55 Registry.

The ADWR measures DTW for individual wells multiple times a year. Well measurements used for analysis in a particular year were those taken only in winter months (October – April), and then averaged to a yearly value in the analysis. The number of measurements for each well in winter months varies by each year and well. Yearly averaged DTW values for individual wells that are missing for one or two consecutive years are then estimated using linear interpolation. Wells with missing measurements for more than two consecutive years from 2010 to 2021 are dropped from the analysis. DTW measures for each well are then averaged by year in each sub-basin. Further elaboration for choosing individual wells to be included in the DTW calculation can be found in Appendix A2.

4.2 Climate

Mean monthly precipitation and temperature values are from PRISM Climate Group Gridded Dataset at a 16 km^2 spatial scale. The mean monthly values are spatially averaged in each sub-basin. Those measurements are then averaged up to the yearly time scale. Precipitation is measured in inches and temperature in Celsius.

Prior studies recommend that temperature and precipitation be analyzed separately as opposed to together through an index such as the Standardized Precipitation and Evapotranspiration Index (SPEI), because they are known to interact with groundwater in opposite ways (Ndehedehe, 2023; Crimmins, 2022; Condon, 2020). Higher precipitation is found to increase water quantity recharged into an aquifer, thus increasing groundwater levels (Ndehedehe, 2023). On the other hand, higher temperatures increase evaporation which inhibits groundwater recovery (Condon, 2020). Consequently, analyzing temperature and precipitation separately can be more informative when it comes to studying groundwater level changes over time (Crimmins, 2022).

4.3 Census Data

The number of households and income levels can give insight into water use behavior. Both aspects can have differing impacts on water use. More households in an area may indicate more water is being used while those with higher income can invest in higher water demanding amenities such as pools and higher water use landscaping, both of which may lead to lower groundwater levels. On the other hand, newer housing may have newer, more water use efficient appliances (Abraham et al., 2020; Richter et. al., 2020), and those with higher income have greater ability to choose lower water use landscaping amenities.

Population was explored in preliminary analysis to be used instead of households. However, changes in the number of households over time seem to represent larger changes in groundwater use behavior. For example, water demand likely increases more significantly when one household of four moves into an area versus one person. Thus, the variable for number of households is chosen as a better indicator for groundwater use behavior changes.

Housing and income characteristics are sourced from the US Census Bureau's American Community Survey (ACS). Yearly values are calculated using a 5-year moving average. Data is chosen at the census tract level, the smallest spatial scale possible to get yearly measurements. The size and shape of census tracts are determined based on population density. Census tracts are drawn to fit within county boundaries. Geographic Information Systems (GIS) are used to choose which census tracts overlay the study areas, so the population accounted for is most relevant. Tracts that overlayed sub-basin boundaries but did not have over 50% of human activity within the intersection are excluded. This method is used to avoid accounting for human activity occurring outside the sub-basin of interest, at least as much as possible since census tracts do not perfectly overlay sub-basin boundaries.

An important consideration is that tract boundaries were changed in 2020 to adjust to population changes, as is the practice at the start of every decade. The outcome of this can be seen as slight drops in each average value for housing units, shown in Figure A1. Average number of households and per capita income were extracted as yearly values at the tract level and averaged by sub-basin.

4.4 Land Cover

The US Cropland Data Layer’s CropScape is a raster file derived using remote sensing imagery classification techniques. It is released yearly with each 30m pixel representing a particular land cover category. The file is used along with Python to extract pixel counts fitted to the sub-basin boundaries using ArcGIS Pro. Pixels are counted for each of the land cover variables by sub-basin by year. The sums are then converted into acres using the conversion factor 0.222394.

The land cover variable used in the analysis is planted acreage. This entails summing each individual crop acreage amount resulting in total amount of cropland cover in each sub-basin. Land use characteristics can give good insight into water use. Since the sub-basins in the study area are all groundwater dependent and yearly rainfall is low, planted acreage is groundwater irrigated. This aspect can be indicative of how agricultural activity interacts with groundwater levels over time. The more planted acreage in a sub-basin likely relates to more water extracted from the ground, especially since a majority of crops planted in this region are relatively water intensive, such as alfalfa, cotton, and tree crops as seen in Table 2 below. The perennial crop, alfalfa, covers the largest amount of land area in most sub-basins. Furthermore, it is likely that perennial crops like alfalfa and tree crops use more water on an annual basis than cotton.

Sub-basin	Cotton	Major Grains	Other Crops	Tree Crops	Alfalfa
Benson	210	451	16	139	1078
Douglas	299	11534	498	3381	4022
Gila Bend	835	10097	1970	3	41304
Harquahala INA & Hassayampa	2077	3423	337	1	30804
SCAMA North	77	33	1	229	617
SCAMA South	62	47	0	94	265
Willcox	2145	37033	3913	5756	9628
Sierra Vista	9	33	4	231	101
Avra Valley	11255	5286	27	898	3988
Butler & McMullen	270	7858	5554	61	15481

Valley, Ranegras Plains					
Eloy	53660	21780	4149	1582	35747
Maricopa-Stanfield	13130	25256	8846	915	35814
Rainbow Valley	24	1878	655	0	3722

Table 2. Distribution of Crop Types (acres) in each Sub-basin Based on 2021 CDL Data

4.5 Groundwater Regulation and Recharge

Each AMA has specific goals unique to their economic activity when it comes to groundwater pumping regulation (ADWR, n.d.d). All of them have in place conservation and best management practices programs that limit agricultural expansion and increase water use efficiency (ADWR, 2020). In the study area, the Harquahala INA and Douglas AMA (previously Douglas INA until 2021) restrict irrigated cropland expansion throughout 2010 to 2021. Eight out of fourteen sub-basins in the study area are groundwater regulated.

Active groundwater recharge projects occur in Harquahala & Hassayampa, Southern portion of the Santa Cruz AMA, Avra Valley, Eloy, Maricopa-Stanfield, and Sierra Vista sub-basins, each in different years throughout the study period. Records of active recharge projects are documented by ADWR (ADWR, 2024). Users deliver water to these facilities to be stored for later use, while policies at these Underground Storage Facilities and Groundwater Savings Facilities require that up to 50% of the water stored be recharged into the aquifer (Bernat, 2024).

Recharge projects and groundwater regulation share the goal to increase groundwater levels. For the analysis they are indicated as dummy variables. The number one designates a sub-basin is not groundwater regulated. Moreover, active recharge projects are assigned a number one for each year in each sub-basin they are active.

4.6 Summary Statistics

Table 3 describes mean and standard deviation for each variable in the panel data set from 2010 to 2021 in each sub-basin. For instance, the mean precipitation for Avra Valley is the average of all yearly means over the study period. The northern Santa Cruz AMA sub-basin has the highest per capita income on average while Gila Bend has the lowest by a significant amount.

Meanwhile, Gila Bend also has the lowest mean number of housing units, yet third highest cropland acreage, with the highest being Eloy with an average of 127,622 acres over time. Moreover, DTW is significantly smaller in the north and south portions of the Santa Cruz AMA compared to the levels in other sub-basins. All sub-basins are comparable in temperature and precipitation levels on average over time. A more detailed table of summary statistics can be found in Appendix A4.

	DTW (Acre Ft.)		**Temperature (C)**		**Precipitation (in)**	
Sub-basin	**Mean**	**St. dev.**	**Mean**	**St. dev.**	**Mean**	**St. dev.**
Avra Valley	245.64	4.96	19.80	0.49	1.07	0.26
Butler, McMullen, & Ranegras*	340.84	5.27	20.87	0.53	0.56	0.14
Benson*	241.44	5.19	17.60	0.51	1.14	0.26
Douglas	190.00	10.10	17.32	0.57	1.08	0.25
Eloy	239.24	3.55	21.74	0.51	0.72	0.19
Gila Bend*	325.16	22.42	22.68	0.46	0.55	0.13
Harquahala INA & Hassayampa	217.01	4.64	21.51	0.56	0.60	0.16
Maricopa Stanfield	314.16	5.74	22.18	0.52	0.59	0.15
Rainbow Valley	365.18	9.39	22.27	0.54	0.59	0.15
SCAMA North	66.79	1.30	17.82	0.45	1.36	0.28
SCAMA South	94.17	1.83	17.43	0.43	1.38	0.29
San Simon Valley*	197.51	10.97	16.71	0.49	1.05	0.23
Sierra Vista*	227.03	3.62	16.99	0.52	1.29	0.30
Willcox*	264.00	12.24	16.16	0.53	1.25	0.27
	Planted Acreage (Acres)		**Per Capita Income (USD)**		**Housing Units**	
Sub-basin	**Mean**	**St. dev.**	**Mean**	**St. dev.**	**Mean**	**St. dev.**
Avra Valley	21,990	1,587	22,352.06	2,369.90	1,892	88
Butler, McMullen,	24,586	6,840	25,772.86	4,113.00	1,812	205

& Ranegras*						
Benson*	1,523	470	23,886.50	3,356.59	2,052	215
Douglas	16,680	1,911	16,851.72	1,846.78	1,467	118
Eloy	127,622	5,736	18,425.70	2,339.49	1,780	146
Gila Bend*	49,242	7,174	7,681.20	861.63	523	31
Harquahala INA & Hassayampa	37,773	4,442	23,917.57	1,618.33	1,861	239
Maricopa Stanfield	86,391	3,096	29,668.07	1,784.95	1,675	40
Rainbow Valley	4,446	1,815	24,026.58	5,438.16	1,844	396
SCAMA North	970	343	32,871.42	4,376.04	1,678	144
SCAMA South	553	169	17,521.43	2,047.94	1,573	155
San Simon Valley*	14,882	2,899	20,668.08	1,379.98	1,150	236
Sierra Vista*	525	303	28,745.19	2,145.61	2,096	139
Willcox*	51,071	4,963	20,651.83	1,425.33	1,442	92
*Groundwater not regulated						

Table 3. Summary Statistics

4.7 Trends

Figure 3 and 4 shows percent changes in DTW from 2010 for each sub-basin. The former presents only those sub-basins that have groundwater regulation in place while the latter shows groundwater unregulated sub-basins. The y-axis is flipped to better relate DTW percent changes with groundwater levels since increasing DTW means decreasing groundwater levels and vice versa. Decreasing trends in groundwater levels can be seen in most unregulated sub-basins. Gila Bend shows the largest groundwater level percent decreases since 2010, followed by Willcox and San Simon Valley. Consistent increases in groundwater levels over the entire study period are seen in Avra Valley and Maricopa-Stanfield. Both are sub-basins with groundwater regulations. The Santa Cruz AMA shows changes from year to year but no significant trends in either direction. Sierra Vista and Benson show a seemingly increasing trend after 2016. Also among the regulated sub-basins are those that show decreasing trends, including Douglas, Rainbow Valley, Harquahala INA and Hassayampa (noted as HarqHass in figure 3), and Eloy.

The varying trends in groundwater regulated sub-basins highlight the differences between each sub-basin that impact groundwater aquifers, demand and regulation.

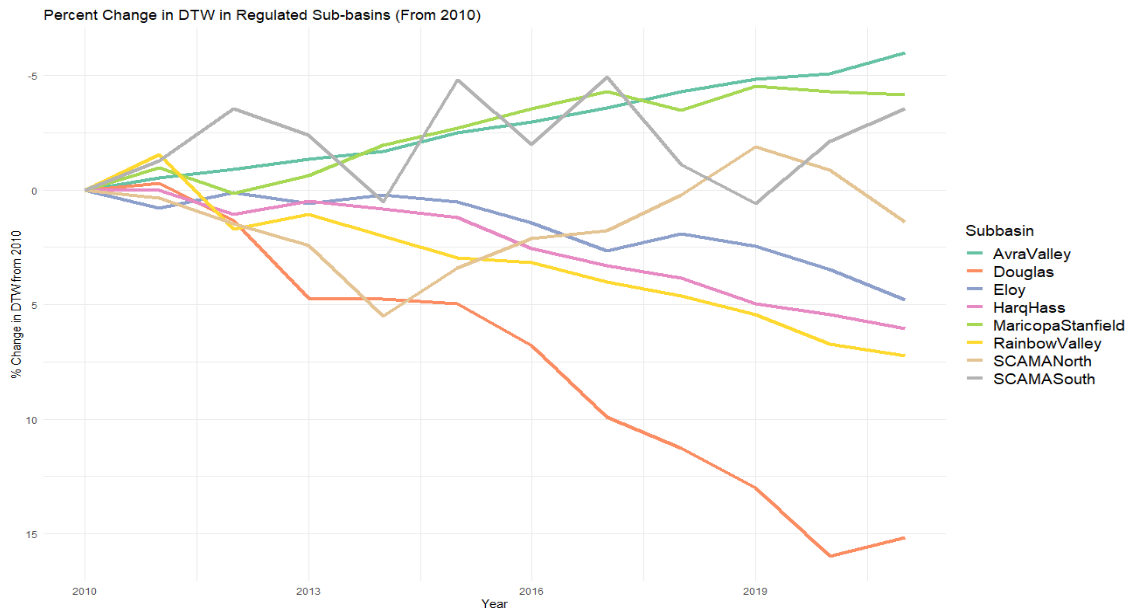

Figure 3. Percent Changes in DTW Regulated Sub-basins Since 2010

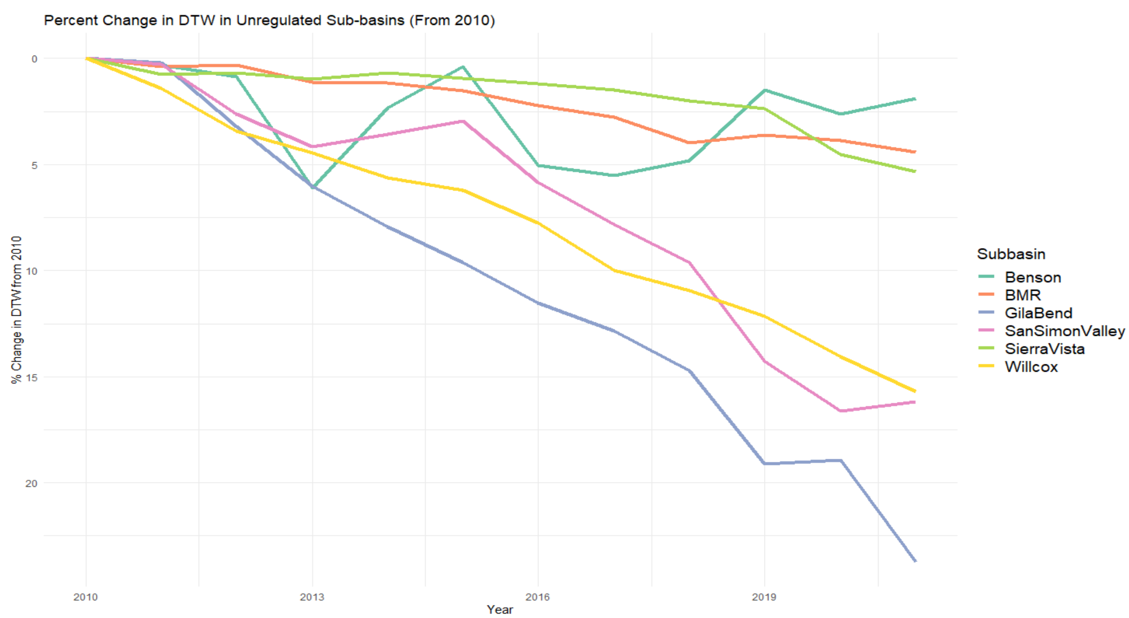

Figure 4. Percent Changes in DTW Unregulated Sub-basins Since 2010

Figure 5 and 6 show planted acreage percent changes over time since 2010 within each sub-basin. Once again, the figures are split between regulated and unregulated sub-basins. Clear increasing trends can be seen in Willcox, BMR (Butler Valley, McMullen Valley, and Ranegras Plain) and Gila bend, which are all unregulated sub-basins. Most regulated sub-basins show fluctuations but no major increases over time, while Eloy shows significant decreases in planted acreage.

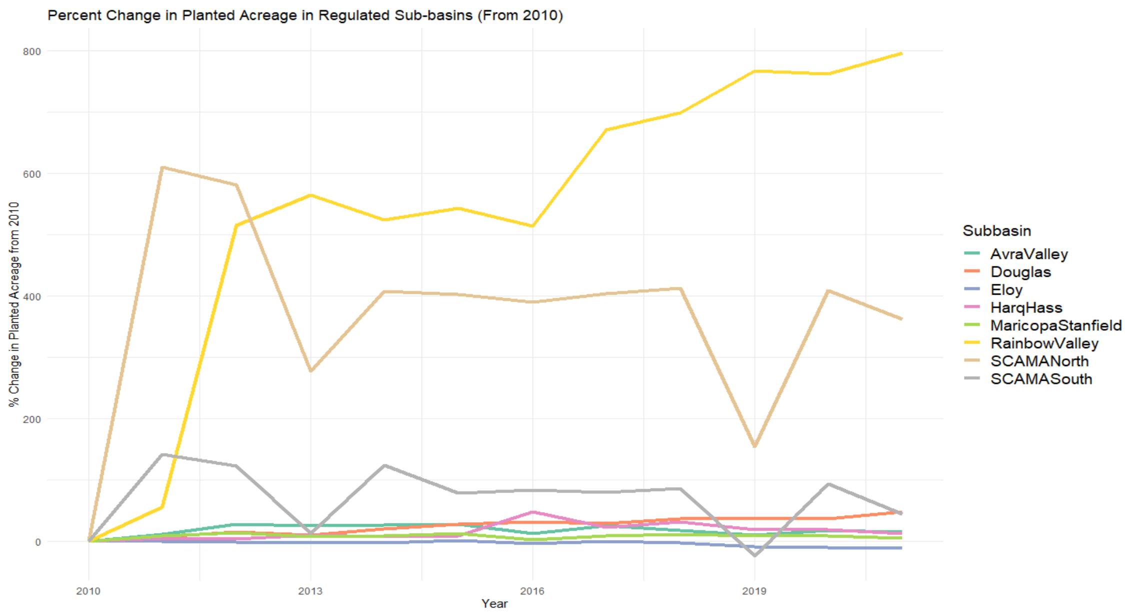

Figure 5. Percent Changes in Planted Acreage Regulated Sub-basins Since 2010

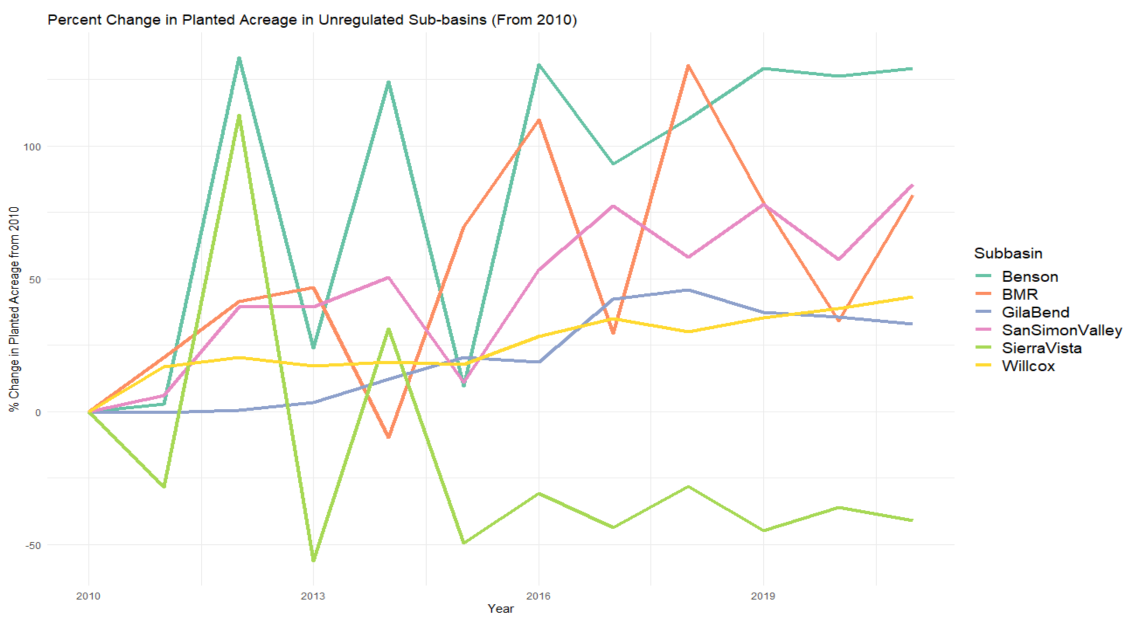

Figure 6. Percent Changes in Planted Acreage Unregulated Sub-basins Since 2010

Trends in sub-basin housing units, temperature and precipitation, along with descriptions of trends, can be found in Appendix A3.

Chapter 5: Econometric Models Estimated

5.1 Choosing Most Suitable Econometric Model

A few econometric model options, as well as the thought process for choosing one, are discussed to analyze the relationship between groundwater levels and economic, climate, and regulatory factors over time.

When it comes to working with panel data, the first models considered are One-way and Two-Way Fixed Effects (FE) models. A One-Way FE model demeans each variable at the sub-basin level, a process of subtracting the sub-basin mean over time of each variable from each observation on the same variable within that sub-basin, while a Two-Way FE model is the same with added year dummy variables. A FE regression could be advantageous in the analysis because the sub-basins are hydrologically and economically heterogeneous and I am primarily interested in investigating relationships over time within each sub-basin. However, one aspect that this model does not distinguish is groundwater regulation's relationship with DTW. This is because regulation status is constant throughout the study period, and the demeaning process of the FE model equates all observations on time-invariant variables to zero. To be able to use a FE model while accounting for regulation, one could split the data into regulated and unregulated sub-basin groups and run two separate models. One drawback of this method is once the data is split, the number of observations for each model is quite small (96 and 48 observations for regulated and unregulated subsets), which may hinder the law of large numbers consideration that would allow the assumption that the data is normally distributed. An interaction variable could instead be incorporated between regulation status and another continuous variable, however the effect of regulation on its own would remain unreported. There is also the issue that some variables, such as cropland, in regulated sub-basins do not vary much over time due to conservation and best management practices standards. In this case, a FE model might lead to imprecise results (Wooldridge, 2010). Therefore, a model that does not demean the data needs to be considered to allow for time-variant and invariant variables to be included.

The Pooled OLS (POLS) Model discussed in Wooldridge (2010) analyzes relationships over time within each sub-basin, and can incorporate time constant explanatory variables, such as groundwater regulation status in this case. Regarding the relationships being studied, there are unobservable effects that introduce endogeneity issues if not controlled for. These are factors that vary across sub-basins but not over time, such as topography, groundwater flow direction, and aquifer depth, and also aspects that vary across time but have the same effect in each sub-basin, such as crop prices, economic shocks, and Covid-19. There are also other random effects (RE) that link the relationships between some of the variables of interest and DTW. For example, regulation status does not directly change groundwater levels. Instead, it puts plans in place that attempt to influence human behavior regarding groundwater extraction in both agricultural and urban settings. Consequently, what goes unobserved includes attitudes towards regulation which may influence water use behavior (i.e. shorter showers, using the dishwasher, changing irrigation times/patterns, etc.).

There are tools one can use to control for unobserved heterogeneity across space and time (Mundlak, 1978 and Wooldridge, 2010). These can be year effects (dummy variable for each year) to control for time aggregate effects (i.e. those that impact DTW in each sub-basin the same), as well as heterogeneous time trends and unit specific time averages to control for unobserved shocks over time in each sub-basin and unobserved heterogeneity among sub-basins regardless of time (Wooldridge, 2010; Mundlak, 1978; Wooldridge, 2021). Mundlak (1978) introduced the use of correlated random effects (CREs) as unit specific time averages and time specific unit averages to control for time constant unobservable characteristics that vary over space and space constant unobservable characteristics that vary over time. Unit CREs average each explanatory variable in each group (in this case sub-basins) over time. This averaging technique provides a time constant value for each observation that only differs for each group. Time CREs average each explanatory variable in each year across all groups. When incorporating these CREs into a POLS model, Wooldridge (2021) finds estimators equate to a Two-Way FE model, if one could control for all the unobservable effects in linear cases with balanced panel data (Wooldridge calls this model a Two-Way Mundlak Model). This paper only utilizes the unit CRMs along with trend and year dummies. Since the data in this study is balanced, and with the assumption that relationships are linear, the POLS model allows us to obtain policy intervention's relationship with DTW while also obtaining unbiased and consistent estimates that are close to a Two-Way FE model (Wooldridge, 2021).

In this paper, a POLS model is used incorporating controls for unobservable aspects that relate to DTW. These controls include (1) a linear trend specification, (2) year effects, and (3) unit CREs. (1) Controls for unobserved trends that vary across time and differ in each sub-basin, (2) controls for aggregate shocks over time and (3) controls for time-constant differences between sub-basins.

5.2 Econometric Model

A pooled OLS model is used because it allows time-varying and unvarying variables to be included. This model is best because we are interested in analyzing interactions between DTW and climate and economic variables over time within each sub-basin, while also incorporating the groundwater regulation aspect, which is constant throughout the study period.

An endogeneity issue is likely present due to unobserved heterogeneity across time, space, and both simultaneously. To account for this, trend and year effects are included as well as sub-basin specific time averages (unit CREs) as discussed in Mundlak (1978) and further in Wooldridge (2021). Trend effects are specific to each sub-basin and provide a variable that counts each year starting in 2010, hence controlling for unobserved trend effects that vary across sub-basin and over time. Dummy variables for each year are also specified in the model to control for aggregate time effects that do not vary across sub-basins (Wooldridge, 2010). Sub-basin specific time averages calculate the mean over time for each explanatory variable in each sub-basin, thus controlling for factors that vary in each sub-basin but not over time.

Planted acreage likely behaves differently over time in groundwater regulated sub-basins. Since water conservation programs exist that limit agricultural expansion, cropland amount likely does not vary much over time in 8 of the 14 sub-basins; however, crop mix can change over time. To account for this difference in the model, an interaction between planted acreage and regulation status is included to isolate the relationship between DTW and planted acreage in unregulated sub-basins.

Fourteen sub-basins and 12 years makes 168 observations in the panel data set. While it would be better to have more years of data, some variables are limited in their availability. Land cover variables were first released in 2008 and yearly census data at the tract level did not become available until 2010. However, data over 12 years is sufficient for exploring correlations between DTW and the economic and climate variables. With time, these analyses will improve as more years of data are available.

Recall the conceptual model derived in Chapter 3 on sub-basin water demand.

$$w_{it} = f(Plant_{it}, Temp_{it}, Precip_{it}, House_{it}, PerCapInc_{it})$$

This model informs the empirical modeling for groundwater level changes in this section.

The pooled OLS regression model is specified as:

$$\begin{aligned} DTW_{it} = \rho + \alpha_t Year_t + \beta_1 Unreg_i + \beta_2 Plant_{it} * Unreg_i + \beta_3 Plant_{it} + \beta_4 Recharge_{it} \\ + \beta_5 PerCapInc_{it} + \beta_6 House_{it} + \beta_7 Temp_{it} + \beta_8 Precip_{it} + \sigma_i U_i + \pi_i T_{t+1} \\ + e_{it} \end{aligned}$$

Model components are as follows:

- DTW_{it} is DTW (feet) in sub-basin i in year t.
- ρ is the intercept.
- $\beta_{1,2,3,4,5,6,7,8}$ are variable coefficients.
- $\alpha_t Year_t$ represent dummy variables for each year.
- $Unreg_i$ is a dummy variable for whether sub-basin, i, has no regulations on groundwater.
- $Plant_{it}$ is the planted acreage in sub-basin i in year t.
- $\beta_8 Plant_{it} * Unreg_i$ is an interaction variable for planted acreage in unregulated sub-basins only in sub-basin i in time t.
- $Recharge_{it}$ is a dummy variable for whether sub-basin, i, has active recharge projects in year t.
- $PerCapInc_{it}$ is the per capita income in sub-basin i in year t.
- $House_{it}$ is a count of housing units in sub-basin i in year t.
- $Temp_{it}$ is mean annual temperature in sub-basin i in year t.
- $Precip_{it}$ is total annual precipitation in sub-basin i in year t.
- $\sigma_i U_i$ represents sub-basin time averages in area i.
- $\pi_i T_{t+1}$ is the number of years, plus one, that have passed since 2010 for each sub-basin i in year t.

- e_{it} is the error term in sub-basin i in year t.

Chapter 6: Econometric Results

The model results are presented in Table 4. All models use the same dependent variable, average DTW measured annually. Model (1) shows results without any year, time average, or trend effects, Model (4) shows results with all these effects included, and Models (2) and (3) show combinations in between.

The Breusch-Pagan Test is employed and suggests heteroskedasticity is likely present in each model, with chi-squared test statistics of 69.982, 80.766, 121.49, and 129.56 for Models (1) through (4), respectively, and all with p-values less than 0.001. Thus, robust standard errors (White's Standard Errors) are calculated to correct for this. Furthermore, planted acreage and per capita income are scaled by 100 acres and $1000.

Models (1) through (4) are presented to show changes in variable coefficients as more effects are added to control for unobserved heterogeneity across space and time. Looking at the R^2 in each model, time trend effects seem to account for the largest amount of variation compared to the other effects. In all the models, a substantial amount of variation in DTW is accounted for.

Coefficients on regulation status and the planted acreage interaction (planted acreage interacted with unregulated sub-basins) remain consistent throughout all four models. The results are expected as groundwater regulations aim to decrease DTW (i.e. increase groundwater levels). Thus, to see groundwater unregulated sub-basins are positively correlated with higher DTW is intuitive. In model 4, unregulated sub-basins have increasing DTW that is 55.86 feet larger than regulated sub-basins on average over study period. Roughly 56 feet is an economically significant difference as the largest DTW on average for a subbasin is about 340 ft. Most sub-basins in the study area have DTW within 200 to 300 feet over time on average. Moreover, increases in planted acreage in unregulated sub-basins correlates with increases in DTW, as all the cropland in the study area rely on groundwater for irrigation. Model 4 shows unregulated sub-basins where planted acreage increases 100 acres also increase in DTW by 0.11 feet larger than regulated sub-basins on average over study period. While a 0.11 difference seems small, 100 acres is a relatively small value to compare considering the average planted acreage among all subbasins over time is 31,304 acres.

Whether a sub-basin has an active recharge project in a particular year is negatively correlated with DTW in Model (4). Thus, sub-basins with recharge projects are also those with decreasing DTW that is 20-foot larger than those with no project. While a 20-foot difference is not large over 12 years, this variable is still associated with preventing DTW increases over time, which is economically significant. This recharge-DTW relationship is unsurprising since artificial recharge projects aim to decrease DTW (to replenish groundwater levels).

When excluding trend and time average effects, housing, temperature, and precipitation show significant correlations with DTW of the expected signs. Higher temperatures lead to increased evaporation which leaves less water to replenish groundwater levels while less rainfall inhibits natural groundwater recharge. Housing units are found to be positively correlated with DTW. However, once more controls are added, the statistical significance disappears as these variables are likely correlated with the trend and time average effects.

Irrigated acreage and per capita income show no significant correlations with DTW. Irrigated acres do not vary much in regulated sub-basins (8 out of the 14 units in the panel data set), and the variation that does occur is likely correlated with the planted acreage interaction.

Dependent Variable: DTW	Model (1)		Model (2)		Model (3)		Model (4)	
term	estimate		estimate		estimate		estimate	
Unregulated (yes = 1)	67.14	***	57.34	***	37.80	***	55.86	***
	(10.31)		*(10.48)*		*(11.08)*		*(15.49)*	
Planted Acreage * Unregulated	0.11	***	0.12	***	0.17	***	0.11	**
	(0.03)		*(0.03)*		*(0.03)*		*(0.04)*	
Planted Acreage (Scaled 100 Acres)	0.01		0.00		-0.010		-0.09	
	(0.01)		*(0.01)*		*(0.11)*		*(0.07)*	
Recharge Project (yes = 1)	-13.59		-10.44		-4.52		-19.57	*
	(9.07)		*(9.98)*		*(12.16)*		*(10.02)*	
Per Capita Income (Scaled $1000)	-0.49		-1.08		-0.28		-1.58	
	(0.88)		*(0.91)*		*(2.19)*		*(1.53)*	
Housing Units	0.062	***	0.07	***	0.005		-0.029	
	(0.01)		*(0.01)*		*(0.04)*		*(0.02)*	
Temperature	11.55	***	7.83	***	-0.98		-6.39	
	(1.43)		*(1.78)*		*(14.15)*		*(6.22)*	

Precipitation	-43.91	***	-106.24	***	2.37		-21.25	
	(14.92)		*(25.93)*		*(39.38)*		*(18.40)*	
(Intercept)	-621.06	***	-285.81	*	132.48		96.33	
	(107.46)		*(143.38)*		*(169.06)*		*(201.97)*	
Year Effects	No		Yes		Yes		Yes	
Unit-Specific Time Average Effects	No		No		Yes		Yes	
Time Trend Effects	No		No		No		Yes	
Observations	168		168		168		168	
R2	0.6956		0.7436		0.7931		0.9597	
Adj. R2	0.6803		0.7107		0.7583		0.9482	
F Stat (8;df=159) | (19;df=148) | (24;df=143) | (37;df=130)	45.42	***	22.59	***	22.83	***	83.66	***

*p<0.1;**p<0.05;***p<0.01

Table 4. Econometric Results

Chapter 7: Social and Environmental Justice in the Colorado River Basin

7.1 Introduction

About 40 million people reside in the Colorado River Basin (CRB) or rely on its water supply and benefit from the environmental amenities it provides (Richter et. al., 2024). Policy makers decide how to allocate the constrained water supply to meet demand for agricultural and municipal sectors, while ensuring good water quality, maintaining groundwater supply and conserving natural habitat. Moreover, multiple water disputes have been litigated and negotiated to decide water rights and build infrastructure for communities to utilize their rights, especially for those residing in tribal nations (Colby et al., 2005).

Groundwater is an important component in water discussion in the CRB. A large portion of communities in the CRB relies on groundwater to meet water demand. Underground infrastructure and air quality contribute to groundwater quality. Figure 4 from the Groundwater Foundation (n.d.) portrays common sources of groundwater contamination. Underground storage tanks (USTs), such as those holding gas or oil, are subject to leaks over time. Air pollution increases contaminants in surface water supply, hindering groundwater quality as water recharges into the surrounding aquifers (Groundwater Foundation, n.d.). Groundwater quantity is connected to surface water supply. For instance, aquifer depletion is found to negatively impact surface water supply, which is needed to support recreational activities and natural wetlands in the CRB (Condon, 2019). In addition, there are households in the CRB that lack complete indoor plumbing. Indoor plumbing includes hot and cold running water. For example, 40% of households in the Navajo Nation haul their water from groundwater wells outside the home (Tanana, 2021).

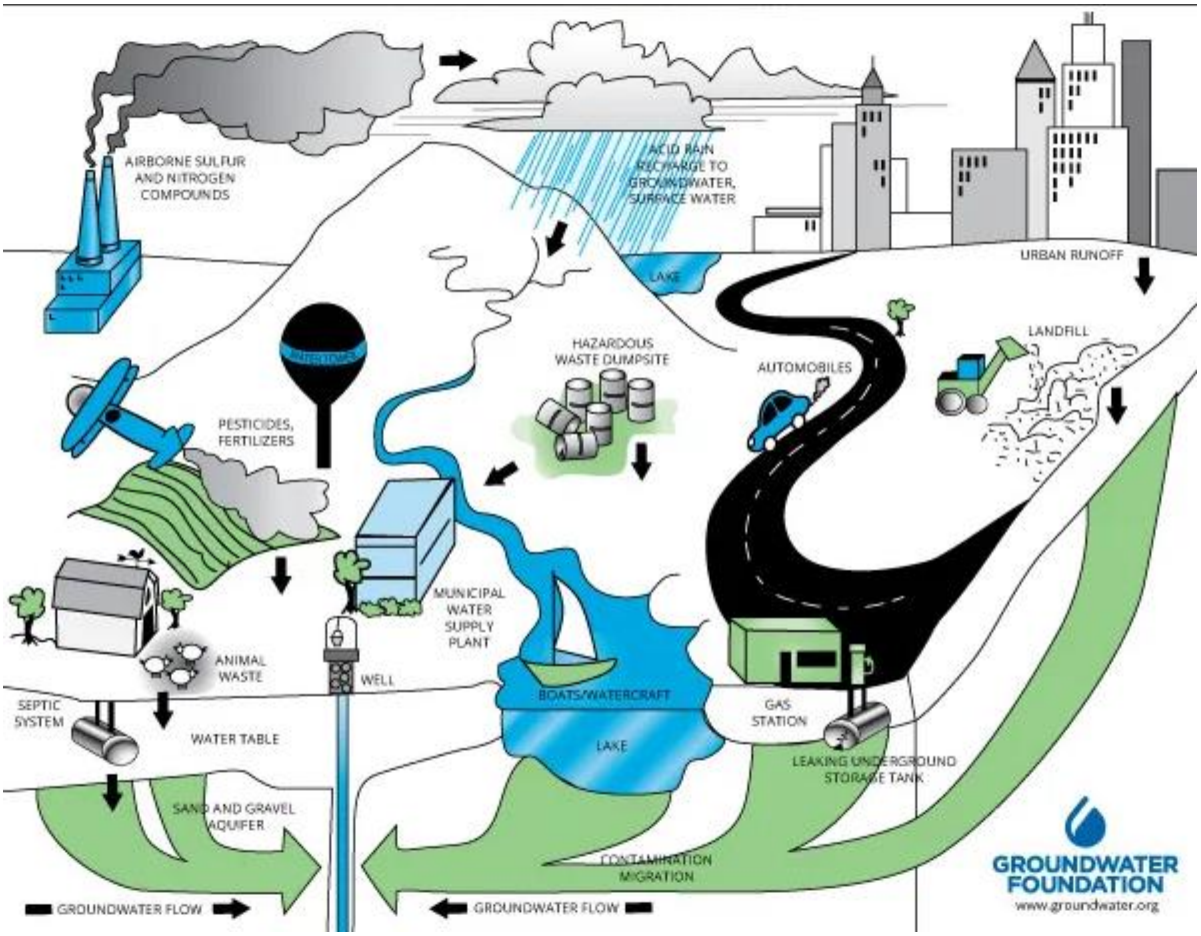

Figure 4. Sources of Groundwater Contamination

This chapter discusses several elements including air and water quality, access to green space or natural landscapes and complete water infrastructure for households. These elements are affected by decisions in the CRB regarding groundwater quality, allocations, and infrastructure and these effects are important for water user's well-being. Air pollution has been shown to impact human, animal and plant health, rain and soil quality and to contaminate groundwater (Groundwater Foundation, n.d.). Leaky USTs can release toxic materials that can contaminate nearby wells and other groundwater sources. Green and natural landscape requires water to maintain amenities such as trees, parks, and riparian habitat. Artificial surfaces, such as cement, roads and cropland, take space away from natural habitat, increasing temperatures and pollution sources and adversely affect mental health (Aram, et al., 2019; ADAA, 2023). Lastly, households with incomplete plumbing inhibit residents from utilizing their full water rights. Communities lacking clean air and water, green or natural landscape, and complete plumbing in households are defined by the Council on Environmental Quality (CEQ) to be "environmentally burdened".

While decisions have been made to mitigate pollution (i.e. the Clean Air and Clean Water Acts in 1970 and 1972), allocate ample amounts of water (i.e. through projects like the Central Arizona Project), and improve household plumbing, environmental burdens persist in the CRB (U.S. Executive Office of the President Council on Environmental Quality, 2022). This research examines whether the burdens relating to groundwater fall disproportionately on certain groups of people in the CRB. This chapter analyzes whether low-income households or racial and ethnic minorities experience higher environmental burden prevalence. More specifically, this chapter explores whether burdens that are known groundwater contaminators (i.e. air pollution and leaky USTs) affect some groups disproportionately. This chapter also explores burdens relating to how groundwater is allocated outside of meeting base level demand (i.e. maintaining natural space or investing in green landscape). Lastly this paper investigates who is more likely to live in areas with households lacking indoor access to water (i.e. households with incomplete plumbing). Incorporating multiple aspects that influence groundwater quality, allocations and access to explore disproportional adverse outcomes can help in guiding further water policy in the CRB in an environmental justice (EJ) context.

The geographic area covered in this analysis is the CRB and areas that receive water exported from the CRB. The analysis applies an OLS regression model to see whether correlations between these environmental burdens (lack of green space, air pollution levels, leaky USTs, and incomplete plumbing) and race, income, and education characteristics are statistically significant. This study adds to the literature by analyzing who is more likely impacted by burdens relating to groundwater and who receives less benefit from how water is allocated in the CRB and adjacent service areas. A newly released data set is utilized from the Council on Environmental Quality (CEQ) in 2022 that compiles environmental burdens, race, ethnicity, income, education, and health variables at the census tract level. The census tract data is spatially matched to the CRB, and econometric analysis is applied to the cross-sectional data. Results align with past literature finding disproportional relationships between minority groups and environmental burdens. Findings highlight the need for increased diversity, equity, and inclusion (DEI) in policy discussion regarding groundwater water supply and access in the CRB, as lacking DEI in water dialogues can lead to environmental injustice (Williams et. al., 2023).

The rest of this chapter is as follows: Chapter 7.2 discusses previous economic literature on EJ in broader contexts, chapter 7.3 summarizes and discusses the data used for the analysis, and chapters 7.4 and 7.5 explain the econometric method and present the results. Finally, the conclusions and policy implications are discussed in Chapter 8.

7.2 Literature Review

EJ literature connects low income, less educated and racial and ethnic minorities with environmental burdens in the United States and around the world. Income at age 35 for those who grew up in low-income families widely varies across the United States (Chetty et. al., 2018). Nonetheless, racial and ethnic minorities are found to be negatively associated with upward mobility (Chetty et. al., 2020). In parallel, low-income households and individuals face higher air pollution incidence, Safe Water Drinking Act violations, vulnerability to natural disaster, and incomplete plumbing prevalence (Miranda et. al., 2011; Kathuria and Khan, 2007; Jorgenson et. al., 2020; Kodros et. al., 2022; Bell and Ebisu, 2012; Bae and Lynch, 2023; Mueller and Gasteyer, 2023; Deria et. al., 2020; Mueller and Gasteyer, 2021; Bandala et. al., 2022). Environmental burdens may negatively contribute to upward mobility, and this is especially an issue if these burdens fall disproportionately on disadvantaged communities.

Factors contributing to poor environmental quality, such as high air pollution levels, increased natural disaster occurrences, higher temperatures, or lack of environmental amenities, are found to increase poor health outcomes around the world, potentially hindering productivity and exacerbating income equality (Oyedele and Tella, 2023; Oliveira et. al., 2023; Johar et. al., 2022; González et. al., 2021; Jorgenson et. al., 2020; Spotswood et. al., 2021; Dell et. al., 2009; Zaveri et. al., 2020; Dell et. al., 2009). Although many systems are in place to mitigate pollution in the United States, pollution and its negative impacts persist with disproportional adverse effects on low-income individuals or racial and ethnic minorities (Kodros et. al., 2022; Kathuria and Khan, 2007; Jorgenson et. al., 2020; Dell et. al., 2009; Bell and Ebisu, 2012). For example, lower income and minority communities as well as racially segregated areas are found more likely to be exposed to higher levels of air pollution (Miranda et. al., 2011; Kathuria and Khan, 2007; Jorgenson et. al., 2020; Kodros et. al., 2022; Bell and Ebisu, 2012). Moreover, regarding water pollution, Safe Water Drinking Act violations are found to likely occur in areas with higher minority populations, while water infrastructure investment benefits decrease as low income or minority populations increase over time (Bae and Lynch, 2023; Mueller and Gasteyer, 2023).

A lack of infrastructure contributes to pollution's deleterious impacts. Nigra et. al. (2023) model lead water service pipes in New York City and find Hispanic populations are more likely to be exposed (Nigra et. al., 2023). Moreover, lower income communities are found to be more vulnerable to natural disasters, such as flooding (Deria et. al., 2020). Across the United States, 489,836 households lacked complete indoor plumbing in 2018, while American Indian communities are found to have higher incidence of housing with incomplete kitchens or plumbing (Mueller and Gasteyer, 2021; Bandala et. al., 2022). Those on reservations also forgo income that could be earned from utilizing senior water rights due to the lack of infrastructure investments (Sanchez et. al., 2023).

Policies undertaken to mitigate pollution's negative impacts include the Clean Air and Safe Drinking Water Acts' standards and enforcements, tree canopy increases, water infrastructure improvements, and access to green space. These policies seem to have disproportional benefits for higher income, non-minority populations (Zhang et. al., 2022; Williams et. al., 2020; Spotswood et. al., 2021; Neier, 2021; Mueller and Gasteyer, 2023; Miranda et. al., 2011; Liu et. al, 2021; Bae and Lynch, 2023). Access to green space and tree canopy, especially in urban areas, can have positive benefits on mental and physical health and improve home values (Zhang et. al., 2022; Williams et. al., 2020; Liu et. al, 2021; Li, 2022). However, studies often find only certain groups benefit from these pollution mitigation strategies. Access to safe parks in cities is less likely for low-income or racial and ethnic minorities while, in areas excluding school yards, there is likely less tree canopy in communities with higher minority populations (Williams et. al., 2020; Zhang et. al., 2022). Where programs exist to plant more trees, minorities may face higher risk of gentrification as housing values increase as Li found for New York city (Li, 2022).

Regarding negotiations for polluting activity placements, such as locations for oil and natural gas mining, wealth is shown to have a positive relationship with bargaining outcomes. This can leave low-income communities vulnerable to drilling violations due to inability to negotiate proper protections (Timmins and Vissing, 2022). State and federal entities can help facilitate and implement transparent and fair decision making, while stakeholder participation is essential in achieving sustainable outcomes (Berggren, 2018).

7.3 Data

This section introduces the Climate and Economic Justice Screening Tool (CEJST) data, defines specific variables used in the econometric analysis, and discusses some potential data limitations.

The newest version of the CEJST data set was released by the CEQ in 2022 (U.S. Executive Office of the President Council on Environmental Quality, 2022). This data set is unique as it compiles demographic, housing, income, and environmental information at the U.S. Census Bureau census tract level. The CEJST consists of indicators for different environmental burdens on communities such as housing, health, income, and environmental burdens. The CEQ combines these data from various sources and also offers each variable as a percentile. The CEJST also contains an indicator for disadvantaged communities based on a set criterion that relates tracts that are at or above the 65^{th} percentile for low-income and that qualify for at least one other burden (White House Council on Environmental Quality's Climate and Economic Justice Screening Tool (CEJST), 2022).

The 2022 version of CEJST consists of cross-sectional data collected within the years 2014 to 2022. The data is at the census tract spatial scale. Tracts included in the analysis are those that lie wholly or partially within the CRB boundary and adjacent areas receiving Colorado River water, such as tracts in Los Angeles. Overlapping census tracts with less than 50% impervious surface or cropland occurring within the CRB boundary intersection are excluded from the analysis.

7.3.1 Environmental Burdens

This section begins with more precise definitions of the environmental burdens which are then elaborated on below. Table 5 also includes the unit of measurement and the years available in the CEJST data.

Environmental Burden	Definition	Measurement Units	Years Available in CEJST
Lack of Natural or Green Landscape	The percent of census tract that is artificial surface (i.e. cement, roads, etc.) or cropland.	Percent	2019
Households with Incomplete Plumbing	The percent of households with incomplete kitchens or plumbing.	Percent	2018
Leaky Underground Storage Tanks (USTs)	The density of leaky USTs and all active USTs within 1500 feet of each census tract.	Density	2021
PM2.5 in the Air	The amount of inhalable particles, less than 2.5 micrometers, in the air.	Micrograms per cubic meter of air	2017

Note. Environmental burdens measured at the census tract level

Table 5. Summary of Environmental Burden Variables

Lack of natural or green landscape is measured by CEJST is the percent of land that is impervious surface (i.e. concrete, pavement, or other artificial surfaces) or cropland. This data is sourced by the CEQ from the Multi-Resolution land Characteristics Consortium which compiles remote sensing land cover data including the National Land Cover Data (NLCD) 2019 Percent Developed Imperviousness. The NLCD provides information on the percent of pixels that are imperious surface, and The Trust for Public Lands converts that into an area at the census tract level (Multi-Resolution Land Characteristics Consortium (MRLC), 2019).

Lack of indoor plumbing, as it is called in the CEJST data, measures the percentage of homes with incomplete indoor kitchens or plumbing. The Department of Housing and Urban Development (HUD) receives detailed data from the American Community Survey (ACS) on the number of households that lack indoor kitchens or plumbing. The ACS reports households that have incomplete plumbing and those with incomplete kitchens separately, and HUD combines them as a part of their Comprehensive Housing Affordability Strategy (CHAS) Data (Department of Housing and Urban Development, n.d.). The ACS data used is a five-year moving average from 2014-2018 at the census tract level. According to the U.S. Census Bureau, households with incomplete plumbing are those that lack at least one of the following characteristics: hot and cold piped water, bathtub or shower, and flushable toilet; whereas households with incomplete kitchens are those that lack a sink with a faucet, stove or gas range, and/or a refrigerator (US Department of Commerce, 2015). Therefore, these criteria are combined by the ACS so that if a household is missing any of these characteristics, they are identified as lacking complete kitchen or plumbing. CEQ then uses the percentage of households in each census tract with incomplete kitchen or plumbing from HUD's CHAS. For simplicity, this study refers to households with incomplete indoor kitchens or indoor plumbing as households with incomplete plumbing.

Leaky underground storage tanks (UST's) are calculated as the density of leaking UST's to the number of active UST's within 1500 feet of each census tract. Leaking UST's can cause groundwater contamination, potentially presenting health risks through impacting drinking water quality and environmental risks creating fire and explosion hazard (US Environmental Protection Agency, 2024a). This data is from the Environmental Protection Agency's (EPA) UST Finder in 2021 and then compiled by EPA's EJScreen (White House Council on Environmental Quality's Climate and Economic Justice Screening Tool (CEJST, 2022).

PM2.5 in the air is the level of inhalable particles, which are less than or equal to 2.5 micrometers. These particles can be made up of various chemicals or heavy metals, which may cause cancer (US Environmental Protection Agency, 2020). This data comes from the EPA's Office of Air and Radiation's (OAR) fusion of model and monitor data in 2017. The EPA National Air Toxics Assessment (NATA) and the U.S. Department of Transportation's (DOT) traffic data sources the PM2.5 data, which is then compiled by EPA's EJScreen and included in the CEJST data. There are about 4000 State and Local Air Monitoring Stations (SLAMS) across the United States that track air pollution levels. Limitations include spatial gaps, filled by the EPA's modeling techniques. Gaps occur especially in rural areas where the SLAMS are less likely to be located (US Environmental Protection Agency, 2020).

7.3.2 Race and Ethnicity

Race and ethnicity data are sourced from the U.S. Census American Community Survey (ACS) as a five-year moving average in 2019 at the census tract level (U.S. Census Bureau, 2019).

Races analyzed include American Indian, Black, and White non-Hispanic population counts. Also used is the population in each tract that identify as Hispanic regardless of race.

While there are race and ethnicity categories included in the CEJST data, these groups overlap between race and ethnicity. For instance, each racial group can either identify as Hispanic or non-Hispanic and the CEJST includes only percentages for racial groups regardless of ethnicity. The ACS does provide data that splits racial groups by ethnicity (either Hispanic or non-Hispanic). These are used to ensure no overlap occurs within the race and ethnicity populations in the models. For further elaboration on how the ACS categorizes race and ethnicity population counts, see figure 5 below. Population percentages by race and ethnicity are discussed in Appendix A4.

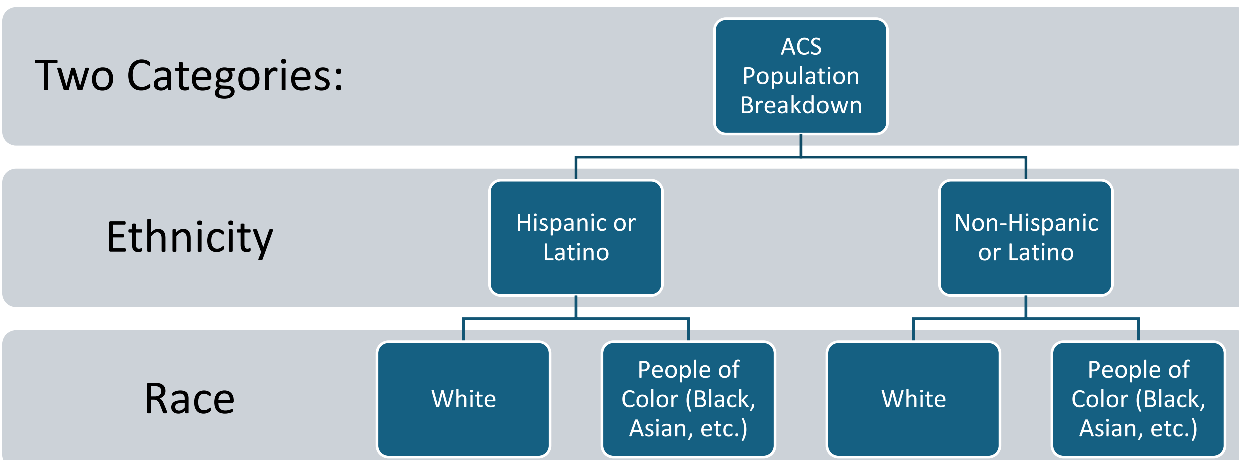

Figure 5. U.S. Census Bureau's Categorization of Race and Ethnicity Categories

7.3.3 Income, Education, and Population

Mean income is sourced from the U.S. Census Bureau's ACS as a five-year moving average in 2019 at the census tract level. The variable equates to the average household income in each tract. The variable to capture education level is one that measures the percentage of the population in each tract at or over the age of 25 that have obtained a high school degree. This education indicator is sourced from the CEJST data and is a five-year moving average estimate in 2019 (averaged value from 2015 to 2019).

To control whether a tract is rural, population density is included in the analysis. It is calculated as the population divided by the area (in acres) in each census tract. This variable is incorporated into the model to avoid endogeneity issues as greater population density shows positive correlations with many of the environmental burdens data (as seen in Figure 5).

7.3.4 Limitations

One drawback of the cross-sectional data is that variables are measured in somewhat different time periods. For example, the leaky UST data is based on measurements for 2021 and the incomplete plumbing data for 2018, while the demographic data uses 2019 values. These variables are still reasonably comparable due to the lack of variability of the observations from year to year. While there are cleanup procedures for leaky USTs in place, the time taken to discover these leaks in the first place is unclear (US Environmental Protection Agency, 2024b). In addition, completing infrastructure for indoor kitchens or plumbing is a costly process that takes time.

In addition to time mismatches between variables, there are also spatial mismatches between some tracts and the CRB. Tracts used in the analysis are those that lie wholly or partially within the CRB and areas which are served by water from the CRB. All tracts that intersect with those boundaries are included. However, the boundary line is not a perfect matchup. Some populations included in the analysis receive no benefit from the CRB, however this is a small percentage.

7.3.5 Correlation Matrix

Figure 6 shows correlations between the environmental burdens, race and ethnicity, income, education, and population variables. White non-Hispanic populations show slight to moderate negative correlations with all the environmental burdens. Tract-level mean income shows similar results except has a positive correlation with PM2.5 in the air, however the relationship is small. American Indian is the only racial group that shows a moderately strong positive correlation with percentage of households with incomplete plumbing. Hispanic and Black non-Hispanic populations show positive correlations with all environmental burdens, excluding the incomplete plumbing variable.

Figure 6. Correlation Matrix of Environmental Burdens and Demographics

7.3.6 Summary Statistics

Table 5 presents summary statistics for each variable discussed in this section as a summary of all the census tracts in the study area. The average share of impervious surface or cropland in CRB census tracts is roughly 50%. While most tracts have zero households with incomplete plumbing, there is a tract where .67% of households lack complete infrastructure, suggesting that lack of complete plumbing is concentrated in specific areas (Deitz and Meehan, 2019). The average income for all tracts in the CRB is $91,406.88, about $10, 000 above the median income. Population density varies across tracts, with the lowest density tract having zero residents (there are eight of these - typically tracts that consist of only an airport or body of water) and the highest density tract having 148.09 people per acre and located in Los Angeles.

Variable	Min	Mean	Median	Max	Stand. Dev.
% Non-green space acreage	0.03%	49.49%	53.02%	97.29%	21.78%
% Households with incomplete kitchen/plumbing	0%	0.01%	0%	0.62%	0.03%

Leaky USTs	0.00	3.44	2.24	42.16	3.98
PM2.5 in the air	4.01	9.54	9.29	13.86	2.65
% Hispanic	0.00%	36.17%	28.57%	100.00%	26.46%
% American Indian	0.00%	1.68%	0.00%	100.00%	9.25%
% Black	0.00%	5.14%	2.36%	84.71%	8.20%
% Without high school degree	0.00%	15.20%	10.00%	75.00%	13.97%
Mean Income	$0.00	$91,406.88	$81,376.50	$434,685.00	$45,269.37
Population Density	0.00	11.79	8.62	148.09	12.76

Table 6. Summary Statistics

7.4 Econometric Models Estimated

This study explores the relationships between environmental burdens and income, race and ethnicity, and education in the Colorado River Basin at the census tract level. Correlations in this analysis are expected to align with past literature regarding disproportionate adverse effects that air and groundwater pollution, households with incomplete plumbing, and lack of access to environmental amenities may have on minority populations or communities that are low-income, as discussed in Chapter 2.

A linear regression model is used to analyze the relationship between each environmental burden and demographics, income, and education characteristics. This model produces the most efficient, consistent, unbiased, and linear estimate. The OLS estimator assumes the following: (1) the environmental burdens are linearly dependent on the explanatory variables, (2) the explanatory variables are linearly independent from each other, and (3) the error terms are not correlated with the explanatory variables ($E(x, \varepsilon) = \underline{0}$), they are homoscedastic ($V(\varepsilon_i) = \sigma^2 \; \forall \; i$), and there is no autocorrelation ($cov(\varepsilon_i \varepsilon_j) = 0 \; \forall \; i$).

Because race and ethnicity characteristics are commonly found in the literature to be correlated with income and education (Chetty et. al., 2020; Povich et. al., 2015), further tests are done to ensure the variance is not overinflated due to collinearity between the explanatory variables (Michler and Wu, 2020). To check for this, the variance inflation factor (VIF) is calculated.

The nature of the data analyzed is cross-sectional with 7,756 observations. Four models are presented, each with the same explanatory variables including race, ethnicity, income, and education. Each dependent variable is a different environmental burden. Excluded from the models as the comparison group (for race/ethnicity) are those that identify as non-Hispanic

White, Hawaiian or Pacific Islander, those that are two or more races, and those that identify as another race not accounted for in the ACS. (White population accounts for 78.7% of these excluded categories).

To avoid endogeneity issues due to unobserved heterogeneity, state controls are included as dummy variables to account for differences in each tract due to the state in which it belongs. These unobserved characteristics could be attitudes and preferences towards these environmental burdens, political beliefs related to social and environmental policies, and environmental amenities that differ across states. Population density is incorporated into the model to account for urban versus rural tracts. The number of people per acre could impact differences in the amount of natural or green landscape, plumbing infrastructure, air pollution levels, and concentration of leaky USTs.

The OLS model is specified below:

$$\begin{aligned} EnvBurden_i = \rho &+ \beta_1 Hisp_i + \beta_2 AmInd_i + \beta_3 Black_i + \beta_4 Edu_i + \beta_5 Inc_i + \beta_6 PopDens_i \\ &+ \beta_7 DumCA_i + \beta_8 DumCO_i + \beta_9 DumNM_i + \beta_{10} DumNV_i + \beta_{11} DumUT_i \\ &+ \beta_{12} DumWY_i + \varepsilon_i \end{aligned}$$

Model components are as follows:

- $EnvBurden_i$ pertains to the four environmental burdens of interest including lack of green space, lack of indoor kitchens or plumbing, leaky USTs, and PM2.5 in the air in tract i.
- ρ is the intercept.
- $\beta_{1,2,3,4,5,6,7,8,9,10,11,12}$ are variable coefficients.
- $Hisp_i$ is the number of those who identify as Hispanic, regardless of race, in tract i.
- $AmInd_i$ is the number of those who identify as American Indian, non-Hispanic, in tract i.
- $Black_i$ is the number of those who identify as Black, non-Hispanic, in tract i.
- Edu_i is the percentage of those, 25 or older, without a high school degree in tract i.
- Inc_i is mean income in tract i.
- $PopDens_i$ is the population density in tract i.
- $DumCA_i$, $DumCO_i$, $DumNM_i$, $DumNV_i$, $DumUT_i$, and $DumWY_i$ represent dummy variables for each state.

7.5 Econometric Results

Table 7 shows the econometric results of four models with different environmental burdens as dependent variables. Table 7 reports VIF values, which all are less than 5.0, which is significantly different than 10.0, the threshold for indicating collinearity is a cause for concern (O'Brien, 2007). The Breusch-Pagan statistics are reported to test for heteroskedasticity, which is found likely to be present in all the models. To correct for this, all models in table 7 are run with White's standard errors.

The model for air pollution shows that much of the variation for this environmental burden is accounted for. The incomplete plumbing model has a relatively low R^2, which is unsurprising as only 0.5% of all households in the CRB are considered to have incomplete indoor plumbing alone (this statistic excludes households with incomplete kitchens). Moreover, the R^2 for the Leaky UST model is low. 90.91% of tracts contain a leaky UST density of at least .01, indicating either unobservable characteristics are likely present between tracts and/or having the data for the same time period might be more important than previously thought. Despite the low $R^2$for three out of four models, the F-statistics are significant suggesting the independent variables in each model have good explanatory power.

Relating to groundwater quality, models (1) and (2) show interesting results. Tracts with higher air pollution prevalence are positively correlated with tracts that are home to higher percentages of Hispanic and Black populations. Tracts with higher income, on average, and those that are more densely populated are also likely to be tracts with higher levels of air pollution. Tracts with a higher percentage of American Indian populations are the only group negatively correlated with air pollution. Areas with higher leaky UST density are less likely tracts with a greater share of Hispanic and American Indian populations. Black and less educated populations are more likely to live in areas where more leaky USTs occur. These areas are also likely densely populated. Moreover, tracts with higher income on average are also those with less leaky USTs.

Corresponding to water allocations contributing to more impervious surface development or agricultural production and to less natural or green landscape is model (3). Census tracts with higher percentages of Hispanic and Black populations are also those with more impervious surface or cropland. American Indian and lower educated populations are likely to reside in areas with more natural or green landscape. Tracts with higher average income are likely to also have more natural or green landscape. Lastly, more densely populated tracts are also likely those with more impervious surface or cropland.

Access to running water in the home is represented in model (4). Those who identify as Hispanic are more likely to live in tracts with less households with incomplete plumbing. In contrast, American Indian populations and those with less education are more likely to live in tracts with higher incidence of households with incomplete plumbing. Higher income census tracts, on average, are likely those with more homes that have access to indoor running water. Population density is positively correlated with higher amounts of households with incomplete plumbing.

The race and ethnicity variables follow the expected relationships as seen in past literature. Hispanic populations, regardless of race, show negative correlations with incomplete plumbing and leaky UST's and a positive correlation with air pollution and impervious surface or cropland. One aspect to consider is the Hispanic variable includes the white Hispanic population. This categorization could impact the relationship between Hispanic populations with environmental burdens in opposing ways if race is a greater determining factor.

Income and population density also have expected signs. One could infer that those with higher income can choose to live in areas surrounded by natural or green landscape. Air pollution, on the other hand, seems to be less avoidable, even for those with a greater ability to choose where they live. Moreover, the positive correlation between population density and each environmental burden suggests where there are more people there is also higher incidence of air pollution, leaky USTs, artificial land surfaces, and households with incomplete plumbing.

Dependent Variable:	(1) PM2.5 in Air		(2) Leaky USTs		(3) Lack Green Space		(4) Incomplete Plumbing	
Variable	Estimate		Estimate		Estimate		Estimate	
(Intercept)	5.96	***	2.16	***	40.66	***	0.0089	***
	(0.066)		*(0.15)*		*(0.98)*		*(0.0009)*	
% Hispanic	1.68	***	-0.81	**	9.51	***	-0.018	***
	(0.14)		*(0.36)*		*(1.66)*		*(0.0034)*	
% American Indian (Non-Hisp)	-0.95	***	-2.46	***	-33.48	***	0.15	***
	(0.20)		*(0.34)*		*(2.16)*		*(0.014)*	
% Black (Non-Hisp)	3.06	***	2.80	***	21.67	***	-0.0041	
	(0.12)		*(0.65)*		*(1.99)*		*(0.0046)*	
% No HS Degree	0.0029		0.031	***	-0.064	**	0.0003	***
	(0.0025)		*(0.0077)*		*(0.032)*		*(0.0001)*	

Mean Income (scaled $10,000)	0.0001	***	-0.0001	***	-0.0007	***	-0.0000005	***
	(0.000004)		*(0.00001)*		*(0.0001)*		*(0.0000001)*	
Population Density (scaled 1000)	28.80	***	87.79	***	769.51	***	0.20	***
	(1.84)		*(7.52)*		*(36.52)*		*(0.035)*	
State Effects	Yes		Yes		Yes		Yes	
Observations	7756		7756		7756		7756	
R2	0.7881		0.2106		0.4859		0.3286	
Adj. R2	0.7878		0.2094		0.4851		0.3275	
F Stat (12; df = 7743)	2400	***	172.1	***	609.7	***	315.8	***
Breaush-Pagan Statistic	969.36	***	467.44	***	329.36	***	793.02	***
Variable	VIF	Df						
Hispanic	4.91	1						
American Indian (Non-Hisp)	1.34	1						
Black (Non-Hisp)	1.14	1						
% No HS Degree	4.93	1						
Mean Income (scaled $10,000)	1.73	1						
Population Density (scaled 1000)	1.50	1						
State Effects	1.95	6						

*p<0.1;**p<0.05;***p<0.01

Table 7. Econometric Results

Chapter 8: Conclusion and Policy Implications

8.1 Motivation for Study

Groundwater use data is lacking for much of rural Arizona as well as much of the world (Lall, 2020, Dantas, 2021). This study seeks to improve understanding of how climate, economic and regulatory factors interact with groundwater in areas where groundwater pumping data is not available because groundwater use is unregulated and unmonitored. This is especially important to inform water management and policy decisions regarding areas where no groundwater regulation is present, leaving communities vulnerable to groundwater shortages.

Chapter 7 explores several types of environmental burdens related to groundwater quality, allocation and access to further identify whether certain groups in the CRB are disproportionately exposed. These burdens include air pollution, leaky USTs, lack of natural or green landscape and households with incomplete plumbing. Environmental burdens around the world have disproportional effects on racial and ethnic minorities, as well as on low-income and less educated individuals (Kodros et. al., 2022; Kathuria and Khan, 2007; Jorgenson et. al., 2020; Dell et. al., 2009; Bell and Ebisu, 2012). Not only do these burdens negatively impact groundwater, but they also lead to adverse health outcomes (Oyedele and Tella, 2023; Oliveira et. al., 2023; Johar et. al., 2022; González et. al., 2021; Jorgenson et. al., 2020; Spotswood et. al., 2021; Dell et. al., 2009). Understanding whether there are disproportional adverse health effects in the CRB can help inform policy decisions ensuring equitable protection while improving the quality and quantity of the Colorado River water supply.

8.2 Discussion of Empirical Findings

8.2.1 Climate, Economic, and Regulatory Signals in Groundwater Level Data

Panel data for 2010-2021 is analyzed through four Pooled Ordinary Least Squares regression models with varying degrees of controls. The models are used to analyze relationships between DTW and housing, climate, agricultural activity, and groundwater regulation. The models highlight correlational relationships only. DTW is the dependent variable and climate, economic, and regulatory factors are the explanatory variables. The models are run with robust standard errors as heteroskedasticity is found to be present.

Model results show significant coefficients on regulation status and planted acreage interacted with regulation consistently in all four models. Sub-basins without groundwater regulation are likely to have 56 feet higher DTW than those with groundwater regulation in place from 2010 to 2021. Unregulated sub-basins that increase in planted acreage by 100 acres are also those with .11 feet higher DTW than regulated sub-basins increasing in planted acreage by the same amount over the twelve year study period.

Recharge is significantly negatively related to DTW changes over time in model 4. Sub-basins with a recharge project during at least one year in the study period are likely those with 20 feet lower DTW, on average over time, compared to sub-basins with no recharge projects occurring.

Temperature, precipitation, and housing units show up as significant in the first two models before controlling for correlated random effects. Per capita income and planted acreage, on its own, show no significant correlation with DTW over time.

8.2.2 Race, Income, and Education Relationships with Environmental Burdens in the CRB

The econometric models utilize four different environmental burdens as the dependent variable: air pollution prevalence, leaky USTs, lack of natural or green landscape and households with incomplete plumbing. Race, ethnicity, income, education, and population density are included as explanatory variables. A cross-sectional data set is analyzed in four separate OLS models, each with the same explanatory variables but different environmental burdens as the dependent variable. The models are run with robust standard errors.

The percentage of those who identify as Hispanic, regardless of race, in a census tract shows positive relationships with air pollution and impervious surface or cropland, and negative relationships with leaky UST's and percentage of households with incomplete plumbing. American Indians and low educated populations are the most likely to live in areas with more households with incomplete plumbing while Black population size is positively correlated with each of the other environmental burdens. Those with higher income tend to live in places with more access to natural or green landscape, less households with incomplete plumbing, less USTs, and higher air pollution. To check for linear dependencies between explanatory variables, a VIF is calculated for each variable in the models. For all the parameters, the variance is not inflated enough to cause concern for collinearity.

8.3 Policy Implications

8.3.1 Groundwater Policy

Understanding how economic, climate, and regulatory factors correlate with groundwater levels can help inform these policy decisions, especially where it is challenging or impossible to obtain water extraction data or estimations based on hydrologic models, remote sensing tools, or proxies, such as energy use to pump groundwater (Brookfield et. al., 2024; Alam et. al., 2023; Martindill et. al., 2021; Burlig et. al., 2021; Wang et. al., 2020; Hurr and Litke, 1989).

Regulation and recharge projects are correlated with DTW in the way they are intended. Not only do groundwater regulated sub-basins show fewer decreasing trends in Figure 2, but also there is a likelihood that regulation relates to lower DTW over time, ceteris paribus. Moreover, sub-basins with recharge projects are also likely sub-basins with lower DTW on average over the study period. The positive relationship between regulation and groundwater levels can also be seen through conservation and best management practices impacting planted acreage variation over time.

When extra controls are not added to account for unobserved heterogeneity, temperature and precipitation have relationships that align with what is discussed in Condon (2020) and Ndehedehe (2023). This result emphasizes the need for continuing discussion about policy surrounding groundwater use as climate change increases.

Housing units, likely correlated with population in this case, show a different relationship with DTW compared to other literature that find a decoupling trend between groundwater use and population growth (Lee et al., 2022). This result suggests rural areas may respond differently to economic growth compared to larger municipalities. Thus, a policy solution may be to incentivize new households in groundwater unregulated sub-basins to invest in newer more water efficient appliances or to require utilities to meet higher water use efficiency standards.

8.3.2 Policy Implications for Vulnerable Communities

Understanding which groups are likely vulnerable to the four environmental burdens examined can help inform policy regarding where to target water allocations, air pollution mitigation strategies, and investments in water quality and household infrastructure. The findings present evidence of positive correlations between minority, less educated and low-income communities and environmental burdens. Much of the literature finds similar results regarding relationships between environmental burdens and race, ethnicity, income, and education. These findings suggest environmental injustice surrounding water users in the CRB is present.

Air pollution directly negatively impacts human and environmental health, and indirectly adversely affects groundwater quality. Findings for air pollution prevalence suggest this burden is pervasive among all groups, regardless of race, ethnicity, income, or education level, excluding American Indian populations who are found negatively correlated with air pollution. Higher leaky UST densities are more likely to impact Black and less educated populations. These results highlight the need for further policy focus on mitigating contaminants from point sources.

Water allocations do not just pertain to satisfying base level agricultural and municipal demand. Policy makers also decide how to allocate Colorado River water towards maintaining natural habitat, by ensuring sufficient flow levels, and investing in green landscapes, such as planting trees or building parks in cities, which require enough water to do so. Some cities, like Los Angeles, have programs that incentivize tree planting. One drawback to this beautification effect trees have on cities is that these programs lead to increases in home values, potentially leading to gentrification, like the scenario seen in New York City's Million Trees Program (Li, 2022). Finding ways to maintain natural habitat and increase green landscape while avoiding gentrification impacts can be useful for creating equitable policy regarding groundwater allocations in the CRB.

Households with incomplete plumbing exist within the CRB boundaries, inhibiting those residing in such households from utilizing access to their full water right. This problem seems most likely experienced by American Indian populations. Aiming household water infrastructure investments towards Reservations could help lessen the burden in the CRB.

Relationships between racial and ethnic minorities as well as low income and less educated populations and environmental burdens found in this study corroborate the need for increased DEI in water dialogue, as discussed in Williams et. al. (2023). The more representation that takes part in water policy decisions, the broader perspectives there are to find an optimal solution for groundwater quality and quantity issues in the CRB while ensuring the well-being of all water users regardless of race, ethnicity, income, or education level.

8.4 Future Research Directions

There is much room for future research to improve upon the analyses regarding groundwater levels and environmental burdens. As more remote sensing data collection and analysis tools are developed, one can extend the areas that prompt use for groundwater level data (where other data obtaining challenges exist) while adding a longer time frame. One can also explore the relationships with environmental burdens and demographics over time with panel data as much of the data has only recently become attainable through technological advancements.

It may be useful to further explore the relationship between income and DTW, as income may have competing effects on groundwater use behavior. For example, those with higher income have options to either invest in higher or lower water demanding amenities (i.e. pools, grass, etc.; newer more water efficient appliances and landscaping decisions, etc.). Those with higher income could also choose to move out of an area completely, decreasing that areas groundwater demand. Thus, looking at influences of income on human behavior and regarding water use in groundwater dominated areas can be interesting.

Modeling further the relationships between the environmental burdens and Hispanic populations split between White and non-White races can be useful in disentangling potentially opposing correlations. It would be interesting to know whether race alone is a larger driver for determining whether a particular group is disproportionately exposed to an environmental burden.

Many census tracts in the study area are very sparsely populated. 30% of the census tracts have less than or equal to about 5 people per acre. It could be interesting to see if these correlations hold when looking at highly rural and urban tracts separately. This separation could also help capture a potential nonlinear relationship between income and population density, since both highly urban and rural areas have both high and low-income individuals. Population density may also have a non-linear relationship with impervious surface or cropland area. Those in less densely populated tracts are more likely to be surrounded by cropland, or just natural space. Those in more densely populated tracts are certainly surrounded by a higher portion of impervious surface. This suggests the relationship between population density and lack of natural or green landscape could be logarithmic and should be further explored.

One might want to further explore models for leaky USTs as more data becomes available to see how much this environmental burden varies over time. This could provide further insight into why the model's explanatory power is not high. Finally, looking into areas concentrated with households with incomplete plumbing to analyze differences between those with and without household water use infrastructure can be useful.

8.5 Summary

Analyzing the relationship between DTW and climate, economic, and regulatory factors shows promise in areas that lack explicit groundwater use data. Insight into policy decisions regarding groundwater extraction can be seen through the regulations and projects already in place compared to communities where such monitoring, use restrictions and recharge projects are lacking. This is especially important as housing continues to be developed in many of these unregulated areas (as seen in Figure A1), and as climate change persists (Crimmins, 2022). This study hopes to provide another option for using sources apart from explicit groundwater use data to inform policy decisions about groundwater: a crucial environmental amenity that many in Arizona and other arid regions around the world rely on.

The analysis on environmental burdens relating to groundwater quality, allocations and access and disadvantaged communities shows evidence that policies may be needed in the CRB to address impacts on communities which are particularly vulnerable to the environmental burdens examined in this study. While mitigation strategies are becoming more common, it is important to work toward more equitable access to water sources and less exposure to environmental burdens in CRB communities, regardless of race and ethnicity or income and education level.

Appendix

A1 Further Elaborations on Sub-basins in Study Area

The Harquahala INA borders the west side of the Phoenix AMA. It is surrounded by four mountain ranges. This rural area relies mostly on groundwater for economic activities including agriculture. Hassayampa is the west most sub-basin in the Phoenix AMA, sharing a border with the Harquahala INA on the left. This region lies outside of the Phoenix metropolitan area and has high agriculture activity. Due to census tract considerations, Harquahala and Hassayampa are evaluated as one entity, because most of each sub-basin's human activity (agricultural and urban development) falls within one tract.

The Gila Bend basin is roughly 821,968 acres and lies south of the Harquahala INA and Hassayampa sub-basin. It has had over 40,000 acres of irrigated cropland from 2010 and 2021, which is 100% reliant on groundwater. The sub-basin is home to the Gila River, which remains dry most months of the year (The Nature Conservancy, 2021).

The Santa Cruz AMA is home to the City of Nogales and Santa Cruz River which flows north through the center. It is majority groundwater dependent and mostly rural, with more of the population residing in the south, in or near Nogales. The area varies in elevation as it encompasses mountain ranges including Pajarito, Tumacacori, and Santa Rita mountains. This paper analyzes the south and north portions as separate entities, splitting the area through the middle along a census tract line, due to differences in population, economic activity, and hydrological features.

The Upper San Pedro watershed lies mostly in Cochise County, Arizona. Two sub-basins in this study splits the area into a north and south portion known as Benson and Sierra Vista sub-basins respectively. The split is along a hydrologic division due to the different levels of agriculture and population size. The south portion is home to the city of Sierra Vista and Tombstone, while the north has the rural town of Benson. Groundwater use in both sub-basins is the majority.

Douglas became an AMA in December 2022. The sub-basin is home to the city of Douglas and town of Bisbee. Topologically, it is relatively flat throughout and surrounded by mountains. The sub-basin has active agriculture, especially in the middle and north portion, and is fully reliant on groundwater as no surface water is present (The Nature Conservancy, 2021). Wilcox is the largest sub-basin in the study area at about 1.2 million acres. There is active agricultural and an expanse of bare land. The area has a large amount of groundwater dependent agriculture activity with about 58,474 acres of irrigated cropland in 2021.

Eloy is the sub-basin on the northeast side of the Pinal AMA. The main economic activity is irrigated agriculture of which the main water supply is groundwater. Northwest of Eloy are the Maricopa-Stanfield and Rainbow Valley sub-basins, which reside in the Pinal and Phoenix AMA's, respectively. 90% of both sub-basins' water supply was sourced from groundwater in 2018 (ADWR, 2022a).

Avra Valley is in the western portion of the Tucson AMA. About 75% of its water supply is groundwater to meet the demand of the dominant economic activity, irrigated agriculture (ADWR, 2020a). San Simon Valley is the southeastern most sub-basin in Arizona, sharing a border with New Mexico. The area has no surface water supply.

Butler Valley, McMullen Valley, and Ranegras Plain sub-basins share a border with the Harquahala and Hassayampa sub-basins. All three sub-basins have similar economic activity, dominated by irrigated agriculture that relies 100% on groundwater sources (ADWR, 2022a). Moreover, due to census tract coverage, these sub-basins are combined and analyzed as one sub-basin.

A2 DTW Calculation – Criteria for Inclusion of Wells

A criterion is developed to further determine which wells should be included or excluded from the analysis. Regarding hydrological characteristics, wells on the outermost edges of sub-basins are excluded to avoid outlier well measurements due to topography changes or unusual activity such as mine site dewatering. Furthermore, wells chosen must be a comparable proximity to human activity (agriculture and/or urban activity) across each sub-basin. This is because each sub-basin has a different proportion of area to human activity. Thus, choosing a well to contribute to a yearly average that lies 50 km away from human activity in Avra Valley would not be comparable to choosing a well in the northern Santa Cuz AMA sub-basin where all wells lie within 20 km of similar activity. To keep average DTW values comparable in each sub-basin, a proximity from a well to human activity is chosen based on the proportion of sub-basin area to acreage of human activity. A maximum well distance in each sub-basin is chosen to equate this proportion to 0.5.

The equation for choosing well distances is as follows:

$$\frac{(Irrigated\ acres + Developed\ acres)km^2}{x^2 km^2} = 0.5$$

Hence, it follows that,

$$xkm = \sqrt{\frac{(Irrigated\ acres + Developed\ acres)km^2}{0.5}}$$

Where xkm is the maximum well distance used in each sub-basin. Any wells that exceed this distance in each sub-basin are excluded from the analysis. Table A1 shows the number of wells included in the yearly average DTW values for each sub-basin.

Sub-basin	**Basin**	**Number of Wells**
Benson	Upper San Pedro*	5
Douglas	Douglas AMA	15
Gila Bend	Gila Bend*	12
Harquahala INA & Hassayampa	Harquahala Basin & Phoenix AMA	44
Santa Cruz AMA North	Santa Cruz AMA	16
Santa Cruz AMA South	Santa Cruz AMA	24
Sierra Vista	Upper San Pedro*	36
Willcox	Willcox*	26
Avra Valley	Tucson AMA	45
Eloy	Pinal AMA	74
Maricopa-Stanfield	Pinal AMA	27
Rainbow Valley	Phoenix AMA	11
Butler Valley, McMullen Valley, Ranegras Plain	Butler Valley, McMullen Valley, & Ranegras Plain*	40
San Simon Valley	Safford Basin*	19

*Groundwater not regulated

Table A1. Well Counts by Sub-basin

A2.1 Sensitivity Check on Well Inclusion Criterion

Sensitivity in running models for DTW wells chosen with the .5 ratio is checked by testing what happens to the results if the criteria changes to .3 or .7 ratio. Sensitivity is found to be relatively low as signs and significance of results do not change from running models with slightly different DTW groups. Because sensitivity is found to be low, choosing a .5 ratio to equate well distances in each sub-basin seemed like the best choice to ensure human activity as well as other activity in the basin regarding groundwater is accounted for in the model. For example, choosing a .3 ratio might have restricted the model to only account for human activity fluctuations in groundwater levels, leading to bias results where a ratio of .7 might cause concern for picking up outlier wells in mountains surrounding a sub-basin.

A3 Housing and Climate Trends

Figures A1 and A2 show housing unit changes since 2010 for each sub-basin in the study area, separated into regulated and unregulated sub-basins. Housing development increases can be seen in both regulated and unregulated sub-basins throughout the study period. The largest increases are seen in Rainbow Valley and HarqHass (Harquahala INA and Hassayampa sub-basins). The drop off seen in all but one sub-basin trend in 2019 is due to census tract being redrawn for the new decade to adjust for population changes.

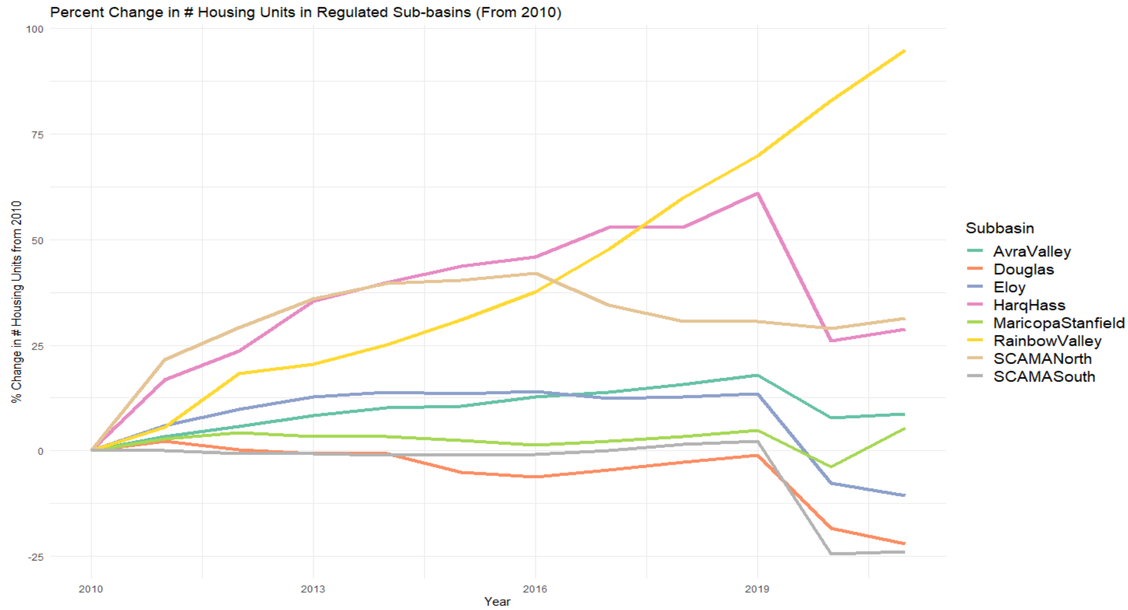

Figure A1. Percent Changes in # Housing Units Regulated Sub-basins Since 2010

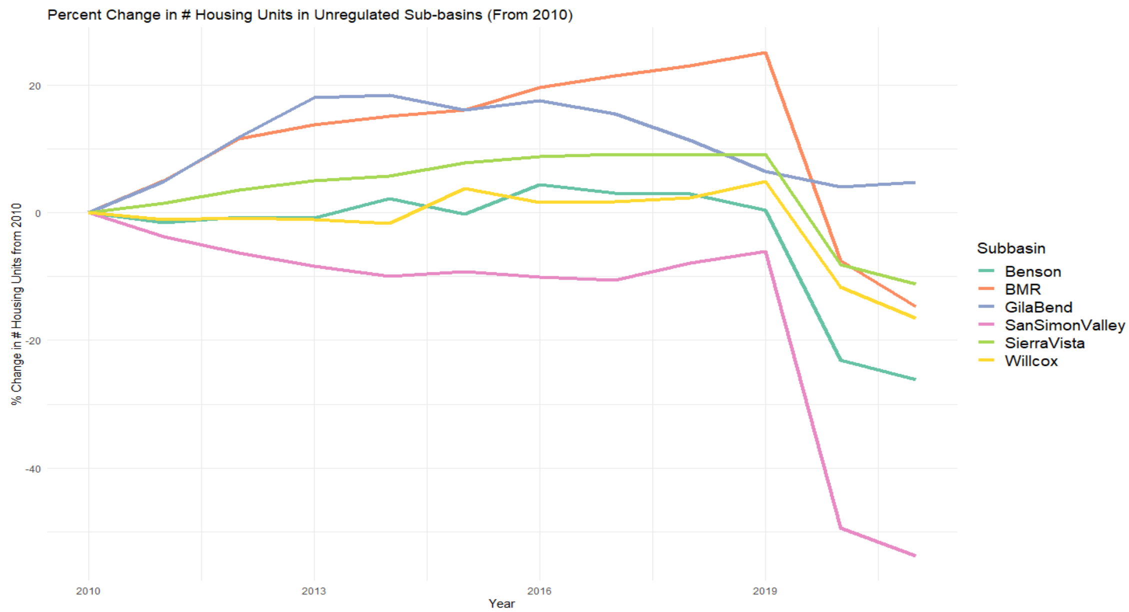

Figure A2. Percent Changes in # Housing Units Unregulated Sub-basins Since 2010

Figures A3 and A4 show temperature trends in regulated and unregulated sub-basins from 2010 to 2021. All sub-basins in the study area have similar trends at different magnitudes. The highest temperatures can be seen in Gila Bend, Maricopa-Stanfield, and Rainbow Valley, which lie in the center of the study area with the lowest elevation on average. The lowest temperatures on an average each year are in Willcox, San Simon Valley, and Sierra Vista. The lowest temperatures experienced by most of the sub-basins was in 2019 and the highest in 2017.

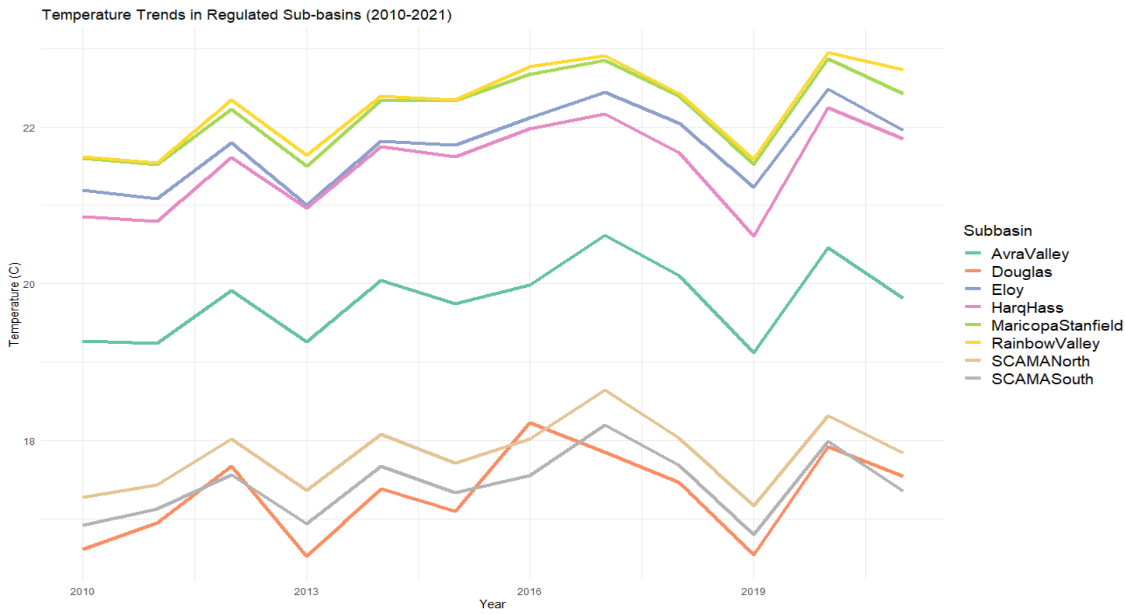

Figure A3. Temperature (C) Changes in Regulated Sub-basins from 2010 to 2021

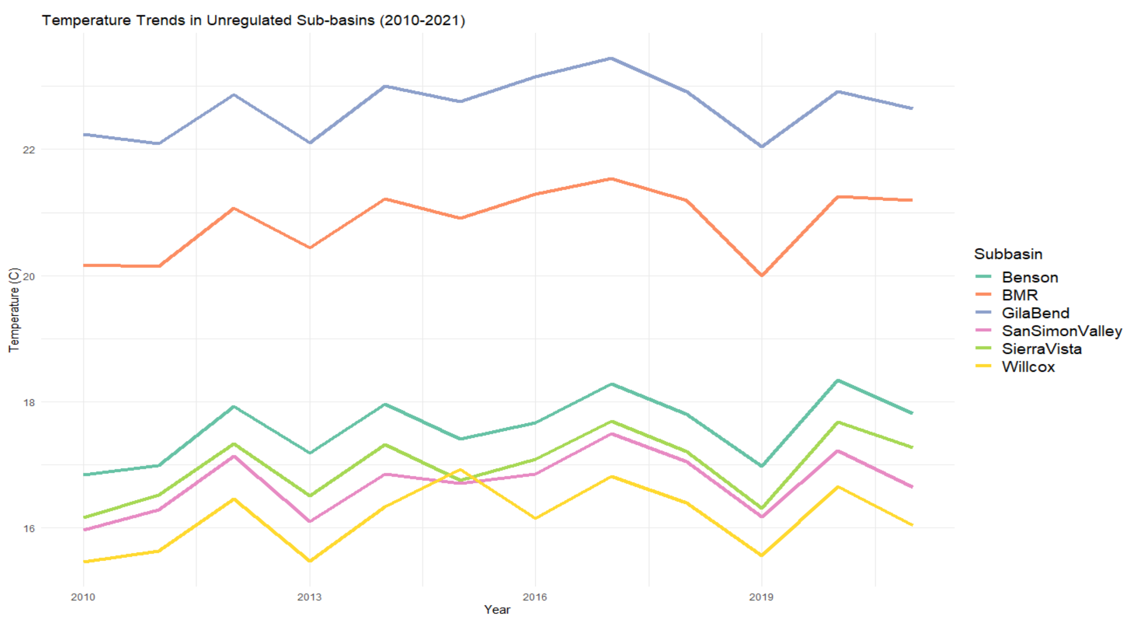

Figure A4. Temperature (C) Changes in Unregulated Sub-basins from 2010 to 2021

Figures A5 and A6 show precipitation trends in regulated and unregulated sub-basins throughout the study period. Like temperature, trends in all sub-basins look similar with the least rain occurring in 2020 and, for most of the sub-basins, the most inches of rain on average occurred in 2015 and 2019. Sub-basin with the highest on average yearly rainfall from 2010 to 2021 are the Santa Cruz AMA, Sierra Vista, and Willcox, which are also those with the lower average temperatures over time.

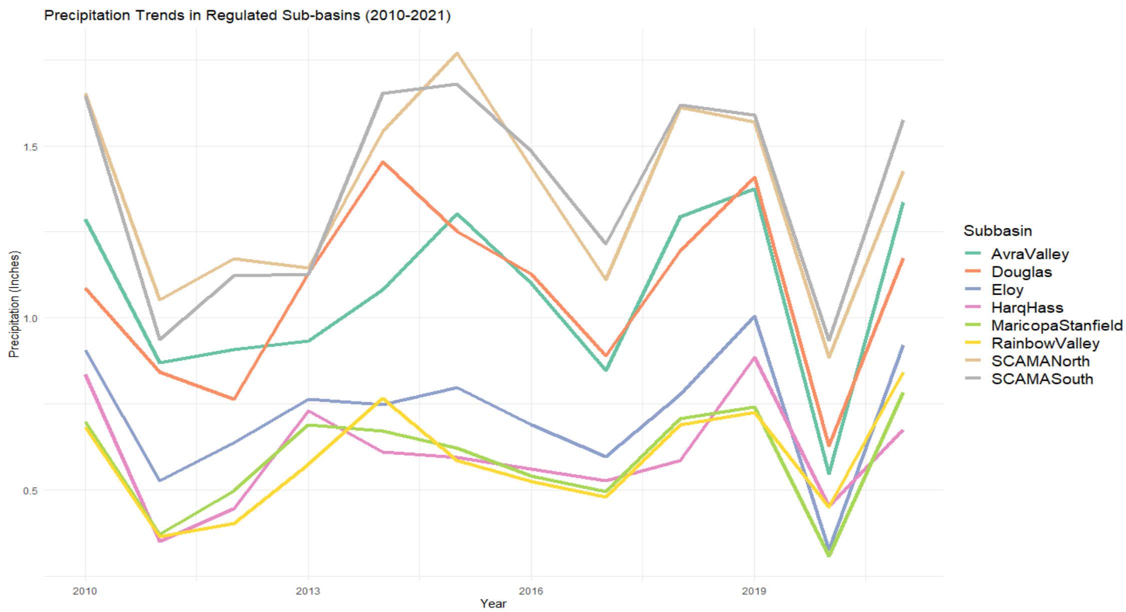

Figure A5. Precipitation (In.) Changes in Regulated Sub-basins from 2010 to 2021

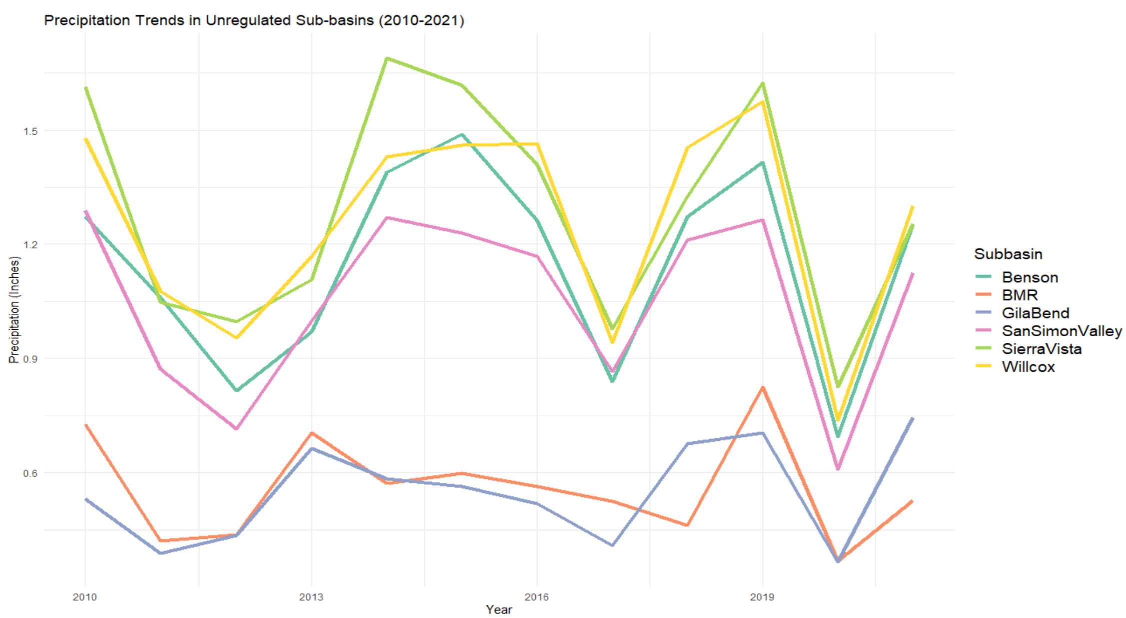

Figure A6. Precipitation (In.) Changes in Unregulated Sub-basins from 2010 to 2021

A4 Summary Statistics

Table A2 presents further summary statistics for each variable in each sub-basin between 2010 and 2021.

	DTW (Acre Feet)					Temperature (Celsius)					Precipitation (Inches)				
Sub-basin	**Min**	**Mean**	**Median**	**Max**	**St. dev.**	**Min**	**Mean**	**Median**	**Max**	**St. dev.**	**Min**	**Mean**	**Median**	**Max**	**St. dev.**
Avra Valley	237.6	245.6	245.8	252.7	5.0	19.1	19.8	19.9	20.6	0.5	0.5	1.1	1.1	1.4	0.3
Butler, McMullen, & Ranegras*	333.8	340.8	340.0	348.6	5.3	20.0	20.9	21.1	21.5	0.5	0.4	0.6	0.5	0.8	0.1
Benson*	235.3	241.4	240.3	249.6	5.2	16.8	17.6	17.7	18.3	0.5	0.7	1.1	1.3	1.5	0.3
Douglas	176.5	190.0	187.5	205.4	10.1	16.5	17.3	17.4	18.2	0.6	0.6	1.1	1.1	1.5	0.3
Eloy	235.5	239.2	238.1	246.8	3.6	21.0	21.7	21.8	22.5	0.5	0.3	0.7	0.8	1.0	0.2
Gila Bend*	293.8	325.2	324.9	363.5	22.4	22.0	22.7	22.8	23.4	0.5	0.4	0.5	0.5	0.7	0.1
Harquahala INA & Hassayampa	211.8	217.0	215.7	224.6	4.6	20.6	21.5	21.6	22.2	0.6	0.4	0.6	0.6	0.9	0.2
Maricopa Stanfield	307.8	314.2	312.3	322.8	5.7	21.5	22.2	22.3	22.9	0.5	0.3	0.6	0.6	0.8	0.2
Rainbow Valley	348.6	365.2	365.0	379.8	9.4	21.5	22.3	22.4	22.9	0.5	0.4	0.6	0.6	0.8	0.2
SCAMA North	64.7	66.8	66.9	69.5	1.3	17.2	17.8	17.9	18.6	0.4	0.9	1.4	1.4	1.8	0.3
SCAMA South	91.4	94.2	94.2	96.7	1.8	16.8	17.4	17.5	18.2	0.4	0.9	1.4	1.5	1.7	0.3
San Simon Valley*	184.6	197.5	193.8	215.3	11.0	16.0	16.7	16.8	17.5	0.5	0.6	1.1	1.1	1.3	0.2
Sierra Vista*	223.1	227.0	225.6	235.0	3.6	16.2	17.0	17.2	17.7	0.5	0.8	1.3	1.3	1.7	0.3
Willcox*	245.2	264.0	262.4	283.8	12.2	15.5	16.2	16.2	16.9	0.5	0.7	1.3	1.4	1.6	0.3

	Irrigated Cropland (Acres)					Per Capita Income (USD)					Housing Units				
Sub-basin	**Min**	**Mean**	**Median**	**Max**	**St. dev.**	**Min**	**Mean**	**Median**	**Max**	**St. dev.**	**Min**	**Mean**	**Median**	**Max**	**St. dev.**
Avra Valley	18664	21990	21871	23808	1587	18963.44	22352.06	22335.29	27473.98	2369.90	1727	1892	1889	2035	88
Butler, McMullen, & Ranegras*	14551	24586	23198	37091	6840	22458.06	25772.86	23707.99	35528.17	4113.00	1397	1812	1874	2047	205
Benson*	826	1523	1793	1926	470	20710.73	23886.50	22577.39	29991.46	3356.59	1568	2052	2121	2217	215
Douglas	13387	16680	17193	19734	1911	14917.32	16851.72	15934.37	19962.84	1846.78	1202	1467	1514	1577	118
Eloy	116916	127622	129013	134587	5736	16499.63	18425.70	17358.63	23725.93	2339.49	1480	1780	1864	1887	146
Gila Bend*	40644	49242	48719	59514	7174	6564.92	7681.20	7585.10	9216.38	861.63	472	523	527	559	31
Harquahala INA & Hassayampa	32780	37773	36227	48541	4442	21953.00	23917.57	23731.81	27798.56	1618.33	1373	1861	1889	2209	239

Maricopa Stanfield	80281	86391	86988	90984	3096	26071.55	29668.07	29431.36	33552.97	1784.95	1574	1675	1684	1724	40
Rainbow Valley	701	4446	4585	6279	1815	17500.00	24026.58	23207.00	32460.00	5438.16	1307	1844	1756	2546	396
SCAMA North	207	970	1044	1473	343	26233.00	32871.42	31934.50	38724.00	4376.04	1287	1678	1686	1828	144
SCAMA South	248	553	591	788	169	15001.23	17521.43	16782.76	21367.17	2047.94	1240	1573	1628	1675	155
San Simon Valley*	10169	14882	15454	18875	2899	18784.00	20668.08	20908.50	22580.00	1379.98	623	1150	1228	1347	236
Sierra Vista*	281	525	427	1356	303	26900.21	28745.19	27708.02	33672.65	2145.61	1801	2096	2137	2214	139
Willcox*	40814	51071	50759	58475	4963	18113.10	20651.83	20756.47	23610.19	1425.33	1222	1442	1458	1536	92
*Groundwater not regulated															

Table A2. Summary Statistics

A4 Race and Ethnicity Population Breakdown in the CRB

Figure A4 shows the percentage of each race and ethnicity residing in the CRB in 2019. These groups are mutually exclusive. All races (White, Black, American Indian, and Other) identify as non-Hispanic. Moreover, the Hispanic group represents anyone who identifies regardless of race. The Hispanic population makes up the largest proportion of the population in the CRB followed by the White non-Hispanic population. Among the lowest percentages are Black and American Indian non-Hispanic populations.

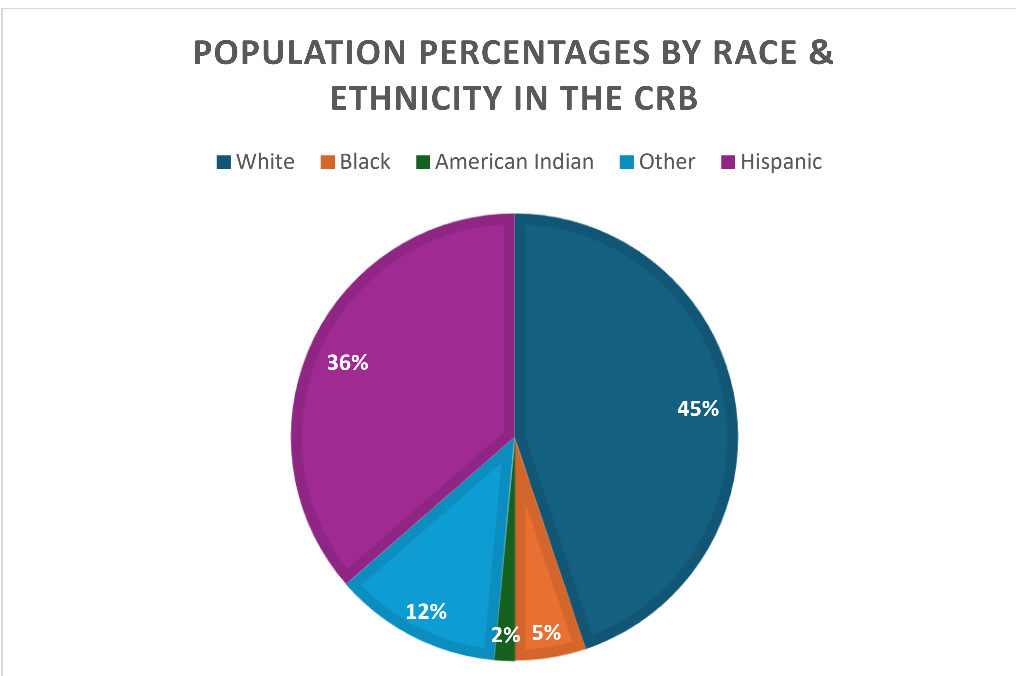

Figure A4. CRB Race and Ethnicity Population Breakdown

A5 Nonlinear relationship among population density, income, and environmental burdens

There is reason to suggest population density has nonlinear relationships with income and environmental burdens. This section discusses each and describes how one might model these relationships in future research.

The relationship between population density and income is interesting. Low-income and high-income households are both likely to live in more dense and less dense areas. Figure A5 below shows a scatter plot between income and population density, which highlights the denseness of census tracts in which those with different income levels live in the CRB. Each point represents a census tract. There is a large spread of high-income and low-income tracts in sparsely populated areas. The more densely populated tracts have a much smaller income range. The shape suggests tracts with lower population density are more segregated by income. Whereas highly densely populated tracts have a greater mix between high and low-income households.

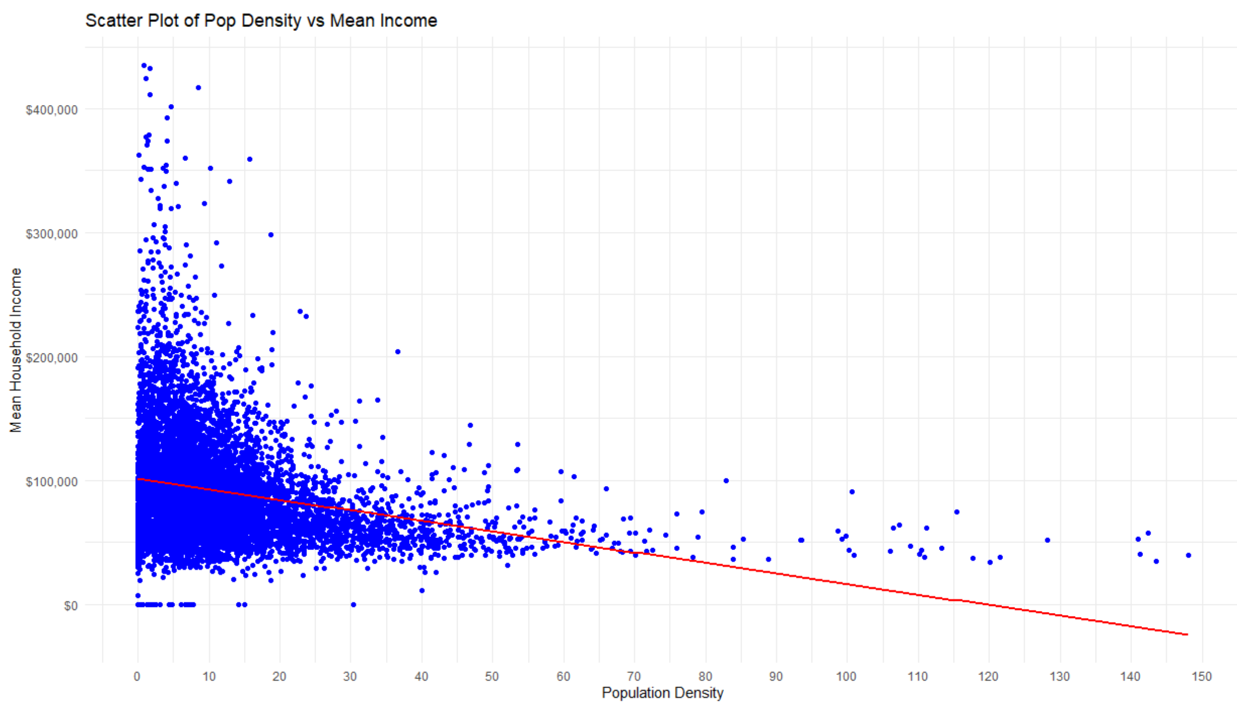

Figure A5. Scatter Plot of Population Density and Mean Income

The relationship between income and each environmental burden when population density is held constant, as seen in Table 7 suggests lower-income tracts face higher environmental burden incidence, except air pollution. Let's look at the lack of natural or green landscape burden as an example. This dependent variable highlights which tracts have higher amounts of impervious surface or cropland. Because of how it is defined, tracts that have low population density can have large amounts of cropland while tracts with high population density likely have high amounts of impervious surface. Figure A6 shows a scatter plot of the relationship between population density and lack of natural or green landscape. Each point represents a census tract. The figure shows there is a large spread of low population density tracts that have high and low amounts of impervious surface or cropland. On the other hand, tracts with a high population density show high percentages of impervious surface or cropland (more likely to be the former than the latter).

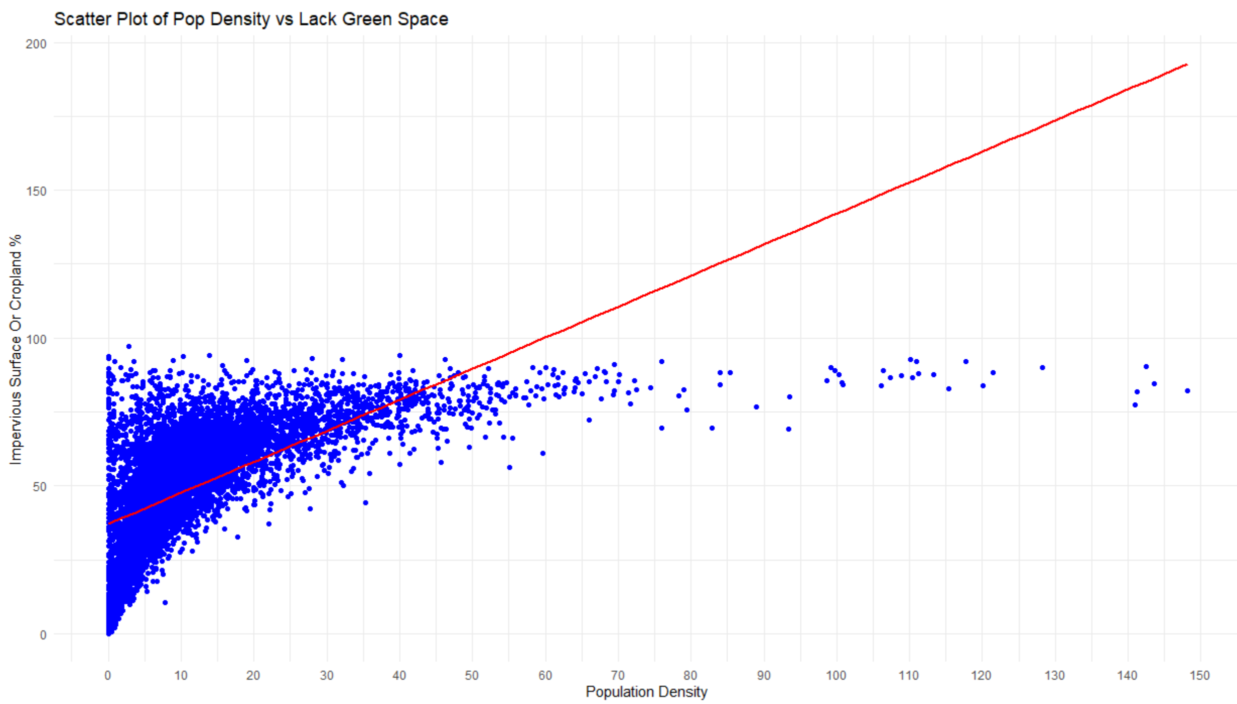

Figure A6. Scatter Plot of Population Density and Lack of Natural or Green Landscape

To isolate the different spreads of population density at each end of the lack of natural or green landscape and income variables, one could split the data into low and high population density subsets. An interaction between population density and income may also be useful to determine whether low-income individuals are more exposed in rural versus urban areas and vice versa. Because of the distribution shape between population density and lack of natural or green landscape, it may be useful to take the log of population density in the model.

A6 Lack of Natural or Green Landscape Error and Solution

This section describes an issue faced with the CEJST's lack of green space variable and how this paper corrected the error. The data set used is Version 1.0 released on November 22, 2022. This version uses 2010 census tract boundaries to align with the 2019 census data and lack of green space (in this paper "lack of green space" is referred to as lack of natural or green landscape). The lack of green space variable is defined by the Multi Resolution Land Characteristics (MRLC) consortium to be the percent of a tract that is impervious surface or cropland (MRLC, 2019). This consortium is what creates this lack of green space variable along the Trust for Public Land and provides it for the CEJST tool. However, in the CEJST's "How to use the list of communities" document, the table with variable definitions describes the lack of green space variable as excluding cropland. This is an error which has been confirmed through conferring with the CEJST through their support email (U.S. Executive Office of the President Council on Environmental Quality, 2022). The original definition from the MRLC is correct and this was confirmed by the CEJST team, as well as staff at the Trust for Public Land. Additionally, the lack of green space variable in the raw data download from the screening tool website is formatted incorrectly (it is supposed to be a percent but has values with no decimals that are four digits). After consulting the CEJST team and Dale Watt, GIS project manager at the Trust for Public Land, we concluded there is a decimal missing in each observation. To correct for this, we added zeros at the front of each observation to ensure each of them are four digits long. Then, we add a decimal between the first two and last two digits. We compared a number of observations with Dale's Trust for Public Land data and found the formatting to be consistent. After correcting for this error, the lack of green space variable was able to be used in the analysis.

A7 Experts Conferred With

Rebeccah Bernat
Manager
Arizona Water Banking Authority

Mike Crimmins
Extension Specialist in Climate Science & Professor
University of Arizona

Laura Condon
Associate Professor in Hydrology & Atmospheric Sciences
University of Arizona

Linda Hwang
Senior Director, Strategy & Innovation
Trust for Public Land

Dale Watt
GIS Project Manager
Trust for Public Land

CEJST Support Team
Screeningtool-Support@omb.eop.gov
Council on Environmental Quality - Climate and Economic Justice Screening Tool

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