Gray, Green, and a Little Blue: Why Stormwater Should Concern You!

Understanding Flooding Rates in Orange County, California.

Salma Abdallah and Hunter Kirn

School of Public Policy, UC Riverside

PBPL289: Capstone

Dr. Andy Crosby

31 May 2024

Abstract

Rapidly changing weather patterns have affected California's rainfall and flooding rates. Our project analyzes Orange County, California's gray and green infrastructure, focusing on disadvantaged and low-income communities to unveil infrastructure inequalities. Using spatial correlation and OLS regression analyses, we better understand stormwater infrastructure and the impacts of flooding. Our data and analysis indicate that low-income and disadvantaged communities experience, to some degree, disproportionate impacts from storm events due to – we hypothesize – poor gray and green stormwater infrastructure. Further research is required to assess how and to what extent these communities experience these disproportionate impacts.

Introduction

In the past decade, California has experienced year-long droughts (California Department of Water Resources) where water storage has been critical. Now with expected changing weather patterns that will bring more rainfall to California (Huang et al. 2020) understanding California's stormwater infrastructure is crucial. Since then, developers and researchers are increasingly looking into green infrastructure in addition to gray stormwater infrastructure to collect stormwater and reduce flooding in communities. Little has been written on the impacts of flooding events have on communities, our research focuses on Orange County, California. We hope our research project shows that research on stormwater state wide is critical. In 2024 counties in California have experienced historical rainfall levels and storms causing mass wide flooding. With changing weather and patterns California is most likely going to experience more storm events in future years (Huang et al. 2020). We focus on Orange County, California due to the availability of data and our time constraints. The aim of this paper is to understand how current gray and green infrastructure affects flooding rates in the community. By understanding gray infrastructure we can see where inequalities are dependent on the quality of the infrastructure in place. With green infrastructure we can understand if green infrastructure is a viable option for reducing flooding rates such as trees, green roofs, and rain gardens.

Therefore, our research question is as follows:

How are low-income and disadvantaged communities in Orange County in California impacted by the condition of the stormwater system (gray, green, and blue infrastructure)?

We investigate our research question using publicly available county, state, and federal data. When looking at gray infrastructure we assess drainage pipes at the local level, inlets, and discharge points in Orange County. When looking at green infrastructure we look at trees and parks. Lastly, when looking at blue infrastructure we are looking at impaired water bodies and rainfall levels. In the following paper we will go over past literature that has been important to understanding variables that affect stormwater infrastructure. Next we will go over our hypotheses for our research project and then go over data sources and variable measures used to test these hypotheses. We will then discuss our findings and discuss the results of our research project. Finally we will reflect on our discussion and talk about our limitations for this research project and suggest future research and will close out with our conclusion.

Hypotheses

Hypothesis One:

Disadvantaged Communities will be associated with a decrease in stormwater infrastructure.

Hypothesis Two:

An increase in the median household income in a census tract will be associated with an increase in stormwater infrastructure.

Hypothesis One will focus on Disadvantaged Communities while Hypothesis Two will focus on Median Household Income per Census Tract. Both hypotheses will look at stormwater infrastructure by looking at flooding rates through population and total area flooded (CDC), Green Infrastructure determined by parks and trees, access and quality of drainage pipes, drainage inlets, and discharge points. Wakhungu et al. (2021) research focused on vulnerability indexes to understand water infrastructure inequalities. This research shows the importance of looking at median household income and race/ethnicity to see if there are inequalities of access and quality of stormwater infrastructure.

Hypothesis Three:

Disadvantaged Communities will be associated with a decrease in green spaces and trees.

Hypothesis Four:

An increase in the median household income in a census tract will be associated with an increase in green spaces and trees.

For Hypothesis Three we will first look at Disadvantaged Communities (OEHHA) and then with Hypothesis Four we will look at Household income to see if there is a correlation with living in a disadvantage community for a lower income community that there will be a decrease in green spaces. Green spaces will be analyzed by the amount of trees in each census block and spatial analysis of parks (Parks for All Californians). According to Berland et al. (2017) Trees can be an important factor in reducing flooding. Trees help slow down flooding by collecting rainfall through the trees canopy or the soil they are planted in. When understanding green spaces in our research we focus on parks. According to Rosenberger et al. (2021) the rise of urban densification, green infrastructure is becoming more important. Rosenberger et al. (2021) looked at solutions to add green spaces to already developed urban areas that can help reduce flooding. Parks can be used as green infrastructure to reduce flooding and also are a benefit to the community.

Hypothesis Five:

Disadvantaged Communities will be associated with an increase in impaired water bodies.

Hypothesis Six:

An increase in the median household income in a census tract will be associated with a decrease in impaired water bodies.

For Hypothesis Five we will analyze if living in a disadvantaged community (OEHHA) will increase the chance of having an impaired water bodies. Hypothesis Six will look at median household income (OC Public Works) to see if there is an increase in household income will there be a decrease in impaired water bodies. These two hypotheses will capture the water quality component of our assessment of stormwater infrastructure quality. Impaired water bodies data was collected through California Office of Environmental Health Hazard Assessment (OEHHA, 2023).

Hypothesis Seven:

Disadvantaged Communities will be associated with an increase in flooding rates.

Hypothesis Eight:

An increase in the median household income in a census tract will be associated with a decrease in flooding rates.

For Hypothesis Seven we use OEHHA to outline disadvantaged communities in Orange County, California. For Hypothesis Eight we will be looking at the median household income per each census tract collected from OC Public Works. We will determine flooding rates through total population affected, total area affected, parks and trees, and access to drainage pipes. Past literature has shown that the US Sewage system can not store that much water causing thousands of flooding instances (Novaes & Marques, 2022a).

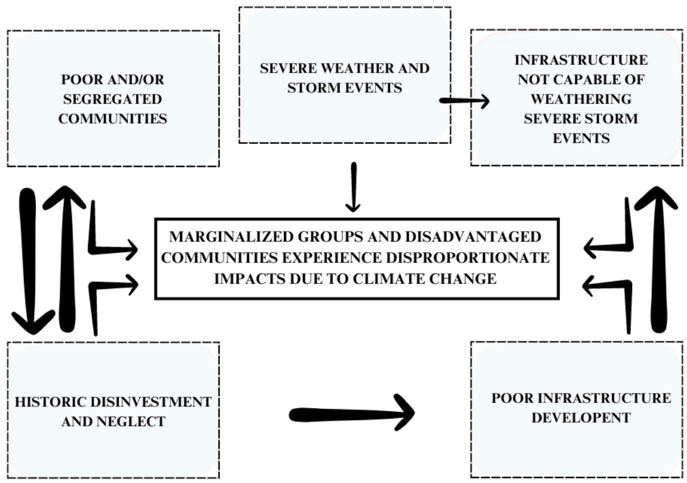

Figure 1. A Flow-Chart on Stormwater Infrastructure, Community Development, and Weather

This figure is a simple visual representation of how infrastructure and community development can impact marginalized communities during severe weather events.

Path Model

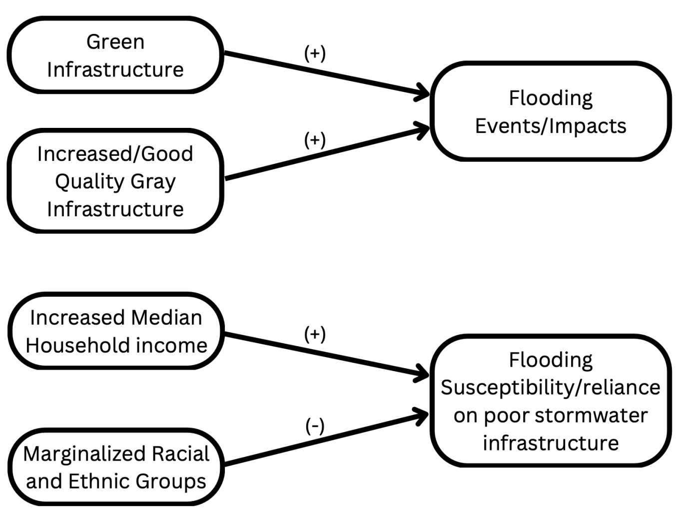

Figure 2. "Tinker Toys" Path Model.

Green Infrastructure will have a positive impact on **Flooding Events/Impacts**. Past research has shown that green infrastructure such as plants, green spaces, and rain gardens can collect rainwater and stormwater runoff reducing the level of flooding in the surrounding community

Increased/Good Quality Gray Infrastructure has a positive impact on **Flooding Events/Impacts**. The more gray infrastructure in the surrounding community such as drains, gutters, and water storage can reduce flooding by collecting stormwater and runoff as well as having water storage large enough that there is no overflow.

An **Increase in Median household** income has a positive effect on **Flooding Susceptibility/reliance on poor stormwater infrastructure**. Areas that have higher income have better quality infrastructure vs lower income areas have lower quality infrastructure and are at higher risks of flooding.

Marginalized Racial and Ethnic Groups will have a negative impact on **Flooding Susceptibility/reliance on poor stormwater infrastructure**. Communities that have a higher population of minorities have lower rates of infrastructure quality. Communities that are predominantly white have better quality infrastructure and have more gray and green stormwater infrastructure in place.

Past Literature

Little research has been done on the quality of stormwater infrastructure and its effects on surrounding communities – especially within Orange County. Additionally, research on green infrastructure has been primarily conducted outside of the United States and through simulations (Berland et al., 2017). Literature indicates that communities with a higher social vulnerability index have a poorer stormwater infrastructure quality (FEMA). Little research has been done on the combination of gray and green infrastructure effects on communities and flooding rates. However, what research that has been conducted, clearly indicates that green infrastructure, especially trees, have been proven to increase community health and reduce flooding impacts (Kondo et al., 2015). We have outlined key themes in preparation for our research project that are important to understanding factors that affect flooding rates and infrastructure.

Infrastructure Conditions (Low-SES → more adverse impacts by poor conditions)

Regulation of urban stormwater management is not a matter of choice, but performance. The US is one of the top countries that has federal regulation on urban stormwater regulation compared to other countries. However, stormwater policy is not a top priority in policy makers' minds with regulations in place. Novaes and Marques (2022a) focuses on stormwater regulation mainly in Brazil but looks to other countries on management of stormwater infrastructure. The US Sewage system is designed to only collect a small amount of stormwater and groundwater which has resulted in an increase of flooding back into buildings for a variety of reasons. “according to the EPA, responsible for about 23,000–75,000 SSO events annually, disregarding the returns to buildings” (Novaes & Marques, 2022a). The minimum has been done to address these events, make sure water pollution is kept just below the maximum Clean Water Act. Though the US has great infrastructure, Novaes et al. statistics show stormwater infrastructure in the US as a whole country and does not go into each state individually or give specific state examples. Each state has different needs and weather occurrences, weather patterns have also been changing due to climate change. Our research focuses on just one county (Orange County, CA) to showcase in more detail urban stormwater infrastructure conditions. By focusing on a county that is not used to heavy rainfall our research will capture the conditions of MS4 infrastructure to see if the current conditions will be able to handle this increase in rainfall perception.

Sustainable stormwater management under the impact of climate change and urban densification. Urban densification is to build more buildings and housing to accommodate our growing population. However with densification urban areas are at a higher risk of flooding especially without the proper infrastructure. Rosenberger et al. (2021) research focuses on green infrastructure to reduce flooding through a simulation in Germany. Research shows that implementing a variety of green infrastructure into urban densification planning helps reduce flooding during high precipitation events. Rosenberger et al. (2021) noted that this simulation is based on one event and does not account for different moisture soil rates. Though we do not focus on green infrastructure in our research it is important to note that more research is needed to see how green infrastructure works year round. Rosenberger et al. (2021) research is important to our policy suggestions, with our focus on MS4 conditions there may not be room to expand the existing infrastructure and policy solutions may need to look to other alternatives. In our research we look at urban densification and development to further understand why stormwater infrastructure is important to maintain and look to other solutions such as green infrastructure solutions. Understanding how different green infrastructure methods work is important to our policy solutions. Additionally, understanding green infrastructure is helpful to understand that green spaces in neighborhoods can be a contributing factor in flooding rates. Disadvantage communities are less likely to have green spaces in their neighborhood. This is important when looking at flooding rates in neighborhoods since green spaces can affect those rates.

The role of trees in urban stormwater management. Trees naturally help with flooding rates through canopy interception, transpiration, and improved infiltration. Berland et al. (2017)

goes over how trees help reduce stormwater runoff and how the kinds of trees and the way trees are planted can all affect stormwater runoff. More research is needed in understanding how different species of trees can help in different ways to maximize stormwater runoff loss year round. Majority of research done on the impacts of trees focus on air quality, Berland et al. (2017) research gives us a better understanding on how trees can affect stormwater runoff which ultimately affects flooding rates. In our research we are able to look at the amount of trees in an area. This is relevant when looking at flooding rates to see if disadvantaged communities have fewer trees in the area that would ultimately affect flooding rates. Our research does not focus on the impacts of trees in stormwater management so Berland et al. (2017) research provides us context when looking at trees and the different factors that can also affect runoff such as if trees are planted on a mound or hill which does not reduce stormwater runoff. This is important for our research as our data does not provide us information on how a tree is planted.

<u>MS4 conditions/capability (Low-SES → more adverse impacts by poor conditions)</u>

Geospatial Vulnerability Framework for Identifying Water Infrastructure Inequalities. Wakhungu et al. (2021) research looks to see if there are inequalities with water infrastructure and flooding rates. Their study uses GIS and they focus on Tampa, Florida. Wakhungu et al. (2021) research used different vulnerability indexes to see if there was a correlation with socially vulnerable areas that are also flooding, water infrastructure, and hazardous waste vulnerable as well. Their findings indicated that Socially vulnerable areas were also vulnerable to these other factors of flooding, waste, and access to water. However, just looking at vulnerability indexes does not show the full picture of flooding rates. Their research looks at other factors such as the environment that can affect someone's living condition. Our research focuses on factors that affect flooding rates such as rain participations, day by day flooding rates by population and total area affected, green infrastructure and drainage pipes and inlets. We focus on current flooding rates and not future predictions of at risk of flooding areas.

Hydrophilic trace organic contaminants in urban stormwater: occurrence, toxicological relevance, and the need to enhance green stormwater infrastructure. Spahr et al. (2020) assess the viability of current green stormwater infrastructure capacity in treating organic contaminants through a comprehensive review of current literature produced from North America, Western Europe, and Australia. They find that there are many and varied avenues for contaminants to impact urban stormwater – too many for the current green stormwater infrastructure capacity to handle. This paper is relevant to our work because it presents a strong case on the importance of green infrastructure in regulating poor water quality due to urban stormwater and runoff.

Reasons/Rationale for Government Interference

Public policy: urban stormwater in a paradigm shift, is it the end or just the beginning? Novaes and Marques (2022b) look at historical policy implications regarding stormwater. Their research looks at past policy solutions on drainage and flooding showing what has been done but also highlighting gaps in policy solutions for stormwater infrastructure. Stormwater policies though where present they have become more on the radar when shifting the lens of looking at stormwater as a resource instead of looking at how to prevent flooding and pollution. Novaes and Marques (2022b) research on policy allows us to understand the history of stormwater policy in a concise way. Our policy analysis takes into account past stormwater but also looks at green infrastructure solutions and policies as well. Novaes and Marques (2022b) research also focuses on stormwater policy on a national level. Our research focuses on California and specifically looking at data for Orange County. This provides a more detailed look into stormwater policy on a state level where there have been recent (2024) record breaking rainfall rates. With this increase in flooding and rainfall, stormwater policy solutions must be addressed.

Rationale for Public Policy

California is not able to handle the expected annual increase in rainfall each year (Huang et al. 2020) with an increase in rain government intervention is needed to be able to handle this increase in rainfall. It should not be put in the private sector or individuals to protect their businesses and property from flooding (Novaes & Marques 2022c). Even with green infrastructure that you can purchase such as rain barrels, these measures do not effectively reduce flooding on individuals' property. There are several compelling reasons to encourage policy intervention on stormwater infrastructure:

Market Failure: Stormwater is regulated by the State of California and is considered a public good. Up until 2012 when AB-1750 Rainwater Capture Act of 2012 rainwater collection was illegal in the state of California. Recently research and literature is showing that states should be viewing stormwater as a resource instead of it being wasted (Becker 2024). There is increasing evidence on wasted stormwater which further shows that the quality of our stormwater infrastructure does not nurture stormwater as a public good. Stormwater that is wasted can go towards agriculture needs during periods of drought (Cooley et al. 2022). With current government intervention of the Clean Water Act when flooding events occur filtration is kept to a minimum that allows the maximum water pollutant (Novaes & Marques, 2022a). More needs to be done on government intervention to update and implement more stormwater infrastructure.

Monopoly/Oligopoly: With gray infrastructure the government has a monopoly on infrastructure that can be implemented. Infrastructure includes gutters, drains, pipes, retention basins, dams, seawalls, roads, and water treatment plants. The lack of competition has led to a decline in maintaining and constructing stormwater collection infrastructure (Augusto et al., 2022). Novaes and Marques (2022c) goes more into depth on if the private sector were to join a capable government would use the private sector as a resource but not to have the private sector replace government intervention.

Environmental Risk: Mismanaged stormwater infrastructure can impact flooding rates, stormwater collection efforts, and disaster management. California has experienced major droughts over the past decade according to the California Department of Water Resources. Droughts have been due to a lack of rain and water storage, droughts pose a major environmental risk that with more stormwater collection and storage infrastructure it can help reduce these risks.

Equitable distribution: There is a long and detailed history of resources not being allocated to low-income and disadvantaged communities. The Infrastructure Act was signed in 2021, this act was to focus on allocating funds to disadvantaged communities for water infrastructure (Husain 2023). However disadvantaged communities were not defined so it is left up to interpretation further indicating that resources are not properly allocated to disadvantaged communities.

Data Sources

We worked with nine separate datasets – all with spatial capacity – in this project. Since the focus of our research question is on Orange County (OC), we pulled most of our community and stormwater infrastructure data from the Orange County Department of Public Works (OCPW) GIS Open Data Portal. We also pulled datasets from data repositories provided by the non-profit organization Parks for All Californians, the Centers for Disease Control (CDC)

National Environmental Public Health (NEPH) Tracking Network, and the California Office of Environmental Health Hazard Assessment (OEHHA).

Orange County Stormwater Network Map: This is a map that is a holistic and detailed spatial representation of the stormwater infrastructure within OC. It includes spatial data on inlets, discharge points, cleanouts, manholes, fittings, network structures, control valves, local drainage pipe systems, and the regional channels. The data is updated to reflect the stormwater infrastructure developed within the county up to 2020. While we used the complete map to understand the spatial distribution of the complete stormwater infrastructure throughout OC, we conducted our analyses on only a few key components of the system.

2021 American Communities Survey, Orange County – Population Density: OCPW took the 2021 American Community Survey, 5-year estimates for Census Tracts and isolated the information to Orange County. The "Population Density" dataset provides demographic information on OC residents (including population rates), assesses the area (in square miles) of each Census Tract, and calculates the total population density at the Census Tract level. This dataset helps us garner a better understanding of the population distribution within OC and, thus, directs our attention to the people being disproportionately impacted by poor quality stormwater infrastructure by who they are and where they live.

2021 American Communities Survey, Orange County – Economic Characteristics: This is another dataset prepared by OCPW that is an OC isolated subset of the 2021 American Community Survey, 5-year estimates for Census Tracts. The "Economic Characteristics" dataset provides financial information on OC residents at the Census Tract level. This dataset helps us test our hypotheses that investigate if OC residents' financial capacity can have an influence on their accessibility to good quality stormwater infrastructure.

Orange County Tree Point – 2011: This is a map that documents spatial point data on just over 1.6 million trees throughout the county; it was most recently updated to 2022. This dataset helps capture the green infrastructure component of our analysis along with the following dataset.

Parks for All Californians: This dataset was accessed through Parks for All Californians (PAC) Local Park Access Planning and Grants. It provides data (updated to 2020) on neighborhood level access to parks and open and preserved areas. The *Parks Access Tool* provides statistical information of the communities ability to access a park. According to the PAC, "64% of residents of Orange live in areas with less than 3 acres of parks or open space per 1,000 residents" (Parks for All California). We accessed this data by downloading the GIS shapefile that included Parks, Open, and Preserved Spaces. This data set also included information on the distance communities were in relation to a park as well as access to a park that had an area of three or more acres. The data set also included information on disadvantaged and severely disadvantaged communities. To access this data, select the Parks for All California to "Parks all over California." We isolated the data through the "Clip" function in ArcGIS Pro 3.3 to display parks in Orange County. We also excluded any information that was not Parks, Open, and Preserved Spaces such as the distance to parks and disadvantaged communities since we used the OEHHA for information on Disadvantage Communities (discussed below) and it was beyond the scope of our research question.

Total People Affected by Flooding: This dataset was pulled from the CDC's NEPH Tracking Network which provides information on a variety of environmental health concerns, indicators, and measurements, throughout the United States. The CDC call this data "research-grade" and develop the datasets from satellite imagery provided through NASA's

Land, Atmosphere Near Real-time Capability for Earth Observing Systems, or LANCE, function (EPH Tracking, 2024). The CDC classifies a Tract as impacted by flooding if a singular raster square within the Tract boundary is flooded. To access this dataset, we selected “Precipitation and Flooding” for the “Content” we were interested in, “Current and Historical Flooding” for our “Indicator,” “Total Population Affected by Flooding” for our “Measure.” We selected the data to be provided to us on the Census Tract level for California from December 1, 2023 – May 25, 2024.

Total Area Impacted by Flooding (km^2): Similarly to the “Total People Affected by Flooding” dataset, this dataset was pulled from the CDC’s NEPH Tracking Network.We utilized the alternative metric of “Total Area Flooded per 1,000 km^2” which was “calculated by multiplying the proportion of the [Census Tract] that is flooded by 1000” (EPH Tracking, 2024). To access this dataset, we selected “Precipitation and Flooding” for the “Content” we were interested in, “Current and Historical Flooding” for our “Indicator,” “Total Area Flooded” for our “Measure,” and “Total Area Flooded per 1,000 km^2” for the “Alternative Metric” selection. We selected the data to be provided to us on the Census Tract level for California from December 1, 2023 – May 25, 2024.

SB535 – Disadvantaged Communities: California OEHHA, through California Environmental Protection Agency, identifies Disadvantaged Communities at the Census Tract level in California so that they may receive proceeds from the California Cap-and-Trade Program (OEHHA, 2024). The designation of “Disadvantaged Community” for Census Tracts is most recently updated to July 2022. We acquired the ArcGIS geodatabase data repository from the California OEHHA’s SB 535 website and extracted the information relevant to our project scope using the “Intersect” function in ArcGIS Pro 3.3.

CalEnviroScreen 4.0: California OEHHA also developed and published the CalEnviroScreen 4.0 data visualization tool which tracks and identifies communities impacted by multiple sources of pollution at the Census Tract level (OEHHA, 2023). The pollution burden information includes assessments on how communities are impacted by the water quality of rivers, streams, and tributaries that run through their communities. The data is most recently updated to May 2023.We acquired the ArcGIS geodatabase data repository from the California OEHHA's CalEnviroScreen 4.0 website and extracted the information relevant to our project scope using the "Intersect" and "Spatial Join" functions in ArcGIS Pro 3.3.

Variables and Measurements

Dependent Variables: **Sum of Drainage Pipe Lengths (m) per Census Tract** is a calculation of the total length of the local stormwater drainages in each Census Tract in Orange County. This calculation was done with ArcGIS Pro 3.3 in two parts. First, we used the "Spatial Join" function to merge the "OC Stormwater Network" and "Economic Characteristics" datasets together. Then, we used the "Intersect" function to develop a field that would accept the output of the "Calculate Geometry" function to calculate the total length of the local drainages per Census Tracts. This is a continuous variable where a singular unit change equals a one meter increase or decrease in pipe length per each Census Tract. This variable captures the majority of our stormwater drainage system data. We do not have the ability to calculate the capacity of the OC's drainage system, but this variable does reflect the extent of the infrastructure available on the local level. This variable will also be used as a control in other analyses.

Total Drainage Inlets per Census Tract is a calculation of the total drainage inlets in each Census Tract in Orange County. This calculation was done with ArcGIS Pro 3.3. With the "Spatial Join" function, we merged the "OC Stormwater Network" and "Economic

Characteristics" datasets together with a focus on the "Inlets" field. This allowed ArcGIS Pro to calculate the total inlets per Census Tract. This is a continuous variable where a singular unit change equals a one inlet increase or decrease per each Census Tract. We consider Drainage Inlets because the inlets collect stormwater and other forms of runoff from the street to reach the drainage system. This variable will also be used as a control in other analyses.

Total Discharge Points per Census Tract is a calculation of the total discharge points in each Census Tract in Orange County. This calculation was done with ArcGIS Pro 3.3. With the "Spatial Join" function, we merged the "OC Stormwater Network" and "Economic Characteristics" datasets together with a focus on the "Discharge Points" field. This allowed ArcGIS Pro to calculate the total discharge points per Census Tract. This is a continuous variable where a singular unit change equals a one discharge point increase or decrease per each Census Tract. We consider Discharge Points because this data reflects where stormwater and other forms of runoff are leaving the local drainage system. This variable will also be used as a control in other analyses.

Total Trees per Census Tract is a calculation of the total trees in each Census Tract in Orange County. This calculation was done with ArcGIS Pro 3.3. With the "Spatial Join" function, we merged the "Orange County – Tree Point 2011" and "Economic Characteristics" datasets together. This allowed ArcGIS Pro to calculate the total points of trees per Census Tract. This is a continuous variable where a singular unit change equals a one tree increase or decrease per each Census Tract. This variable will also be used as a control in other analyses.

Percent Impaired Water Bodies (%) reflects the total percentage of impaired water bodies that Orange County residents encounter within their Census Tract. This is a continuous variable where a singular unit change equals a one percent increase or decrease in impaired water bodies within the Census Tract. This variable captures the water quality component of our assessment of stormwater infrastructure quality.

Total Area Impacted by Flooding (m^2) reflects the total area within a Census Tract that the CDC calculated to be impacted by flooding. In the original dataset, this variable reflected the total area impacted by flooding per 1,000 km^2 per Census Tract. However, in order to ensure that this variable is comparable to other variables that have 'meters' as their unit, we multiplied the variable with a factor 0.000001. This changed the units of the Total Area Impacted variable from kilometers squared to meters squared. This is a continuous variable where a singular unit change equals a one meter squared increase or decrease in flooding impact per each Census Tract.

Total People Impacted by Flooding per Census Tract reflects the total number of people whom the CDC determined to be impacted by flooding events within a Census Tract. This is a continuous variable where a singular unit change equals a one person increase or decrease per each Census Tract.

Control Variables: **Percent Non-White Population (%)** reflects the population proportion of non-white Orange County residents compared to the rest of the population in the Census Tract. This was calculated using STATA 18 where we subtracted the population of white residents from the total population and multiplied by 100. This is a continuous variable where a one unit change equals a one percent increase or decrease in the population of non-white Orange County residents in the Census Tract. We also use the control variable **Non-White Population** to reflect population count for the model testing Total People Impacted by Flooding in order to keep the variables comparable to one another. That variable is continuous where a one unit change equals a one person increase or decrease in the population of non-white Orange County residents in the Census Tract.

Percent Hispanic or Latino Population (%) reflects the population proportion of Hispanic or Latino Orange County residents compared to the rest of the population in the Census Tract. This was calculated using STATA 18 where we subtracted the population of non-Hispanic or Latino residents from the total population and multiplied by 100. This is a continuous variable where a one unit change equals a one percent increase or decrease in the population of Hispanic or Latino Orange County residents in the Census Tract. We also use the control variable **Hispanic or Latino Population** to reflect population count for the model testing Total People Impacted by Flooding in order to keep the variables comparable to one another. That variable is continuous where a one unit change equals a one person increase or decrease in the population of non-white Orange County residents in the Census Tract.

Total Population reflects the total population of each Census Tract. This is a continuous variable where a one unit change equals a one person increase or decrease in the total population of Orange County residents in the Census Tract.

Total Households reflects the total count of households within each Census Tract. This is a continuous variable where a one unit change equals a one household increase or decrease in the Census Tract.

Area Square Miles (mi^2) reflects the area of each Census Tract in Orange County. This is a continuous variable where a one unit change equals a one square mile increase or decrease in the area of the Census Tract.

Population Density (population/mi^2) reflects the ratio of the total population compared to the area of the Census Tract. This variable was already calculated and present within the "Population Density" dataset. This is a continuous variable where a one unit change equals an one person per one square mile increase or decrease in the Census Tract.

Independent Variables: **SB535 – Disadvantaged Communities** reflects the Disadvantaged Communities status or classification of Census Tracts throughout the county. We isolated the Disadvantaged Communities Census Tracts polygons within Orange County using ArcGIS Pro 3.3 and generated a dummy binary variable coded as 1 to represent the Disadvantaged Community status. This is a binary variable where 1 is coded to represent Census Tracts with Disadvantaged Communities status and 0 is coded to represent the rest of the Census Tracts within the county.

Median Household Income in $1,000 reflects the median household income of each Census Tract. This was calculated with STATA 18 where the original 'Median Household Income' variable in the "Economic Characteristics" dataset was divided by 1,000. This is a continuous variable where a one unit change equals a $1,000 increase or decrease in the median household income of the Census Tract.

Descriptive statistics on the variables can be found in Table 1 in the Appendix.

Analysis Strategy

For our analyses, we conducted a collection of spatial correlations (single variable and bivariate spatial correlations) and Ordinary Least Squares (OLS) Regression models (multivariate) to test our hypotheses. Bivariate spatial correlation is an excellent data visualization tool that gives us an understanding of the spatial distribution of two variables across a particular location. With this tool, we will be able to observe where there are clusters of resources (in this case, gray and green infrastructure) in comparison to OC residents' financial capacity. OLS Regression modeling will help us in determining if there is a linear relationship between the error in our dependent variables and our independent variables. With a series of multivariate OLS Regression models, we will be able to confirm or refute our hypotheses that are based on simple linear relationship terminology. The combination of spatial correlations and OLS Regression models will provide us with a holistic view on how communities within Orange County are supported or hindered by their local stormwater infrastructure.

We split our analyses into two main parts. First, we want to test where and to what extent OC residents have access to gray and green stormwater infrastructure. We will be testing access to gray stormwater infrastructure through three different variables: summation of drainage pipe length (m) per Census Tract, total inlets per Census Tract, and total discharge points per Census Tract. We will be testing access to green stormwater infrastructure through two variables and two analysis strategies: total tree count per Census tract with an OLS regression model and spatial correlation and park locations with spatial correlations.

Second, we want to test where and to what extent OC residents are impacted by stormwater infrastructure quality. We will be testing stormwater infrastructure quality through three different proxy variables: percent impaired water bodies per Census Tract, total people impacted by flooding per Census Tract, and total area impacted by flooding (m^2) per Census Tract.

Accessibility to and Quantity of Gray and Green Stormwater Infrastructure – OLS Regression Models

Model One – Summation of Drainage Pipe Length (m) per Census Tract:

$$Y_1 = \beta_0 + \beta_1^{nonwhite\ pop\%} + \beta_2^{hispanic\ pop\%} + \beta_3^{total\ households} + \beta_4^{median\ HI} + \beta_5^{SB\ 535} + \beta_6^{pop\ density} + \beta_7^{area\ sq\ mi} + \epsilon$$

Model Two – Total Inlets per Census Tract:

$$Y_2 = \beta_0 + \beta_1^{nonwhite\ pop\%} + \beta_2^{hispanic\ pop\%} + \beta_3^{total\ households} + \beta_4^{median\ HI} + \beta_5^{SB\ 535} + \beta_6^{pop\ density} + \beta_7^{area\ sq\ mi} + \epsilon$$

<u>Model Three – Total Discharge Points per Census Tract:</u>

$$Y_3 = \beta_0 + \beta_1^{nonwhite\ pop\%} + \beta_2^{hispanic\ pop\%} + \beta_3^{total\ households} + \beta_4^{median\ HI} + \beta_5^{SB\ 535} + \beta_6^{pop\ density} + \beta_7^{area\ sq\ mi} + \epsilon$$

<u>Model Four – Total Trees per Census Tract:</u>

$$Y_4 = \beta_0 + \beta_1^{nonwhite\ pop\%} + \beta_2^{hispanic\ pop\%} + \beta_3^{total\ households} + \beta_4^{median\ HI} + \beta_5^{SB\ 535} + \beta_6^{pop\ density} + \beta_7^{area\ sq\ mi} + \epsilon$$

Potential Indicators of Stormwater Infrastructure Quality – OLS Regression Models

<u>Model Five – Percent Impaired Water Bodies per Census Tract</u>

$$Y_5 = \beta_0 + \beta_1^{sum\ pipe\ length} + \beta_2^{total\ inlets} + \beta_3^{total\ discharge\ pt} + \beta_4^{total\ trees} + \beta_5^{area\ mi\ sq} + \beta_6^{pop\ density}$$
$$\beta_7^{total\ households} + \beta_8^{total\ pop} + \beta_9^{nonwhite\ pop\%} + \beta_{10}^{hispanic\ pop\%} + \beta_{10}^{sb535} + \beta_{11}^{median\ HI} + \epsilon$$

<u>Model Six – Total Area Impacted by Flooding (m^2) per Census Tract</u>

$$Y_6 = \beta_0 + \beta_1^{sum\ pipe\ length} + \beta_2^{total\ inlets} + \beta_3^{total\ discharge\ pt} + \beta_4^{total\ trees} + \beta_5^{area\ mi\ sq} + \beta_6^{pop\ density}$$
$$\beta_7^{total\ households} + \beta_8^{total\ pop} + \beta_9^{nonwhite\ pop\%} + \beta_{10}^{hispanic\ pop\%} + \beta_{10}^{sb535} + \beta_{11}^{median\ HI} + \epsilon$$

<u>Model Seven – Total People Impacted by Flooding per Census Tract</u>

$$Y_7 = \beta_0 + \beta_1^{sum\ pipe\ length} + \beta_2^{total\ inlets} + \beta_3^{total\ discharge\ pt} + \beta_4^{total\ trees} + \beta_5^{area\ mi\ sq} + \beta_6^{pop\ density}$$
$$\beta_7^{total\ households} + \beta_8^{total\ pop} + \beta_9^{nonwhite\ pop\%} + \beta_{10}^{hispanic\ pop\%} + \beta_{10}^{sb535} + \beta_{11}^{median\ HI} + \epsilon$$

Results

The full regression result tables can be found in the Appendix. A summary of the results of the seven models in comparison with the hypotheses is at the end of this section. In this section, we discuss the results of the OLS Regression Models.

OLS Regression Model Results for Models One through Four

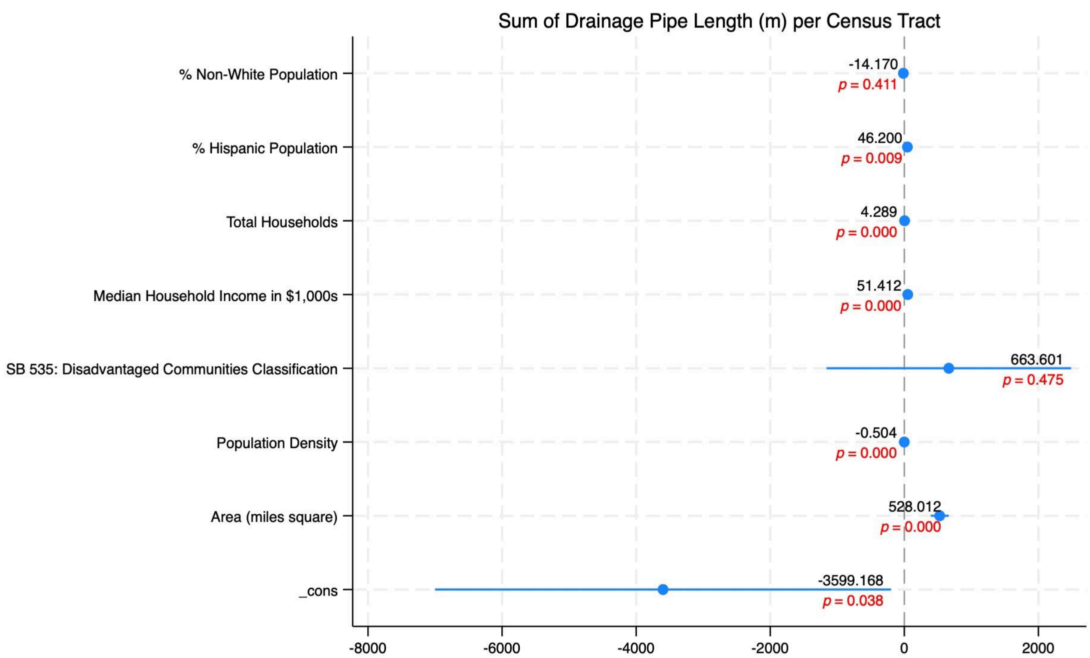

Figure 3. Model One – Sum of Drainage Pipe Length (m) per Census Tract, Orange County, CA

This model is the first of three that tests Hypotheses One and Two: the linear relationship between the classification of disadvantaged communities and the median household income at the Census Tract level (independent variables) with the quantity of gray stormwater infrastructure available to them (dependent variable). In this model, the portion of stormwater infrastructure we are assessing is the Summation of Drainage Pipe Length in meters in a Census Tract. Of the seven independent variables and controls within this model, only two coefficients are not significantly different from zero. The coefficient for the independent variable SB535: Disadvantaged Communities Classification (*$p = 0.475$)* was not significantly different from zero.

Meaning, we were not able to confirm Hypothesis Seven; Disadvantaged Communities within Orange County are not disproportionately impacted in the meters of drainage pipes available to them.

However, the coefficient for our other independent variable – Median Household Income in \$1,000s – was significant *(p = 0.000)*. We find that with a \$1,000 increase in the median household income of a Census Tract, there is an increase of approximately 51 meters of drainage pipes available to the community. We can confirm Hypothesis Eight in this model.

Approximately 39% of the variation in the dependent variable Summation of Drainage Pipe Length (m) is explained by this multivariate regression model.

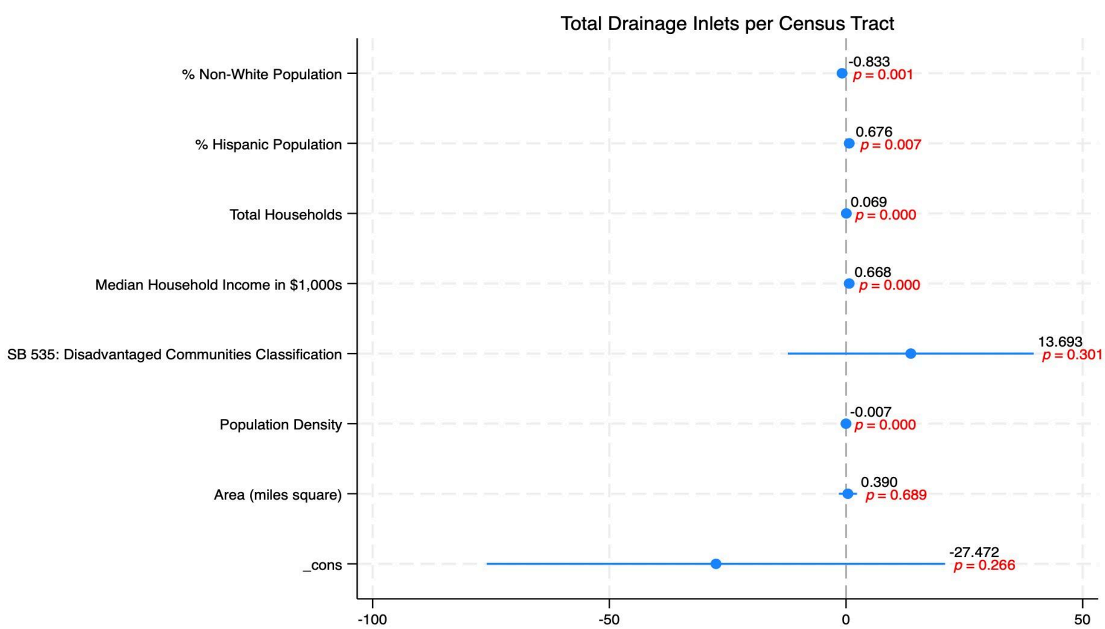

Figure 4. Model Two – Total Drainage Inlets per Census Tract, Orange County, CA

This model is the second of three that tests Hypotheses One and Two: the linear relationship between the classification of disadvantaged communities and the median household income at the Census Tract level (independent variables) with the quantity of gray stormwater infrastructure available to them (dependent variable). In this model, the portion of stormwater infrastructure we are assessing is the Total Drainage Inlets per Census Tract. Of the seven independent variables and controls within this model, only two coefficients are not significantly different from zero. The coefficient for the independent variable SB535: Disadvantaged Communities Classification *(p = 0.301)* was not significantly different from zero. Meaning, we were not able to confirm Hypothesis One; Disadvantaged Communities within Orange County are not disproportionately impacted in the total drainage inlets available to them.

The coefficient for our second independent variable – Median Household Income in $1,000s – was significant *(p = 0.000)*. However, we find that it is a marginal positive result: a $1,000 increase in the median household income of a Census Tract resulted in a 0.7 increase in drainage inlets available to the community. We can confirm Hypothesis Eight in this model.

Approximately 35% of the variation in the dependent variable Total Drainage Inlets is explained by this multivariate regression model.

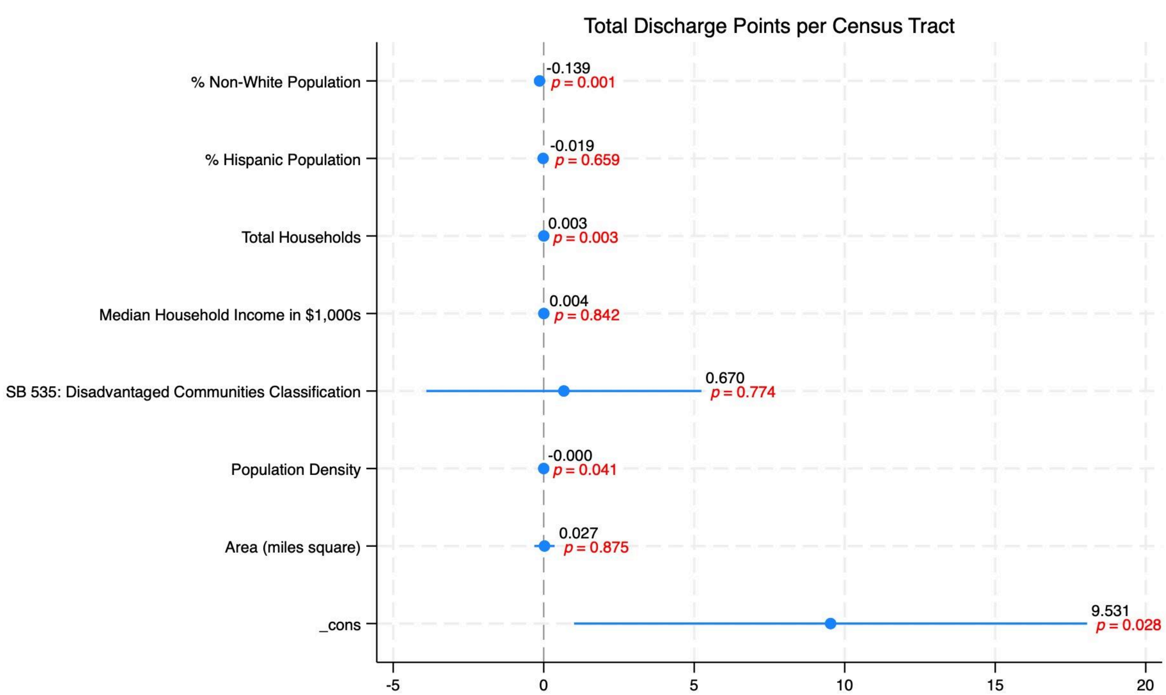

Figure 5. Model Three – Total Discharge Points per Census Tract, Orange County, CA

This model is the third and final of three that test Hypotheses One and Two: the linear relationship between the classification of disadvantaged communities and the median household income at the Census Tract level (independent variables) with the quantity of gray stormwater infrastructure available to them (dependent variable). In this model, the portion of stormwater infrastructure we are assessing is the Total Discharge Points per Census Tract. Of the seven independent variables and controls within this model, four coefficients were not significantly different from zero.

We were not able to confirm either Hypothesis One or Two with this model: the coefficients for SB535: Disadvantaged Communities Classification *($p = 0.774$)* and Median Household Income in $1,000s *($p = 0.842$)* were both non-significant. Meaning, Disadvantaged and Low-Income Communities are not disproportionately impacted in the total discharge points available to them.

Approximately 8% of the variation in the dependent variable Total Discharge Points is explained by this multivariate regression model.

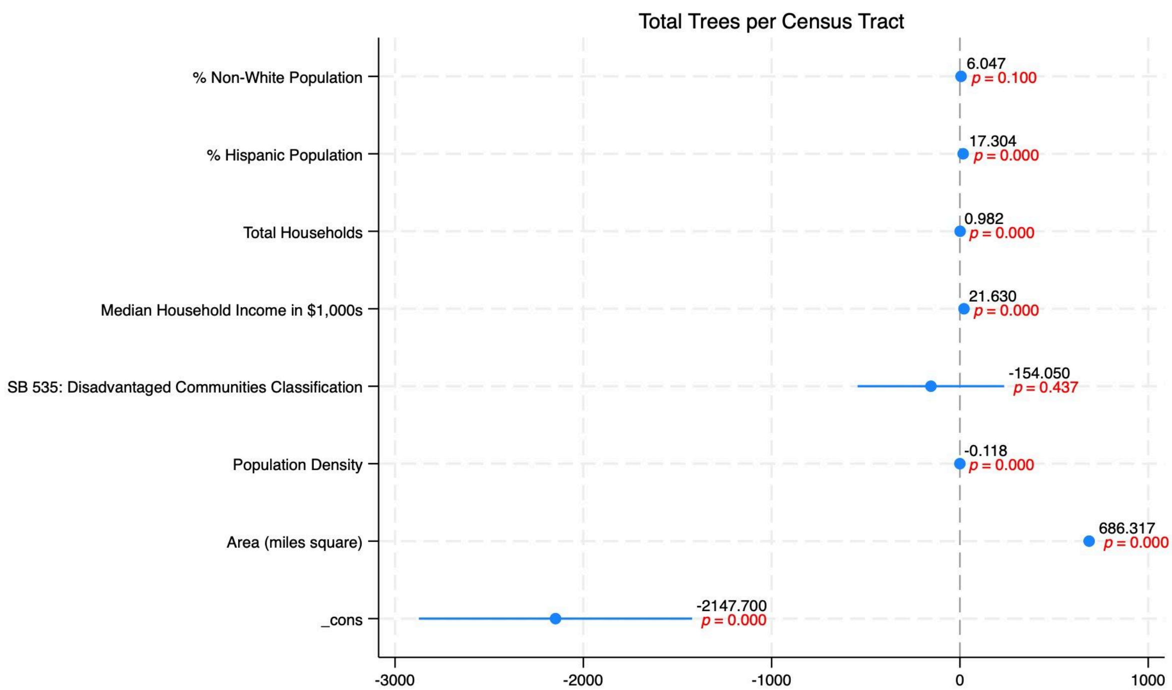

Figure 6. Model Four – Total Trees per Census Tract, Orange County, CA

This model tests Hypotheses Three and Four: the linear relationship between the classification of disadvantaged communities and the median household income at the Census Tract level (independent variables) with the quantity of green stormwater infrastructure available to them (dependent variable). In this model, the type of green stormwater infrastructure we are assessing is the Total Trees per Census Tract. Of the seven independent variables and controls within this model, only two were not significantly different from zero. The coefficient for the independent variable SB535: Disadvantaged Communities Classification (p = 0.437) was not significantly different from zero. Meaning, we were not able to confirm Hypothesis Three; Disadvantaged Communities within Orange County are not disproportionately impacted in the total trees available to them.

The coefficient for our second independent variable – Median Household Income in $1,000s – was significant (p = 0.000). We find that with a $1,000 increase in the median household income of a Census Tract, there is an increase of approximately 22 trees in the Tract. We can confirm Hypothesis Four in this model.

Approximately 84% of the variation in the dependent variable Total Trees is explained by this multivariate regression model.

OLS Regression Model Results for Models Five through Seven

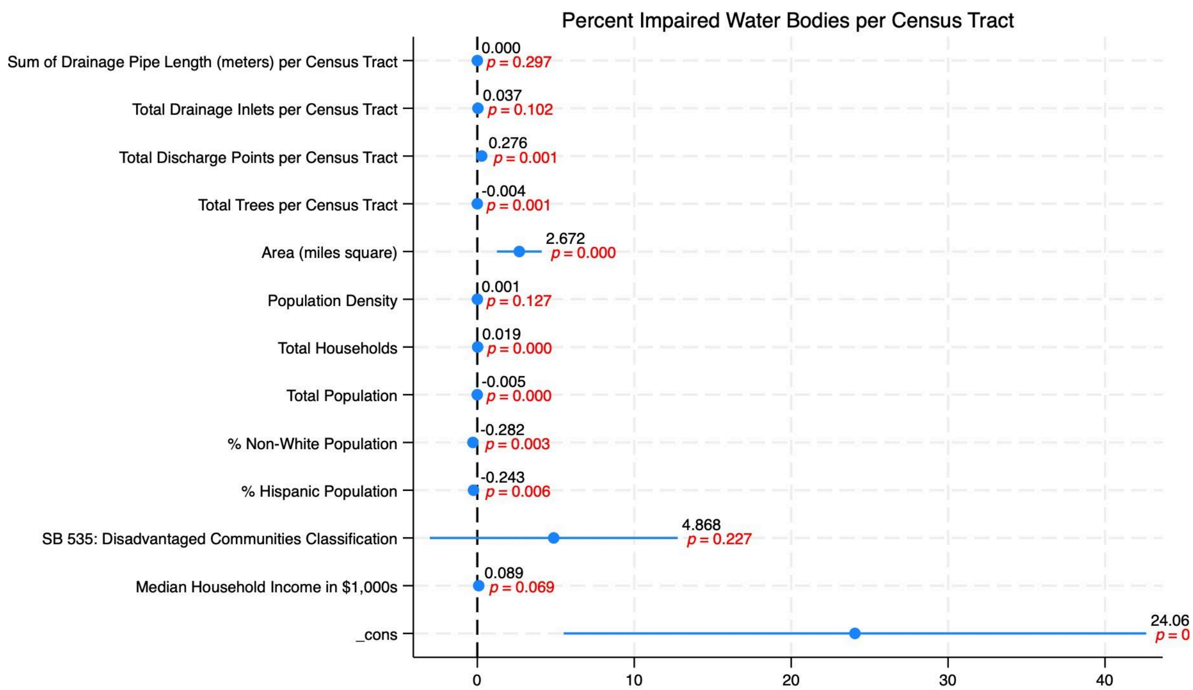

Figure 7. Model Five – Percent Impaired Water Bodies per Census Tract, Orange County, CA

This model tests Hypotheses Five and Six: the linear relationship between the classification of disadvantaged communities and the median household income at the Census Tract level (independent variables) with the percentage of impaired water bodies within their tract. Of the twelve independent variables and controls in this model, four coefficients were not significantly different from zero. We were not able to confirm either Hypothesis Five or Six with this model: the coefficients for SB535: Disadvantaged Communities Classification *($p = 0.227$)* and Median Household Income in $1,000s *($p = 0.069$)* were both not significant. Meaning, Disadvantaged and Low-Income Communities are not disproportionately impacted by impaired water bodies in their communities.

Notably, though, of the four added controls of gray and green stormwater infrastructure in the model, two coefficients were significant. An increase of one discharge point in a Census Tract results, we find, in an increase of 0.3% impaired water bodies in the Tract. Additionally, an increase of one tree in a Census Tract results in a decrease of –0.004% impaired water bodies in the tract. This means across all 613 Census Tracts in Orange County, the variation of gray and green stormwater infrastructure did not result in disproportionate impacts to Disadvantaged Communities and Low-Income Communities due to impaired water bodies.

All else held equal, Orange County residents experience an impact of 24% impaired water bodies in their communities. Approximately 33% of the variation in the dependent variable Percent Impaired Water Bodies is explained by this multivariate regression model.

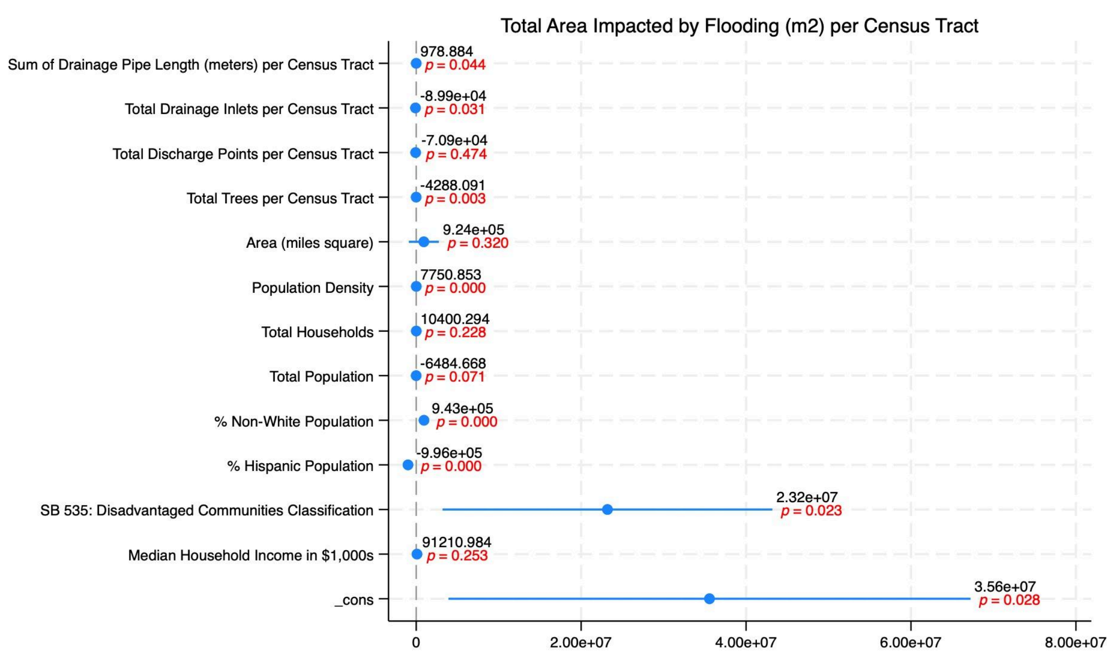

Figure 8. Model Six – Total Area Impacted by Flooding (m^2) per Census Tract, Orange County, CA

This model is the first of two that tests Hypotheses Seven and Eight: the linear relationship between the classification of disadvantaged communities and the median household income at the Census Tract level (independent variables) with flooding impacts in their tract (dependent variable). In this model, the type of flooding impact we are assessing is the Total Area Impacted by Flooding in meters squared in a Census Tract. Of the twelve independent variables and controls within this model, five coefficients were not significantly different from zero. The coefficient for the independent variable SB535: Disadvantaged Communities Classification ($p = 0.023$) was significant. We find that Disadvantaged Communities within Orange County experience flooding impacts totaling up to 23.2 km^2. We can confirm Hypothesis Seven in this model.

The coefficient of our second independent variable – Median Household Income in $1,000s – was not significant ($p = 0.253$). We cannot confirm Hypothesis Eight; Low-Income Communities are not disproportionately impacted by the total area flooded in their communities. We also find that the coefficients of our controls, the Sum of Drainage Pipe Length (meters) and Total Drainage Inlets, are significantly different from zero. An increase in meters of drainage pipes results in an increase of 978.9 m^2 flooding impacts in a Census Tract and an increase in drainage inlets results in a decrease of –0.0899 km^2 of flooding impacts in a Census Tract.

Additionally, we find that the coefficient of the control Total Trees is also significantly different from zero; an increase of trees in a Census Tract results in a decrease of –4288 m^2 of flooding impacts in the community.

All else held equal, Orange County residents experience 35.6 km^2. Approximately 11% of the variation in the dependent variable Total Area Impacted by Flooding is explained by this multivariate regression model.

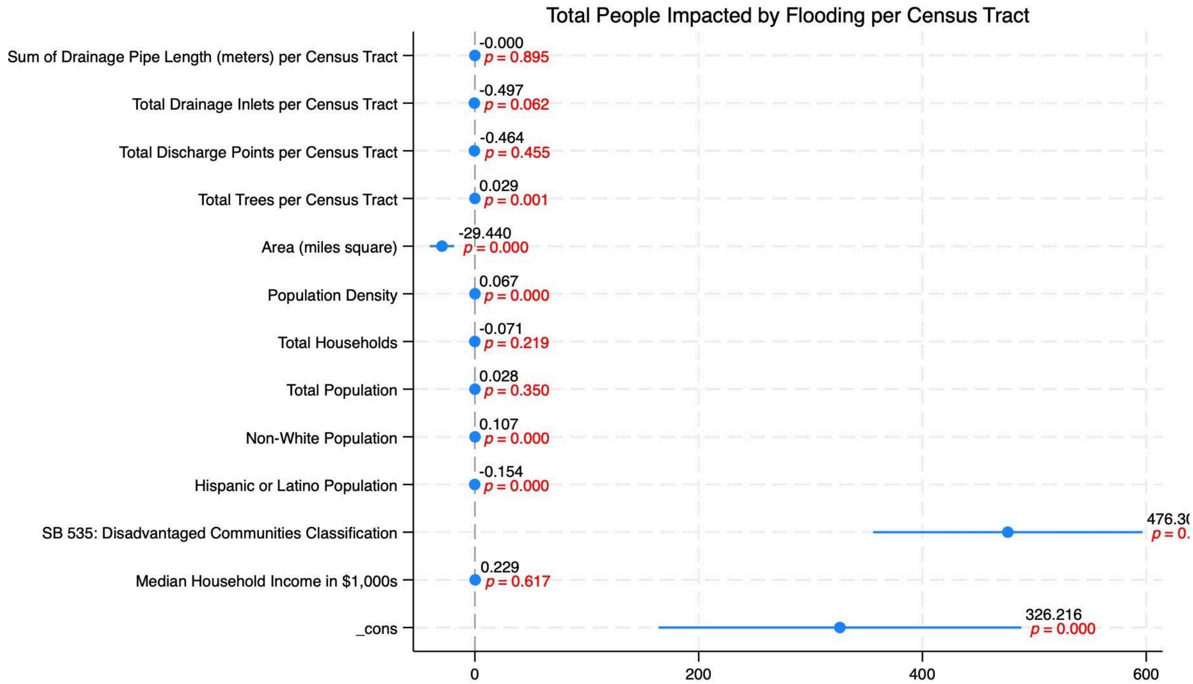

Figure 9. Model Seven – Total People Impacted by Flooding per Census Tract, Orange County, CA

This model is the second of two that tests Hypotheses Seven and Eight: the linear relationship between the classification of disadvantaged communities and the median household income at the Census Tract level (independent variables) with flooding impacts in their tract (dependent variable). In this model, the type of flooding impact we are assessing is the Total People Impacted by Flooding in a Census Tract. Of the twelve independent variables and controls within this model, half of the coefficients were not significantly different from zero. The coefficient for the independent variable SB535: Disadvantaged Communities Classification (*p = 0.000*) was significant. We find that Disadvantaged Communities within Orange County experience flooding impacts totaling up to 476 people. We can confirm Hypothesis Seven in this model.

The coefficient of our second independent variable – Median Household Income in $1,000s – was not significant (*p = 0.617*). We cannot confirm Hypothesis Eight; Low-Income Communities are not disproportionately impacted in terms of the total people impacted by flooding in their communities.

The coefficients on our gray stormwater infrastructure control variables were not significantly different from zero; however, the coefficient on our Total Trees control variable was significant but positively marginal.

All else held equal, 326 people within Orange County are impacted by flooding events. Approximately 25% of the variation in the dependent variable Total People Impacted by Flooding was explained by this multivariate regression model.

Table 1. Summary of Results and Hypothesis Confirmations

Hypothesis	*Model*	*Result*	*Model-Hypothesis Confirmation (Y/N)*	*Total Hypothesis Confirmation*
H1	One	Not Significant	*No*	*No*
	Two	Not Significant	*No*	
	Three	Not Significant	*No*	
H2	One	Significant (+ & S)	*Yes*	*Partial Confirmation*
	Two	Significant (+ & M)	*Yes*	
	Three	Not Significant	*No*	
H3	Four	Not Significant	*No*	*No*
H4	Four	Significant (+ & S)	*Yes*	*Yes*
H5	Five	Not Significant	*No*	*No*
H6	Five	Not Significant	*No*	*No*
H7	Six	Significant (+ & S)	*Yes*	*Yes*
	Seven	Significant (+ & S)	*Yes*	
H8	Six	Not Significant	*No*	*No*
	Seven	Not Significant	*No*	
+ & S: Positive and Strong + & M: Positive and Marginal				

Discussion

Given our hypotheses, data, and analyses, our results were only somewhat as expected. We were able to definitively confirm that 1) Low-Income Communities were disproportionately impacted with less access to green stormwater infrastructure compared to more affluent communities; and, 2) Disadvantaged Communities were disproportionately impacted by storm events that resulted in flooding impacts to the people and area of the community. We were able to partially confirm that Low-Income Communities were disproportionately impacted with less access to gray stormwater infrastructure compared to more affluent communities. We were not able to definitely confirm the rest of our hypotheses with our multivariate OLS Regression models.

This could be for several reasons. We limited the scope of our analysis to Orange County, California because it has one of the most robust stormwater infrastructure datasets publicly available compared to other neighboring counties. That limitation meant that we were working with a limited amount of observations in terms of Census Tracts and Disadvantaged Community Classifications. We were severely limited with the number of observations of publicly available Flooding Impacts data. We were also limited in terms of our household income data – according to our own analyses, the median and average Median Household Income of Orange County for 2021 was $102,500 and $106,860, respectively.

However, our results could also indicate that our chosen statistical model may not be the best analysis strategy for our research. As indicated in our Analysis Strategy section earlier, we conducted a series of single variable and bivariate spatial correlation analyses with our data. We would like to take the time to discuss them here.

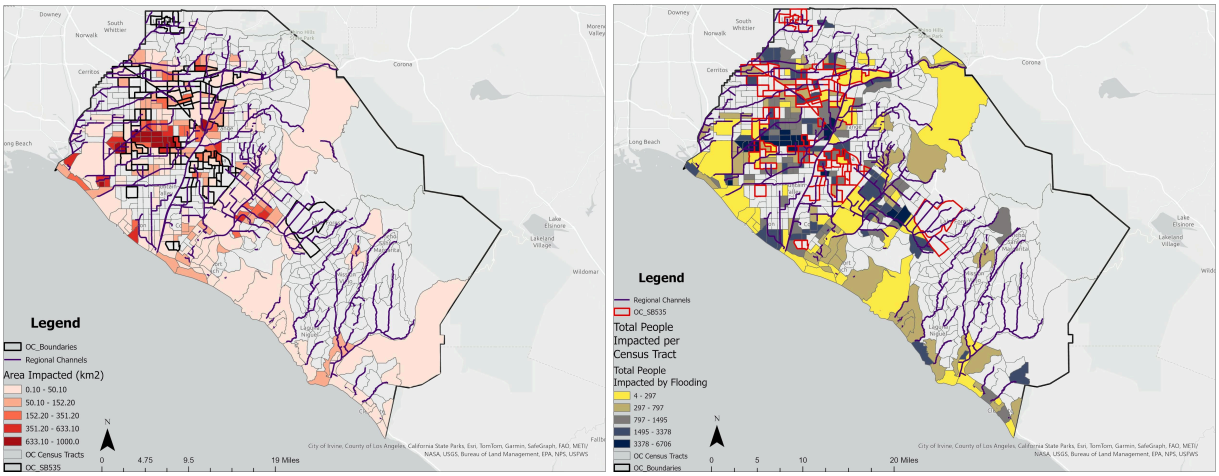

Figure 10. Total Area Impacted by Flooding (km^2) and Total People Impacted by Flooding

Both of these maps are single variable choropleth maps with five Natural (Jenks) Break classifications. The map on the left is the Total Area Impacted by Flooding (km^2) and is demarcated with a pink-to-red gradient and the map on the right is the Total People Impacted by Flooding and is demarcated by a yellow-to-blue gradient. Both maps show the concentration of flooding impacts in the heart of North Orange County (the Santa Ana Area).

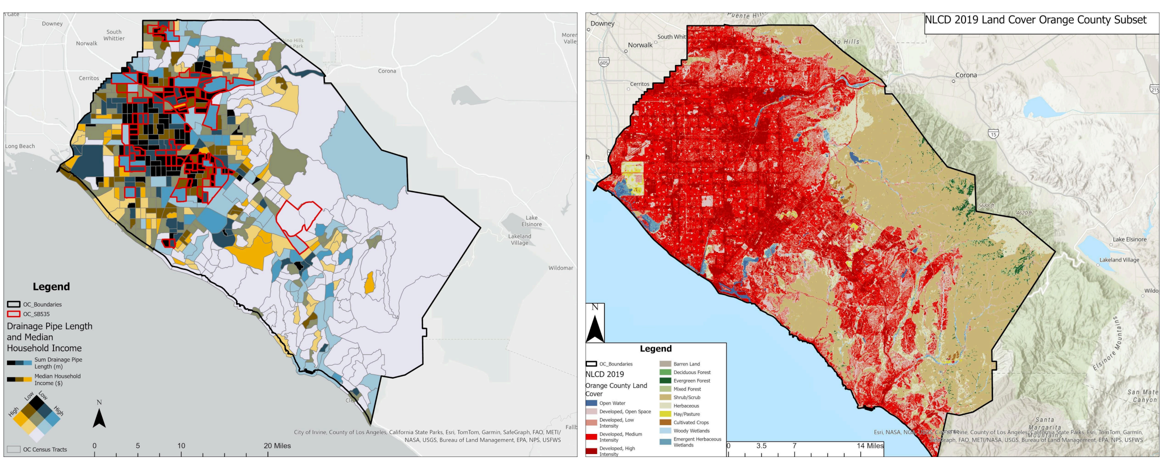

Figure 11. Sum of Drainage Pipe Length (m) and Median Household Income ($) and NLCD 2019 Land Cover OC Subset.

The map on the left is a bivariate spatial correlation model that correlates the Sum of Drainage Pipe Length in meters with the Median Household Income ($) of the Census Tract.

Both variables are split into three Natural (Jenks) Breaks classifications with a dark color representing low sum of drainage pipe length and low median house income for the Census Tract. When we compare this map with the maps in Figure # above, we can clearly see that there is a spatial correlation between low sum of drainage pipe length, low median household income, and high flooding impacts on people and area in the Santa Ana area.

The map on this right in this figure is an Orange County subset of the 2019 National Land Cover Database prepared by the U.S. Geological Survey. The bright and deep red color represents areas that are developed with moderate and high intensity and is clearly concentrated in North and Central Orange County.

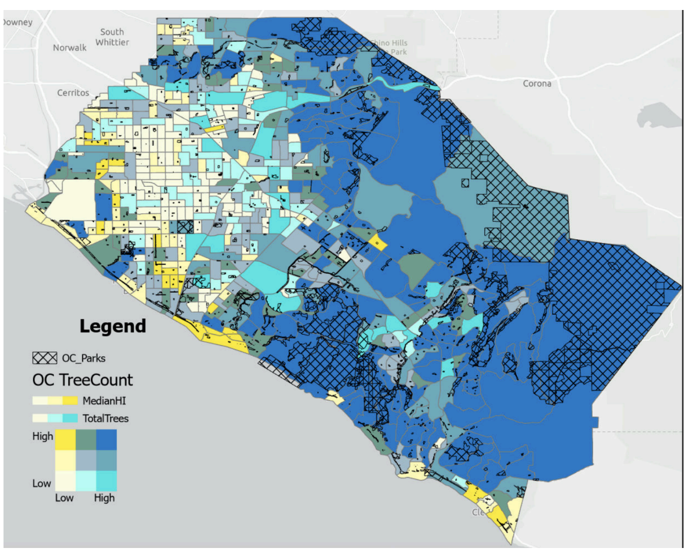

Figure 12. Trees, Parks, and Median Household Income

This figure displays the overlay of parks in Orange County on the bivariate spatial correlation of tree count and median household income by Census Tract. The areas of concern here is, once again, the Santa Ana Area where there are minimal parks, low count of trees, and low median household income by Census Tract. The NLCD map along with the four other maps we have highlighted here show that there is room for concern that an area that is highly developed is also an area with 1) low total of drainage pipe length, 2) low median household income, 3) high flooding impacts to people and area, and 4) minimal opportunities for stormwater to be absorbed in the ground due to impermeability of the surface.

Limitations

We had significant data accessibility challenges and time constraints during our research timeframe. We could only access publicly available data in terms of gray and green stormwater infrastructure and flooding data. The flooding data that was available to us was incredibly limited. Data collected from the CDC did not provide data on total population affected and total area impacted by flooding from February 1st – 20th, 2024. This is critical because California experienced record rainfall levels specifically within this timeframe (OC Hydstra, please see accompanying data visualization function). Additionally when analyzing the total population affected by flooding data was given on a day by day basis. Though people affected by flooding can be affected multiple times the total population does not give an accurate representation on major storm events where the numbers are higher. While we analyzed the day-to-day impacts of flooding on populations, we were unable to analyze the property damage and the long-lasting impacts on communities after severe storm events.

Lastly with the CDC historical flooding data at the time of writing May 30, 2024 the CDC removed December 2023 and January 2024 from their data access of historical and current flooding rated for population and total area affected. We are unsure on why this is, yet this makes it difficult for other researchers if they would like to reproduce our results. Our research only considers flooding impacts from December 1st, 2023, to May 25th, 2024. With the data available to us, we were unable to analyze the historical changes to the weather and the subsequent impacts on infrastructure quality. This further shows the need to have historical flooding data when the CDC removed two months that we used in our research from their publicly available data site.

Future Research

Future research will be needed to fully understand what California's gray stormwater infrastructure is capable of – beyond Orange County. With the expected increase in rainfall in California moving forward, future research would need to look into how we can adapt to the increase in rainfall. Future research will be needed to assess stormwater infrastructure on a statewide scale. Orange County only provides a small insight into California stormwater infrastructure. Research done on a state and region wide level will further advance understanding of infrastructure and the effects of flooding. Other research would need to be conducted on the viability of green infrastructure in California and to have it be tested for a whole year since past research on Green infrastructure has been done through simulations or on a short time frame not accounting for the dry periods. Within our research we choose to focus on certain variables, future research will need to look into other factors that can also showcase the effects of flooding and stormwater infrastructure. Other variables can help provide a clearer picture on the effects of flooding on the community and individuals.

Conclusion

The research question that was asked in this paper was:

> **How are low-income and disadvantaged communities in Orange County in California impacted by the condition of the stormwater system (gray, green, and blue infrastructure)?**

In our paper we went over past literature to help us understand different factors that affect stormwater infrastructure. We then went over our hypotheses focusing on gray and green infrastructure and data and analysis strategies we would be using to test our hypotheses. This was followed by our results of the impacts green infrastructure has on each census block according to medium household income as well as disadvantaged communities. We discussed our results of gray infrastructure looking at medium household income and race and ethnicity to see any inequalities amongst these factors. This was followed by a discussion of our limitations of our research and data that we had available to us and go into suggestions on future research that needs to be done for further understanding stormwater infrastructure and inequalities amongst flooding events.

Our findings indicate that with green infrastructure disadvantage communities and low-income communities have a lack of green infrastructure in place and our results indicated that there are less trees in these communities and also have a lack of parks available to them. We were also able to confirm that among disadvantaged communities and lower-income communities there is a higher population affected during flooding events. We were not able to confirm our other hypotheses that disadvantaged communities and lower income communities are disproportionately affected by gray infrastructure along with impaired water bodies. As we discussed this can be due to our limited scope of focusing on Orange County, California. We hope to encourage future researchers to conduct studies on stormwater infrastructure state and region wide in California. As such, the conclusion of this paper is disadvantage and lower income communities have less access to parks and trees and have higher populations affected during flooding events.

References

Alexandridis, K. (2023). OCACS 2021 Economic Characteristics for Census Tracts. [Data set]. OCPW. https://data-ocpw.opendata.arcgis.com/datasets/OCPW::ocacs-2021-economic-characteristics-for-census-tracts/about

Alexandridis, K. (2023). OCACS 2021 Census Tract Population Density. [Data set]. OCPW. https://data-ocpw.opendata.arcgis.com/datasets/OCPW::ocacs-2021-census-tract-population-density/about

Becker, R. (2024, February 29). *California's urban runoff flows down the drain. Can the drought-plagued state capture more of it?* CalMatters. https://calmatters.org/environment/water/2024/02/capturing-california-stormwater/

Berland, A., Shiflett, S. A., Shuster, W. D., Garmestani, A. S., Goddard, H. C., Herrmann, D. L., & Hopton, M. E. (2017). The role of trees in urban stormwater management. Landscape and Urban Planning, 162(C), 167–177. https://doi.org/10.1016/j.landurbplan.2017.02.017

California Department of Fish and Wildlife. (2023). NLCD 2019 Land Cover California Subset. [Data set]. https://gis.data.ca.gov/maps/CDFW::nlcd-2019-land-cover-california-subset/about

California Office of Environmental Health Hazard Assessment. (2022, May). *SB 535 Disadvantaged Communities.* [Data set]. California Environmental Protection Agency. https://oehha.ca.gov/calenviroscreen/sb535

California Office of Environmental Health Hazard Assessment. (2022, May). *SB 535 Disadvantaged Communities.* California Environmental Protection Agency. https://oehha.ca.gov/calenviroscreen/sb535

California Office of Environmental Health Hazard Assessment. (2023, May). *CalEnviroScreen 4.0.* California Environmental Protection Agency https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-40

California Office of Environmental Health Hazard Assessment. (2023, May). *CalEnviroScreen 4.0.* [Data set]. California Environmental Protection Agency. https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-40

Centers for Disease Control. (2023, May). *Indicators and Data.* National Environmental Public Health Tracking Network, Centers for Disease Control. https://ephtracking.cdc.gov/indicatorPages?selectedContentAreaAbbreviation=36&selectedIndicatorId=217

Centers for Disease Control. (2024, May). *Current and Historical Flooding | Total Area Flooded.* [Data set]. National Environmental Public Health Tracking Network, Centers for Disease Control. https://ephtracking.cdc.gov/DataExplorer

Centers for Disease Control. (2024, May). *Current and Historical Flooding | Total Population Affected by Flooding.* [Data set]. National Environmental Public Health Tracking Network, Centers for Disease Control. https://ephtracking.cdc.gov/DataExplorer

Cooley, H., Shimabuku, S. A. M., Thebo, A., Gleick, P., & Diringer, S. (2022). The Untapped Potential of California's Urban Water Supply: Water Efficiency, Water Reuse, and Stormwater Capture. In *Policy File*. Pacific Institute for Studies in Development, Environment and Security.

Gharaibeh, N. G., Lee, C.-C. (Barry), Alhalbouni, T., Wang, F., Lee, J., Newman, G., Güneralp, B., & Van Zandt, S. (2023). Quality of Stormwater Infrastructure Systems in Vulnerable

Communities: Three Case Studies from Texas. *Public Works Management & Policy, 28*(4), 518-536. https://doi.org/10.1177/1087724X231164415

Huang, X., Swain, D. L., & Hall, A. D. (2020). Future precipitation increase from very high resolution ensemble downscaling of extreme atmospheric river storms in California. *Science Advances*, *6*(29), eaba1323–eaba1323. https://doi.org/10.1126/sciadv.aba1323

Husain, M. (2023). Drawing the lines: How defining "disadvantaged communities" impacts water infrastructure in the West. *Trends : ABA Section of Environment, Energy, and Resources Newsletter*, *54*(4), 4–6.

Kondo, M. C., Low, S. C., Henning, J., & Branas, C. C. (2015). The impact of green stormwater infrastructure installation on surrounding health and safety. *American Journal of Public Health, 105*(3), e114–e121. https://doi.org/10.2105/AJPH.2014.302314

Li, Y. (2023). CA OrangeCo tree point 2011. [Data set]. OCPW. https://data-ocpw.opendata.arcgis.com/datasets/OCPW::ca-orangeco-tree-point-2011/about

Novaes, C. A. F. de O., & Marques, R. C. (2022a). Regulation of urban stormwater management is not a matter of choice, but performance. Water Policy, 24(8), 1325–1342. https://doi.org/10.2166/wp.2022.097

Novaes, C., & Marques, R. (2022b). Public policy: urban stormwater in a paradigm shift, is it the end or just the beginning? Water Science and Technology, 85(9), 2652–2662. https://doi.org/10.2166/wst.2022.127

Novaes, C., & Marques, R. (2022c). Attracting the Private Sector to Urban Stormwater: A Feasible Task or Just a Pipe Dream? Water (Basel), 14(14), 2164-. https://doi.org/10.3390/w14142164

Orange County Department of Public Works. (2024, May). *Orange County Data.* OCPW. http://hydstra.ocpublicworks.com/web.htm

Orange County Department of Public Works. (2022). *Stormwater Network Map*. [Data set]. OCPW. https://data-ocpw.opendata.arcgis.com/maps/OCPW::stormwater-network-map/about

Parks for All Californians. (2024). Park Access Tool. [Data set]. https://www.parksforcalifornia.org/parkaccess/?overlays1=parks%2Cnoparkaccess&overlays2=parks%2Cparksper1000

Rosenberger, L., Leandro, J., Pauleit, S., & Erlwein, S. (2021). Sustainable stormwater management under the impact of climate change and urban densification. Journal of Hydrology (Amsterdam), 596, 126137-. https://doi.org/10.1016/j.jhydrol.2021.126137

Spahr, S., Teixidó, M., Sedlak, D. L., & Luthy, R. G. (2020). Hydrophilic trace organic contaminants in urban stormwater: occurrence, toxicological relevance, and the need to enhance green stormwater infrastructure. *Environmental Science Water Research & Technology*, *6*(1), 15–44. https://doi.org/10.1039/c9ew00674e

Wakhungu, M. J., Abdel-Mottaleb, N., Wells, E. C., & Zhang, Q. (2021). Geospatial Vulnerability Framework for Identifying Water Infrastructure Inequalities. Journal of Environmental Engineering (New York, N.Y.), 147(9). https://doi.org/10.1061/(ASCE)EE.1943-7870.0001903

Appendix

Table 1. Descriptive Statistics

Variable	N	Mean	Median	Min	Max	SD
Sum of Drainage Pipe Length (meters) per Census Tract	613	6883.381	4388.082	29.34022	87222.44	8237.231
Total Drainage Inlets per Census Tract	613	94.486	55	0	950	113.668
Total Discharge Points per Census Tract	613	5.613	0	0	245	16.763
Total Trees per Census Tract	613	2610.684	1667	0	388849	3438.633
Area (miles square)	613	1.324	0.65097	.133	65.587	3.962
Population Density	613	8116.096	7533.292	1.655	38205.71	5180.171
Total Households	613	1725.272	1641	0	6518	671.317
Total Population	613	5192.37	5036	3	17960	1944.039
% Non-White Population	613	43.985	42.224	0	88.729	18.915
% Hispanic Population	613	32.473	23.434	.9695	100	24.3598
SB 535: Disadvantaged Communities Classification	613	0.1517	0	0	1	0.359
Median Household Income in $1,000s	613	106.860	102.5	0	239.048	38.030
Percent Impaired	557	23.91	0	0	98.068	33.004

Water Bodies						
Total People Impacted by Flooded	2235	586.621	319	4	6706	813.316
Total Area Impacted by Flooding (km^2)	2268	61.512	21.9	.1	1000	120.505

Table 2. Accessibility to and Quantity of Gray and Green Infrastructure

	Model One		Model Two		Model Three		Model Four	
% Non-White Population	-14.17 (-17.209)		-0.833 (-0.245)	**	-0.139 (-0.043)	**	6.047 (-3.673)	
% Hispanic Population	46.2 (-17.5)	**	0.676 (-0.249)	**	-0.019 (-0.044)		17.304 (-3.735)	**
Total Households	4.289 (-0.405)	**	0.069 (-0.006)	**	0.003 (-0.001)	**	0.982 (-0.086)	**
Median Household Income in $1,000s	51.412 (-8.904)	**	0.668 (-0.127)	**	0.004 (-0.022)		21.63 (-1.9)	**
SB 535: Disadvantaged Communities Classification	663.601 (-928.67)		13.693 (-13.219)		0.67 (-2.326)		-154.05 (-198.183)	
Population Density	-0.504 (-0.071)	**	-0.007 (-0.001)	**	0 (0)	*	-0.118 (-0.015)	**
Area (miles square)	528.012 (-68.493)	**	0.39 (-0.975)		0.027 (-0.172)		686.317 (-14.617)	**
Intercept	-3599.168 (-1732.026)	*	-27.472 (-24.653)		9.531 (-4.339)	*	-2147.7 (-369.624)	**
Observations	613		613		613		613	
R-Squared	0.39		0.35		0.08		0.84	
dfres	605		605		605		605	

** p<.01, * p<.05
Model One: Summation of Drainage Pipe Length (m) per Census Tract
Model Two: Total Inlets per Census Tract
Model Three: Total Discharge Points per Census Tract

Model Four: Total Trees per Census Tract

Table 3. Potential Indicators for Stormwater Infrastructure Quality

Variable	Model Five		Model Six		Model Seven		Variable
Sum of Drainage Pipe Length (meters) per Census Tract	0 (0)		978.884 (-485.634)	*	0 (-0.003)		Sum of Drainage Pipe Length (meters) per Census Tract
Total Drainage Inlets per Census Tract	0.037 (-0.022)		-8.99E+04 (-41661.338)	*	-0.497 (-0.267)		Total Drainage Inlets per Census Tract
Total Discharge Points per Census Tract	0.276 (-0.081)	**	-7.09E+04 (-99068.532)		-0.464 (-0.622)		Total Discharge Points per Census Tract
Total Trees per Census Tract	-0.004 (-0.001)	**	-4288.091 (-1433.191)	**	0.029 (-0.009)	**	Total Trees per Census Tract
Area (miles square)	2.672 (-0.728)	**	9.24E+05 (-9.29E+05)		-29.44 (-5.565)	**	Area (miles square)
Population Density	0.001 (0)		7750.852 (-953.845)	**	0.067 (-0.006)	**	Population Density
Total Households	0.019 (-0.004)	**	10400.294 (-8619.907)		-0.071 (-0.057)		Total Households
Total Population	-0.005 (-0.002)	**	-6484.668 (-3587.564)		0.028 (-0.03)		Total Population
% Non-White Population	-0.282 (-0.095)	**	9.43E+05 (-2.40E+05)	**	0.107 (-0.027)	**	Non-White Population
% Hispanic Population	-0.243 (-0.088)	**	-9.96E+05 (-2.51E+05)	**	-0.154 (-0.027)	**	Hispanic Population
SB 535: Disadvantaged Communities Classification	4.868 (-4.022)		2.32E+07 (-1.02E+07)	*	476.301 (-61.351)	**	SB 535: Disadvantaged Communities Classification

Median Household Income in $1,000s	0.089 (-0.049)		91210.988 (-79820.098)		0.229 (-0.458)		Median Household Income in $1,000s
Intercept	24.063 (-9.45)	*	3.56E+07 (-1.61E+07)	*	326.216 (-82.677)	**	
Observations	557		2268		2235		
R-Squared	0.33		0.11		0.25		
dfres	544		2255		2222		

** p<.01, * p<.05
Model Five: Percent Impaired Water Bodies per Census Tract
Model Six: Total Area Impacted by Flooding (m^2) per Census Tract
Model Seven: Total People Impacted by Flooding per Census Tract