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What's the Dam Problem? Hazardous Dams, Flood Risk, and Dimensions of Vulnerability in California

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What's the Dam Problem?

Hazardous Dams, Flood Risk, and Dimensions of Vulnerability in California

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Master of Urban and Regional Planning

by

Britta McOmber

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ABSTRACT OF THE THESIS

What's the Dam Problem?

Hazardous Dams, Flood Risk, and Dimensions of Vulnerability in California

by

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Master of Urban and Regional Planning

University of California, Los Angeles, 2018

Professor Susanna B. Hecht, Chair

In the state of California, dams are aging, underfinanced, and in many cases ill-maintained. The Oroville Dam Spillway Failure in February 2017 demonstrates that even dams with satisfactory condition ratings can be at risk of failing from a combination of climatic, political, economic, and structural factors. It is therefore necessary to look beyond the condition assessment of a dam and instead consider the hazard potential status. California has 833 High Hazard Potential (HHP) dams – which the U.S. Army Corps of Engineers defines as dams that would cause significant loss of life, property destruction, or environmental damage in the case of failure or misoperation (2016). Expanding on previous literature on the sociodemographic determinants of flood-risk in cases of sea-level rise, climate change, high precipitation, and storm events, this project analyzes variables of social vulnerability within HHP dam inundation boundaries. I rely on a series of

geostatistical analyses, two-tail independent samples statistical tests, and multiple linear regressions to answer the overarching research question – Who is most vulnerable to dam-induced floods in California?

The data underpinning this research comes from the National Inventory of Dams, statewide dam inundation boundary maps, and the 2012 -2016 American Community Survey. Results from independent samples t-tests show that individuals and households are disproportionately located within hazardous dam flood zones if they are U.S. Citizens, live with a disability, are less educated, are unemployed, are single parents, have lower median household incomes, live at, below, or near the federal poverty line, and identify as either Black and African American, American Indian and Native Alaskan, or Native Hawaiian and Pacific Islander.

Furthermore, people whose highest educational attainment is a high school degree, unemployed individuals, those living with disabilities, Hispanic or Latino individuals, female-headed households, renters, and people who identify as Black and African American, American Indian and Native Alaskan, Asian, and Native Hawaiian and Pacific Islander represent variables of social vulnerability that are statistically significant predictors of living within a hazardous dam flood zone. This project therefore reveals the spatial and social characteristics of vulnerability to dam-induced flood risk in California.

Planners and policymakers can use this information to improve existing disaster management and response plans by incorporating targeted and specific strategies to reduce the flood-risk of highly vulnerable populations. It also provides information necessary for planners and policymakers to address and mitigate the existing social and spatial inequalities in dam inundation zones to create a more environmentally just California.

The thesis of Britta McOmber is approved.

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Chapter 1: Introduction

In the state of California, dams are aging, underfinanced, and in many cases ill maintained. Similar to other massive, immobile, and unyielding infrastructures, dams are acutely vulnerable to seismic activity and changing climatic patterns. These two natural forces are highly unpredictable and variable, and can cause even the most structurally sound dams to fail or collapse.

Oroville Dam Spillway Failure

The 2017 Oroville Dam Spillway Failure exemplifies the critical issues of risky dam infrastructure and associated flood hazard in California. Oroville is a High Hazard Potential dam located in Placer County. The U.S. Army Corps of Engineers assigns a High Hazard Potential (HHP) classification to a dam if failure or misoperation will cause significant loss of life, property destruction, or environmental damage within the dam's inundation zone (2016). Oroville dam holds back the second largest reservoir in California, which has a storage capacity of 3.5 million acre-feet of water (NID 2016). The Lake Oroville reservoir is capable of inundating more than 3,600 square miles of land, representing one of the furthest reaching dam flood zones in the state.

Following a significant six-year drought, California experienced the wettest water year ever recorded in 2017 (Gomez 2017). Heavy and frequent storms throughout January and February quickly refilled state reservoirs depleted from the drought. The continuous runoff from these winter storms caused the water level of Lake Oroville to approach dangerous, unsafe, and unprecedented levels. From December 2016 to February 2017, the reservoir level increased from 41 percent to over 100 percent, eventually overtopping the dam on February 12 (Lin 2017).

Dam operators opened the main spillway in early February in an attempt to lower the reservoir level. After a few days, they noticed the water was flowing abnormally down the spillway. When Oroville's operators reduced the flow to investigate the matter they discovered a crater 300 feet wide, 500 feet long, and 45 feet deep in the middle of the 3,000-foot long concrete spillway (Graham 2017). The gates of the main spillway closed completely on February 7 to address concerns over the erosion of rock and material beneath the spillway and to make decisions on how best to proceed. However, the lake level continued to rise overtopped the dam at a point known as the "emergency spillway" on February 11. This situation was extraordinary – In 50 years of operation, Oroville's water levels had never been high enough to reach the emergency spillway.

Unlike the main spillway, which is controlled via release gates, when water reaches the lip of the 1,700-foot emergency spillway it washes uncontrolled down a wooded hillside (Sabalow and Kasler 2017). By February 12, the rock beneath the 30-foot concrete weir that reinforces the lip of the emergency spillway had significantly eroded. This prompted fears that the weir would collapse and send 30 vertical feet of the reservoir's surface area rushing unchecked through the dam's inundation zone. A failure of the emergency spillway effectively amounts to total dam failure, as the quickly eroding hillside would eventually empty the lake.

Emergency crews struggled to reinforce the emergency spillway with boulders and concrete blocks while authorities ordered a desperate emergency evacuation of over 180,000 people. Dam operators had no choice but to reopen the heavily damaged main spillway on February 12. Fortunately, Mother Nature acquiesced. Within a few days the reservoir levels began to drop as the rates of inflowing winter deluge significantly slowed.

In the aftermath of this narrowly avoided disaster, the main and emergency spillways incurred significant damage and left the main spillway inoperable. The estimated costs of the dam repairs to both spillways is over $500 million (Rogers 2017). Other harmful impacts included damage to riverbanks, personal property, and farmland, roads used in the evacuation, the Thermalito power generating facility, and the Feather River Fish Hatchery.

Subsequent investigations identified a number factors contributing to the failure of the main spillway and near-failure of the emergency spillway. Among these, investigators found that flawed original engineering designs, superficial and behind schedule inspections, unidentified erosion and leakage problems, and aged and dilapidated components ("Independent" 2018). Together these factors had severely weakened parts of the dam and spillways. These structural issues were exacerbated and in part caused by decades of underfinanced legislative allocations for dam maintenance, repair, safety, and inspection programs.

Finally, the record-setting water year and series of high precipitation winter storms set in motion the chain of events that led to the spillway failure. Climate change models predict these types of "outlier" weather patterns will be more common, if not more intense and frequent, in the future.

It is therefore entirely possible for another dam in California to experience the same rapid increases in water levels that led to the Oroville crisis.

Hazardous Dams and Social Vulnerability

Both the National Inventory of Dams and the California Division of Safety of Dams consider the Oroville dam to be in satisfactory condition, which makes these findings even more troublesome (2016, 2016). If a satisfactory dam can come so close to failing, what does that mean for dams classified as fair, poor, or unsatisfactory? The serious physical and structural problems masked by a satisfactory condition rating are not an anomaly among California's dams. Rather, the issues leading up to the spillway failure exemplify the current shortfalls in policy, planning, and action for managing large-scale water infrastructure and safeguarding the public from avoidable environmental hazards.

The convergence of complex physical, structural, political, economic, and climatic factors increases the disaster- and flood-risk for communities living within inundation zones of dams. The near-crisis shows that even dams with satisfactory condition ratings have the potential to fail, and suggests that condition status is not the best indicator for identifying hazardous dams in California. Thus, I use downstream hazard status as a proxy for assessing vulnerability to dam-induced flood-risk. The California Division of Safety of Dams explains that the hazard status of the dam is separate from the condition rating; whereas the former refers to the scope and degree of damage possible in an inundation scenario, the latter is an assessment of the dam's structural integrity (2017). The U.S. Army Corps of Engineers rates 833 of the state's 1,585 dams as High

Hazard Potential (HHP), where failure or misoperation will result in significant loss of life, property destruction, or environmental damage (2016).

This project therefore proposes to analyze aspects of social vulnerability for individuals and households located in the flood zones of High Hazard Potential dams in California. The consensus among researchers and planners is that a multitude of demographic and socioeconomic factors influences an individual's social vulnerability to environmental hazards. These social vulnerability characteristics create an uneven capacity for preparedness, response, or recovery to disasters (Hazards & Vulnerability Research Institute 2014). For example, while certain people may be exposed to hazards due to physical factors, like living in a floodplain, they may also suffer additional and greater relative losses due to a lack of social, financial, or political support networks (Maantay & Maroko 2009).

The academic literature supports that individuals who are nonwhite, Hispanic, low income, younger than 14 or older than 65, female, disabled, renters, unemployed, non-automobile owners, non-college educated, and foreign-born are less prepared for floods, face additional hurdles to evacuating during a flood, and take longer to recover to a pre-flood livelihood after the disaster (Chakraborty et al. 2014, Cutter et al. 2003, Donner and Rodriguez 2011, Fielding and Burningham 2005, Maldonado et al. 2015).

It follows that these 11 demographic and socioeconomic categories of race, ethnicity, income, age, gender of the head-householder, ability, employment status, home ownership, car ownership, educational attainment, and citizenship are determinants of an individual's social vulnerability to flood hazards.

Research Questions and Overview of Results

With social vulnerability framed by these 11 categories, the following research questions guide this project:

1) Are socially vulnerable households more likely to live within dam flood zones than outside of them in California?

2) Are socially vulnerable households more likely to live within HHP dam flood zones than outside of them in California?

3) Which factors of household social vulnerability are significantly correlated with living in a dam flood zone? Do these differ from factors significantly correlated with living in an HHP dam flood zone?

4) Is there a relationship between social vulnerability and the HHP dam characteristics of age and inspection compliance?

    a. Do HHP dams built more than 50 ago have higher proportions of socially vulnerable households within their inundation zones than HHP dams built less than 50 years ago?

    b. Do HHP dams with failed inspection compliance have higher proportions of socially vulnerable households within their inundation zones than HHP dams in compliance?

To answer these questions, I use Geographic Information Systems and Statistical Package for the Social Sciences software to perform geoprocessing, two-tail independent samples tests, and multiple linear regressions on variables spanning three distinct datasets. The datasets include a state subset of the National Inventory of Dams, California dam inundation maps, and a state subset of the 2012-2016 American Community Survey. The expected contributions of this research project are a comprehensive analysis and understanding of the demographic, socioeconomic, and spatial characteristics of vulnerability to dam-induced flood risk in California.

Results from independent samples t-tests show that individuals and households are disproportionately located within hazardous dam flood zones if they are U.S. Citizens, live with a disability, are less educated, are unemployed, are single parents, have lower median household incomes, live at, below, or near the federal poverty line, and identify as either Black and African American, American Indian and Native Alaskan, or Native Hawaiian and Pacific Islander.

Furthermore, people whose highest educational attainment is a high school degree, unemployed individuals, those living with disabilities, Hispanic or Latino individuals, female-headed households, renters, and people who identify as Black and African American, American Indian and Native Alaskan, Asian, and Native Hawaiian and Pacific Islander represent variables of social vulnerability that are statistically significant predictors of living within a hazardous dam flood zone.

Comparing the means of social vulnerability variables by the grouping factor "Dam Age" reveal that people who lack car ownership, foreign-born individuals, people with at least a 2- or 4-year degree, non-Hispanic or Latino, female-headed households, living at, below, or near the federal poverty threshold, renters, and those who identify as White, as Black and African American, American Indian and Native Alaskan, Asian, and Native Hawaiian and Pacific Islander are more likely to live in HHP dam flood zones aged 50 years or older.

Finally, the independent samples test for social vulnerability and the grouping factor "Inspection Compliance" show that those lacking car ownership, foreign-born individuals, people aged 65 or older living with a disability, individuals with at least a 2- or 4-year degree, non-Hispanic or Latino, unemployment, living at, below, or near the federal poverty threshold, renters, and those who identify as Black and African American, Asian, and Native Hawaiian and Pacific Islander are more likely to live in HHP dam flood zones with failed inspection compliance.

Research Significance

Emergency and disaster planners depend on knowledge of socially vulnerable populations to ensure sufficient disaster preparedness and response policies in a given place. For example, a community with a high percentage of older adults will require a different type of emergency response in terms of warning, evacuation, and assistance. Failing to account for the spatial patterns and geographic concentrations of socially vulnerable populations in the planning process can have devastating consequences. Consider that in the aftermath of Hurricane Katrina, almost 50 percent of nearly 1,000 fatalities were adults aged 75 or older (Brunkard et al. 2008). Many of these older adults lived alone and lacked the means to evacuate, either because they did not own a car or were unable to drive, or lived in care facilities that did not provide transportation during the evacuation (Brunkard et al. 2008). It is possible that many of these fatalities could have been avoided had different disaster response policies and plans been in place.

Spatially informed disaster preparedness, response and emergency planning has the ability to reduce the flood-risk for socially vulnerable populations. The theoretical framework for this assertion comes from the field of environmental justice. Environmental justice is broadly defined as equitable environmental quality for all social groups, with particular consideration that socially vulnerable groups are not disproportionately exposed to environmental hazards (Montgomery and Chakraborty 2015). In addition to older adults, flooding from Hurricane Katrina disproportionately affected African-American and low-income residents in New Orleans during and after the disaster. According to Montgomery and Chakraborty, the stark social and economic inequalities of who was impacted by the flood hazard led to an expansion of the EJ framework to include natural disasters, and initiated empirical investigations on the EJ implications of flooding (2015, 2).

This project reveals spatial and social characteristics of vulnerability to dam-induced flood hazards in California. Planners and policymakers can use this information to improve existing disaster management and response plans by incorporating targeted and specific strategies to reduce the flood-risk of highly vulnerable populations. Furthermore, it provides the information necessary for planners and policymakers to address the existing social and spatial inequalities in dam inundation zones to create a more environmentally just California.

There is a breadth of social vulnerability literature on the demographic and socioeconomic determinants of flood risk in cases of sea-level rise, climate change, and high precipitation and storm events. However, social vulnerability and dam-induced flood risk is an area less explored or documented. My research has the ability to fill this existing gap in the flood-risk literature. Notably my results, findings, and conclusions can inform an initial understanding and comparison of social vulnerability and flood-risk between the scenarios of sea-level rise, climate change, high precipitation and storm events, dam-induced flooding. The similarities across these categories reveal which factors social vulnerability may be universal predictors of flood-risk, and the differences reveal which factors are specific to dam inundation areas in California.

This project focuses on the patterns revealed at the broader geographic scale of the state of California, which may mask regional and local differences of social vulnerability. The methods presented in this project are replicable at different geographic scales to provide the most useful, relevant, and necessary information for local disaster and emergency planners throughout the state.

Chapter 2: Background

History of Dam-building in California

Dams are inherently multi-purpose structures. Their uses span hydroelectricity generation, flood protection, improved navigability, water supply for drinking, irrigation, and industrial purposes, and making the surrounding region more resilient to drought. In the American West, and particularly in California, dams play a crucial role in capturing, storing, and delivering water to arid and water-scarce regions. The absence of such large-scale water management infrastructure would make it impossible for California to sustain its thriving urban and agricultural economies.

There are currently 1,585 total dams in California, with 1,249 falling under state jurisdiction through Department of Water Resources Division of Safety of Dams. The remaining 336 are managed by federal agencies such as the Federal Energy Regulatory Commission, Army Corps of Engineers, Department of Defense, and Department of the Interior (2016). The majority of these dams were built between 1920 and 1980, though the history of dam building dates back to the Gold Rush era. Beginning in 1848, miners harnessed the power of rivers by constructing dams, sluices, aqueducts, and canals to aid in the search for gold. In the following decade hydraulic mining emerged as one of the most environmentally destructive mining methods, damming and diverting entire streams and rivers to generate high-pressure torrents to blast at hillsides (Kahrl 1982, 27).

The gold rush put California on the map quite literally, ushering statehood in 1850. The prospect of mineral wealth and the completion of transcontinental railroads in the 1870s and 1880s encouraged a steady stream of migration to the state. While the urban areas established during the gold rush, such as San Francisco and Sacramento, continued to grow, many settlers turned to the fertile alluvial plains of the Central Valley to pursue a livelihood. The legacy of dam, canal, and sluice building from the mining era expanded into a system of channels and levees for irrigation purposes. These systems tended to be small-scale in nature, and designed with local conditions in mind. Though they made the flood-prone Central Valley more suitable for agriculture, they proved inadequate for successful regional flood control.

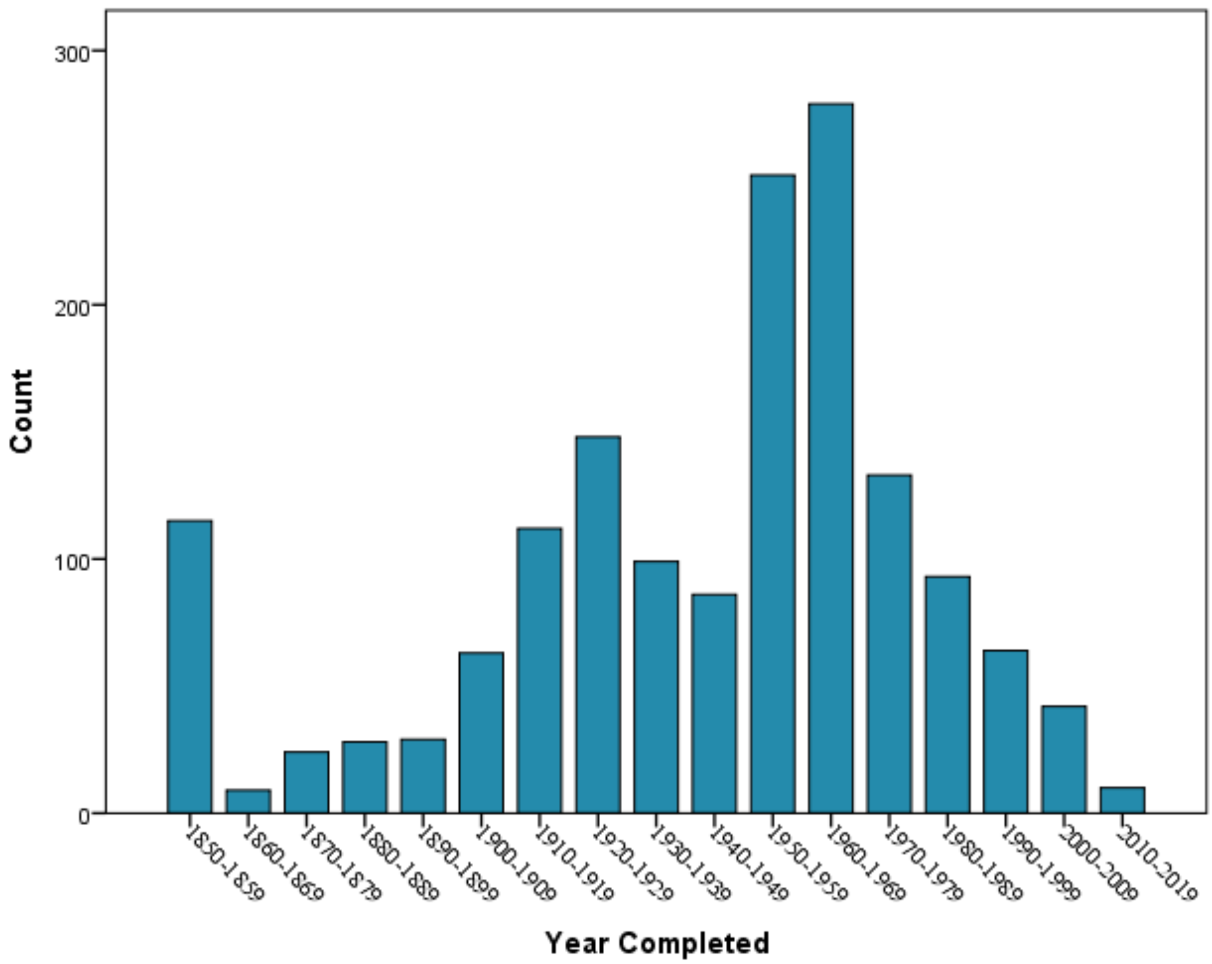
To address flood control issues, the state legislature passed the Wright Act in 1887. The Act authorized the formation of irrigation districts with the power to acquire water rights, construct water projects, and sell bonds to support water development and distribution (Kahrl, 1982, 30). Newly formed irrigation districts financed and built the first regional-scale dam and canal systems to store and distribute water on a regional basis (Kahrl 1982, 30). However, the arid southern region of the state lacked a local water supply that could sufficiently support growing populations. The burden of financing projects on the scale needed to move water from where it was available to where it was scarce disproportionately impacted places like Los Angeles, where local capital fell short of the cost of such infrastructure (Karhl 1982, 31). The size, scope, and cost of large-scale water storage, supply, and transport systems was typically beyond the capacity of cities, counties, or irrigation districts to undertake.

At the turn of the 20th century, California had the nation's fastest-growing economy and population. This growth required a shift in water and flood policy from local to interregional projects that could manage water over much larger distances (Kahrl 1982, 31). Between 1900 and 1940, both the federal and state government became increasingly involved in large water projects. State and local policymakers viewed these large dam and reservoir projects as an effective solution to the problem of water scarcity in much of the state, exacerbated by the ever-growing urban and agricultural communities. Projects at this scale also were able to bypass many of the financial and political barriers that delayed most local water supply and flood control projects.

The 1930s through the 1970s saw a period of unmatched dam and reservoir building across the state. Recognizing the importance of the Central Valley in national food production, the Bureau of Reclamation and the Army Corps of Engineers devised an ambitious water capture, storage, and delivery project known as the Central Valley Project (CVP). Authorized in 1933, the CVP presented a comprehensive plan to transfer water from the Sacramento Valley to the San Joaquin Valley for irrigation, power generation, and prevention of salt-water intrusion in the Sacramento-San Joaquin Delta (Stene 2015). Following the construction of several dams and reservoirs of the CVP, the state developed the State Water Project (SWP) in 1957 with the main objective of providing domestic water supply to urban centers in the state. Together, the CVP and SWP are among the world's largest water storage and transport systems, with 56 reservoirs providing water to 27 million domestic users and irrigating 3.5 million acres of land a year (California Department of Water Resources 2017).

The majority of California's dams, including the major projects of the CVP and SWP, were completed before 1975. By the late 1970s, a growing number of people and organizations contested new dam construction. The high price tag of water infrastructure created political and financial opposition between constituents and governing agencies. Awareness of the compounding and often irreversible environmental impacts of dams, such as ecological degradation, habitat destruction, and species endangerment, fueled further resistance to new dam projects. Furthermore, nearly every significantly flowing river or tributary in California was dammed or diverted by 1975.

Figure 1:Number of Dams by Year Completed



The Geography and Typology of California's Dams

Dams in California vary in type, size, purpose, and location. They range from a shallow irrigation pond behind a three-foot dam to a major reservoir impounded by a 770-foot dam. The volume of water stored in the state's reservoirs are between 0 and 30 million acre-feet, depending on the time of year, type, and purpose of the dam (DHS 2015, 42; NID 2016).

Table 1: Primary Purpose of Dams in California	Count
Water Supply	750
Hydroelectric	281
Flood Control	233
Other	167
Irrigation	47
Unknown	37
Fish and Wildlife Pond	30
Fire Protection, Stock, Or Small Fish Pond	17
Recreation	14
Debris Control	5
Tailings	4
Total	1585

Figure 2: Geographic Distribution of Dams in California

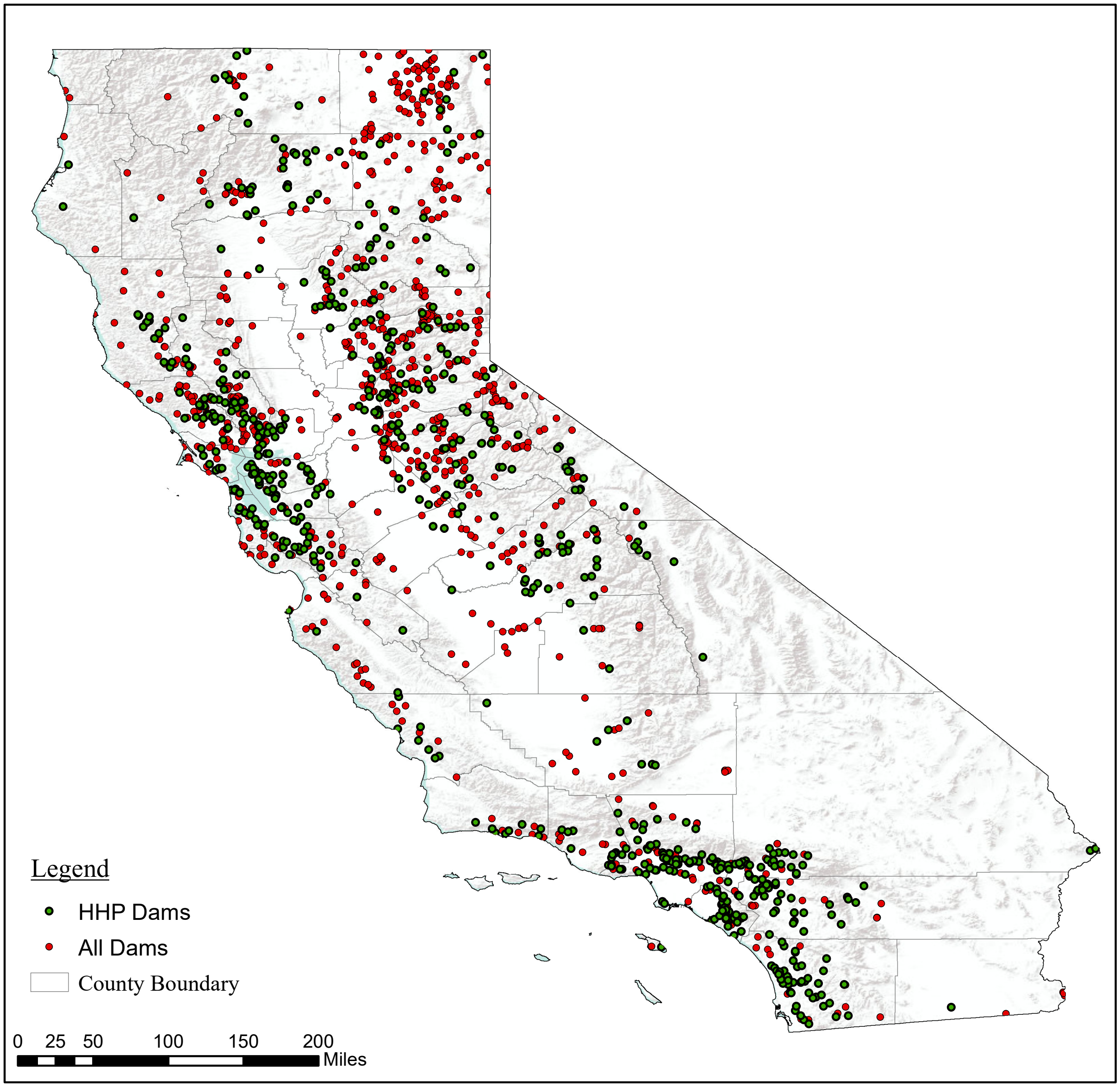
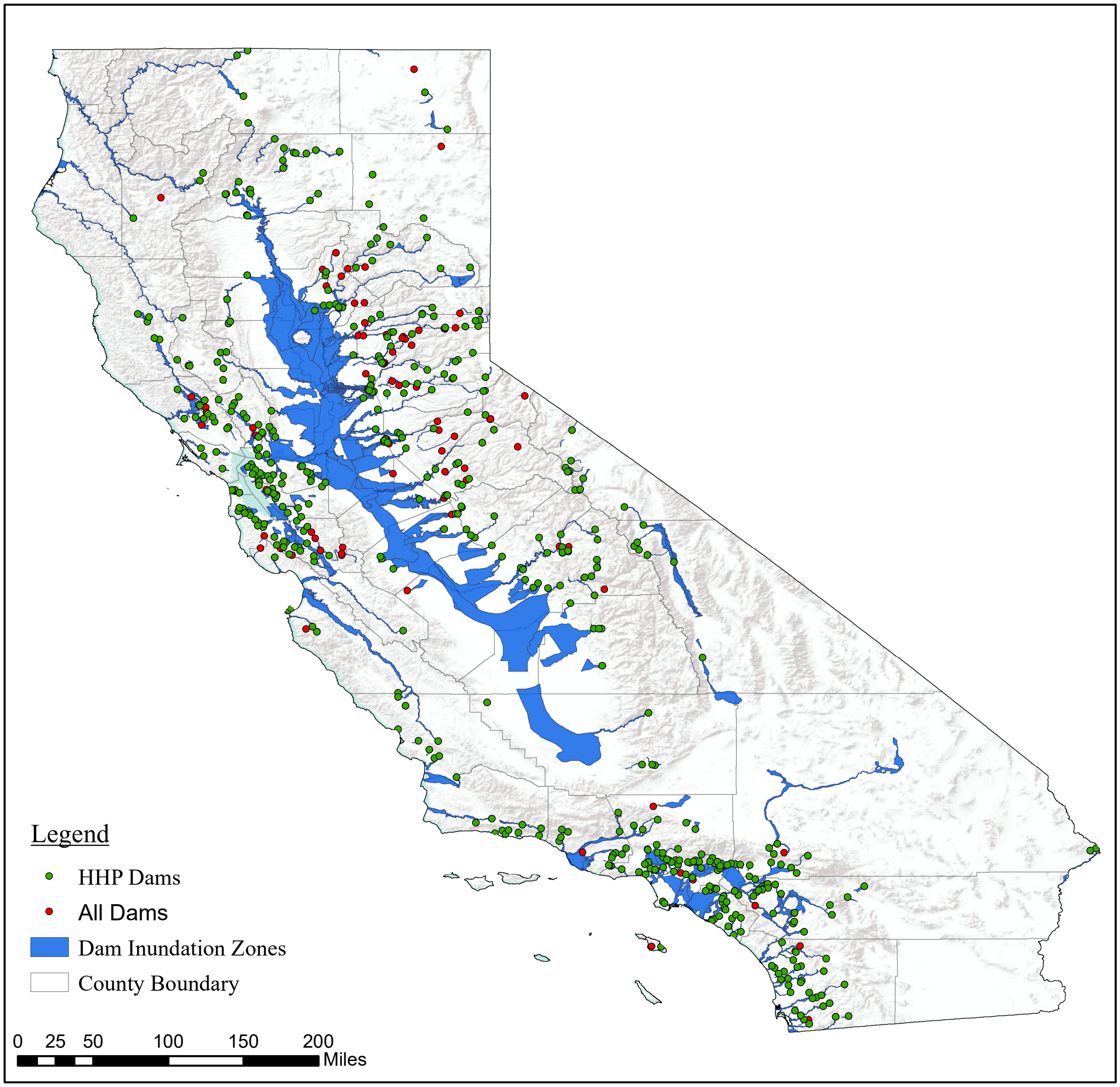


Figure 3: Geographic Distribution of Dams with Inundation Zones in California



What's the Dam Problem? Political, Economic, and Structural Context

The issue of aging dam infrastructure is a broad problem across the U.S. The federal government estimates that the useful economic life for a dam is 50 years, and though the physical life span of dams is typically greater than 50 years, the physical diminishment of dams and their components result in high budgets for maintenance and repair (Ho et al. 2017). In California, over 70 percent of dams are 50 years or older, with the average dam age being 70 years old (USACE 2016). Furthermore, the American Society of Civil Engineers indicates that 97 percent of the dams in the U.S. are inadequately funded, which increases the probability of at-risk dams going undetected (Ho et al. 2017). California is no exception; the Department of Water Resources recently estimated the cost of repairing dams statewide to be $5 billion (Editorial Board 2017).

At the time of construction, many dams were low-hazard and surrounded by undeveloped agricultural land. However, as populations grew, communities added homes, businesses, public buildings, and roads downstream, increasing the amount of people and infrastructures at risk (Spillman et al. 2017). The U.S. Army Corps of Engineers defines High Hazard Potential (HHP) dams as those that have the potential to result in significant loss of life, property destruction, or environmental damage in the case of failure or misoperation (USACE 2016). This compounds the problem of aging dam infrastructure in California, where 833 of the state's 1,585 dams (53 percent) are High Hazard Potential. This is the fourth most of any state, and well above the national average of 15 percent (Spillman et al. 2017).

On March 12, 1928, the sudden failure of St. Francis Dam in Southern California resulted in a major disaster and 431 casualties. Before this, State supervision and oversight of dams was limited in scope and applied to only about half of the state's dams. This prompted the enactment of a new statute in 1929 that gave regulatory jurisdiction of all non-federal dams to the State, and led to the creation of the California Dam Safety Program, now known as the Division of Safety of Dams (Babbitt 1993, 1). The new laws provided for (1) examination and approval or repair of dams completed prior to the effective date of the statute, (2) approval of plans and specifications for and supervision of the construction or modification of dams and (3) supervision of operation and maintenance of dams (Babbitt 1993, 1). There are 1,249 dams currently under the supervision of the DSOD, though the legal owner of the dam is responsible for the operations, maintenance, and repair of dams and its facilities ("Dam Rating" 2017). Dam owners can be Federal, State, local public agencies, utilities, private landowners, and water and irrigation agencies ("Dam Rating" 2017).

California has one of the best dam safety inspection programs in the nation (Adler 2017). Though the program is severely understaffed and underfunded, Lori Spragens from the Association of State Dam Safety Officials claims, "every other state is more understaffed and underfunded… Other states still look to California" (Adler 2017). For context, the state of Oklahoma budgeted just $106,376 for dam safety for 4,601 dams in 2016, while California budgeted $13,711,000 for 1,249 dams the same year ("State Program" 2016).

A recent analysis of dam inspections in the state showed that nearly 44 percent failed to be examined within the required inspection frequency (Spillman et al. 2017). Currently, 22 field engineers are responsible for inspecting 1,249 dams, which rounds out to about 57 dam inspections per engineer per year (Adler 2017). Though the amount of money California budgets for its dam safety program increases every year, from about $6.5 million in 1999 to about $13.5 million in 2015, the number of full-time equivalent dam safety staff has declined from 68 to 61 FTE positions in the 1999-2015 period ("Dam Safety" 2016). Furthermore, original dam designs rely on simplistic assumptions about hydrology and earthquakes. More than 90 need major upgrades to better handle large floods or withstand earthquakes. Dam operations also need to be updated to work with improved weather forecasting technology and account for a changing climate (Escriva-Bou et al. 2017).

The DSOD dam safety inspectors will assign a condition rating to the dam after inspection or after recommended actions have been taken, including Remediated, Not Rated, Unsatisfactory, Poor, Fair, and Satisfactory. Out of 1,249 dams under the state's jurisdiction, 92 percent are in satisfactory condition (NID 2016). This condition assessment can mask serious design and operating issues filed in inspection reports. Consider that an investigation of Oroville's last three inspection reports revealed that the DWR and the dam operator had knowledge of significant structural weaknesses, including cracking and water seepage on the dam face and main spillway, and concerns that the high-tensile steel anchor tendons used to strengthen the spillway concrete needed replacement (Street 2017).

Despite reservoir restrictions for these deficiencies, the Oroville dam reservoir filled rapidly and overflowed, setting off a chain of events that ended with the spillway failure and a narrowly avoided dam failure. The Oroville example demonstrates how even dams deemed to be in satisfactory operating condition by the Department of Water Resources Division of Safety of Dams can be at risk of failing under a combination of circumstances. It is therefore useful and necessary to analyze dams by their hazard potential, since High Hazard Dams are those that pose the highest risk to human life, property damage, regional and state economy, and environmental and ecological function and integrity.

Chapter 3: Literature Review

Dams as Critical Infrastructures

Dams are critical infrastructures. The U.S. Department of Homeland Security defines critical infrastructure sectors as those “whose assets, systems, and networks, whether physical or virtual, are considered so vital to the United States that their incapacitation or destruction would have a debilitating effect on security, national economic security, national public health or safety, or any combination thereof” (DHS 2017).[1]

The federal government added the Dams Sector to the list of critical infrastructures in 2003, recognizing the substantial economic, environmental, and social contributions of its assets and resources (DHS 2015, iii). Furthermore, the Dams Sector supports many other critical infrastructure sectors and industries as it delivers water retention and control services, hydroelectric power generation, municipal and industrial water supplies, agricultural irrigation, sediment and flood control, river navigation for inland shipping, industrial waste management, and recreation (DHS 2015, v). The interdependencies of the Dams Sector with other critical infrastructure sectors such as the Communications, Energy, Food and Agriculture, Transportation Systems, and Water and Wastewater Systems sectors mean that complete or partial dam failure would have significant and widespread consequences. As such, identifying and assessing the threats, vulnerabilities, and hazards facing the Dams Sector are a top priority of the Department of Homeland Security.

[1] There are 16 identified critical infrastructure sectors in the U.S., including the Chemical, Commercial Facilities, Communications, Critical Manufacturing, Dams, Defense Industrial Base, Emergency Services, Energy, Financial Services, Food and Agriculture, Government Facilities, Healthcare and Public Health, Information Technology, Nuclear Reactors, Materials, and Waste, Transportation Systems, and Water and Wastewater Systems sectors.

In the most recent “Dams Sector-Specific Plan,” the DHS identifies natural disasters and extreme weather as the most significant risks to the Dams Sector (2015, 9). Since dams and reservoirs are massive, concrete, and unyielding structures, they are acutely vulnerable to both seismic activity and climate change. This is especially true in California, a state known for its earthquakes and unpredictable precipitation patterns.

Impacts from Seismic Activity and Climate Change

California is predisposed to high rates of earthquakes due to the convergence of several tectonic plates and volcanism. These seismic forces result in the active and major San Andreas, San Jacinto, Owens Valley, Hayward, and Garlock Faults, as well as over 15,000 other fault lines throughout the state. Earthquakes occur when small, additional increments of stress are added to a fault that is loaded close to its breaking point (Foulger et al. 2017). This can happen from natural processes like plate tectonic movement and melting snow or ice, or from human activities like oil and gas extraction (Foulger et al. 2017).

There is ample evidence documenting the impacts of seismic activity to dams. Earthquakes can seriously impede dam function and cause heavy damage, depending on the intensity of the earthquake and dam type. Of California's 1,585 dams, 74.7 percent are earthen embankment dams, while 12.1 percent are unknown, and around 3.5 and 3.7 percent are rockfill embankment and gravity dams, respectively (NID 2016). According the Federal Energy Regulatory Commission, instability for earthen embankment dams after an earthquake is not a frequently occurring event (2005, 6). However, seismic activity can cause soil liquefaction, where saturated sand and silt behaves like a liquid when shaken by an earthquake (USGS 2006). Earthquake waves cause water pressures to increase in the sediment, causing the sediment to lose strength and lead to ground settlement (USGS 2006). Soil liquefaction and ground settlement near a dam or reservoir can seriously affect the physical dam structure and create embankment deformations. FERC states, "If liquefaction of the dam embankment or foundation has occurred, the dam may have already failed or may be on the verge of failure" (2005, 6).

While structural flaws are more likely to cause dam failure than seismicity, the processes of earthquakes, soil liquefaction, and ground settlement can exacerbate existing structural weaknesses. For example, internal erosion from piping seepage, external erosion caused by the wear from water over time, settlement of the dam crest over time, and foundational defects have caused about 50 percent of all U.S. dams to fail (DHS 2015, 9). When the California Division of Safety of Dams or FERC identifies structural problems, they place operating restrictions or conditions on the dam. Restrictions might include limiting the amount of water in the reservoir or reducing the allowable speeds of water flowing through dam gates or spillways. Additionally, the DSOD or FERC will recommend seismic retrofits for dams with identified deficiencies. This is especially important for older dams, because engineers in the early part of the 20th century did not realize that the loose rock and soil they used to form the base of some dams could liquefy in a strong earthquake, potentially causing the top of the structure to deform and spill (Carlton 2017).

The Perris Dam in Riverside County, Calaveras and San Pablos dams in Alameda County, and Anderson, Calero, and Guadalupe dams in Santa Clara County are either currently planning, undergoing construction, or recently completed seismic retrofits (Lin 2017). In addition to the seismic retrofits, the Anderson Reservoir near San Jose has a state-imposed limit of holding no more than 68 percent of its total water capacity because it lies near an active fault (Carlton 2017). Similarly, the Calaveras Dam must keep the 31 billion-gallon capacity of Calaveras Reservoir no more than 40 percent full because the 92-year old structure is built atop loose earth on the site of a previous failed dam (Carlton 2017).

The most well-known seismic damage to an earthen embankment dam in the state came from the 1971 San Fernando earthquake. The Department of Homeland Security acknowledges that a large number of high hazard potential dams are located within active seismic areas. Despite progress in seismic analysis methods and assessment procedures, predicting the behavior of dams and levees under earthquake conditions remains a significant challenge (2015, 9).

Technological, geological, and remote sensing advancements have led to the discovery of new fault lines in California in recent years, uncovering new vulnerabilities and risks for critical infrastructures. The Daily Mail reports that the discovery of the Polaris Fault came as a surprise to scientists who thought they had found all of California's seismic danger spots (2011). Though experts already knew of two faults near the structure, the Polaris Fault is just 200 yards from the Martis Creek Dam near Truckee, California (Daily Mail 2011). The Army Corps of Engineers owns the dam and keeps the water levels as low as possible, though a dam failure could potentially endanger 16,000 people in Placer County (Daily Mail 2011).

The function of dams is influenced by existing weather and climatic patterns. These impacts will be exacerbated by projections of climate change in the state in coming years. Storms, hurricanes, and high precipitation events can cause water deluges and flooding that overwhelm the flood storage or water capture capacity of a given reservoir. In these cases, the volumetric pressure of impounded water can overly stress the physical structure of the dam or reservoir. For dams with structural weaknesses, cracks, and deficient or aged components, the pressure of the water alone can be enough to cause the entire structure to fail.

Many large multipurpose dams operate with conflicting goals. For example, to manage floods, operators must release enough water to create space in reservoirs for winter floodwaters, which increases the chances that reservoirs will not be full in spring. Over the summer, when recreation demands are highest, reservoirs draw down to meet water and hydropower demands. Finally, many dams are required to conserve and slowly release the cold water collected at the bottom of reservoirs to support downstream salmon and steelhead habitat. Managing these trade-offs is becoming increasingly challenging as California's climate warms and precipitation becomes more variable (Escriva-Bou et al. 2017).

Changing climatic and weather patterns as a result of anthropogenic global warming pose a risk for areas around dams and reservoirs. The drainage infrastructure for U.S. cities was originally designed for a vastly different built environment, and was tailored to hydrologic conditions that are now historically outdated. Urban sprawl and the disappearance of permeable surfaces throughout the metropolis increase the chances that drainage networks are overburdened during high precipitation events, and cause higher volumes and velocities of stormwater runoff to accumulate in reservoirs. Climate scientists agree that the intensity and frequency of storms will become more variable and less predictable in the coming years, which will increase the likelihood of dam failure if water begins to overtop reservoirs or rises higher than designated safe operating levels (Pittock and Hartmann 2011).

In the recent Hurricane Harvey event, there was more rainfall than from any U.S. storm in 138 years of record-keeping, with more than 60 inches of rain reported in two locations (Feldblum 2018). Fifty thousand 911 calls were made on the first night alone, at least 68 people died and half a million cars flooded out (Feldblum 2018). This extreme weather event added billions of gallons of floodwater to the area's reservoirs which takes many months to safely release. As part of this release of water from the Addicks and Barker reservoirs in West Houston, many nearby communities were flooded (Satija et al. 2017). The Oroville dam flooding threat was also a direct result of severe weather patterns and climate change, for which the aging dam was not designed to deal with (Nagourey et al., 2017).

The relationship between climate change, seismic activity, and dams is even more complex with research that shows large dams and reservoirs can actually induce minor earthquakes. The first way a reservoir can cause an earthquake is through either rapid filling or rapid emptying of the lake behind the dam, which changes the weight and force acting on a fault (Lin 2017). Though water levels in reservoirs normally fluctuate in an annual cycle in line with precipitation patterns, a drastic change in the water levels over a short time period can cause tremors.

Furthermore, a recent study by Johnson et al. linked the alternating wet and dry cycles in California to the rates of earthquakes, concluding that crustal stress changes from variations in fluid pressure during wet months lead to more earthquake ruptures (2017, 1161). Christiansen et al. also conclude that stresses associated with the hydrological loading cycle are sufficient to fracture critically stressed rocks and cause microquakes along the San Andreas Fault (2007). The pattern found by both studies show the Earth's crust depressing under the load of rain and snow in winter months, and rebounding as the snow melts and rivers drain, where the stress changes associated with unloading make faults fail more often in late summer and early fall (Christiansen et al. 2007).

Secondly, as the water stored in reservoirs percolates deep into the earth, it changes the normal compression stresses acting on geologic faults. This process, known as “unclamping,” occurs when fluid pressure counteracts the normal stresses, allowing two sections of rock to slip or move along the fault, resulting in an earthquake (Kuchment 2016). This phenomenon occurs in cases of oil and gas production, horizontal drilling, and hydraulic fracturing, when the pressure from injected fluid or wastewater triggers earthquakes (Kuchment 2016). Research linking fluid pressure and induced earthquakes dates back to a seminal study by a team of U.S. Geological Survey geophysicists and hydrologists in 1976, along with recent studies analyzing oil and gas injection wells and the high, historically unprecedented rates of earthquakes in in Oklahoma, Kansas, Ohio and Texas (Raleigh et al. 1976, Petersen et al. 2016). The biggest uncertainty with these reservoir-induced earthquakes is the difficulty in measuring how close to failure a fault is, or predicting the scope or intensity of a potential earthquake (Lin 2017).

Dam Tradeoffs: Are the Benefits Worth the Costs?

The most prevalent debate about dam building has to do with their necessity, utility, and tradeoffs. Dams can bring large-scale grid electrification to an area through hydropower generation, and in many areas, dams are the heart of the engine of economic development. They are the main mechanism for water storage, supply, delivery, and flood-control, and vital for ensuring a steady flow of water year-round to agriculturalists, industries and manufacturers, urban powerhouses, and domestic users. Reservoirs also provide a recreational resource for citizens and tourists. While nearly 15 percent of California's electricity supply comes from hydropower, the water stored and delivered through the dam and reservoir network supports the most populated state in the country and the sixth largest economy in the world (Escriva-Bou et al. 2017).

Despite these many benefits, dam-building comes at an enormous and often irreparable cost to the environment by altering or degrading natural riverine and delta hydrology, ecology, and animal habitat and life (Nilsson et al. 2005). For example, the dams and reservoirs of the Central Valley Project block access for salmon and steelhead to reach their native spawning grounds, leading to their status as endangered species. Furthermore, the diversion of water for irrigation resulted in a loss of over half of the valley's native freshwater wetlands and destroyed habitat for native migrating birds and fish species (Kahrl, 1982, 61). The Sacramento-San Joaquin Delta smelt population has declined by more than 90 percent since the completion of large-scale CVP and SWP dams and reservoirs (Kahrl, 1982, 61). In terms of social impacts, dam projects may forcibly displace existing populations, and can pose significant risks to flooding or destruction of life and property. As with many large infrastructural projects, dams tend to be extremely expensive and have years-long construction timelines, which can lead to political, financial, and taxpayer holdouts.

Over the past three decades, support for dam removal and river restoration projects have increased across the U.S. Since 1987, California removed more than 36 dams (Escriva-Bou et al. 2017). There are many reasons to remove a dam, including the costs of improving or retrofitting aged and dilapidated dams, protecting endangered species (i.e. salmon and steelhead fish, migratory bird habitats), the decreasing energy share from many hydroelectric dams, earthquake safety hazards, and reduced benefits (Johnson and Graber 2002, Poff et al. 1997, Stanley and Doyle 2003). The 2015 breaching of San Clemente Dam on the Carmel River was the largest dam removal in state history (Escriva-Bou et al. 2017). Several other large dams are ready for removal, including Matilija Dam in Southern California and four aging hydropower dams on the Klamath River in Northern California (Escriva-Bou et al. 2017).

On the other side of the issue is a camp of thinkers who believe in the face of climate change, dams are more necessary than ever. For example, Beatty et al. argue that artificially created waterbodies can serve as barriers to invasive species, and actually maintain habitats for endangered aquatic organisms where changing climatic conditions dewater, reduce, or warm their habitat water bodies (2017). Moreover, water-poor regions under climate change can use additional dams and reservoirs to increase resilience to droughts and secure adequate water supply for their populations.

California is an area expected to experience warmer average temperatures along with more variable rain and snowfall due to climate change, which has the potential to diminish the future supply of water (Pittock and Hartmann 2011). Additionally, the majority of surface water precipitation falls in the Northern part of the state as snow over the Sierra Nevadas, leaving the Southern part of the state extremely water-scarce. These factors, along with historic and projected long, mid, and short-term droughts, contribute to the dam debate in California being focused on maintaining, repairing, and adding to existing infrastructure, rather than on removing dams. There are currently several water supply expansion projects that involve constructing four new reservoirs using Proposition 1 funds, including a large-scale dam on the San Joaquin River in Fresno County, which would hold enough water for 6.5 million people a year and become the second tallest in the state (Rogers 2017).

The Social Vulnerability Concept: What Is It, and Why Is It Important?

The attitude of California policymakers and constituents is favorable to maintaining existing and building additional dams and reservoirs. Given what we know about California's aging dam infrastructure, and that 833 of the 1,585 dams are High Hazard Potential dams, it is necessary to take a critical look at who is most vulnerable to flood-risk in a scenario of dam failure or misoperation. To do this, this project employs a method to measure the social vulnerability to HHP dams in the state.

Considerable research has examined components of biophysical vulnerability and the vulnerability of the built environment, with less attention payed to understanding the social aspects of vulnerability. Social vulnerability is described using the individual characteristics of people (i.e. age, race, health, income, type of dwelling unit, employment, etc.) and is partially the product of social inequalities – or social factors that influence the susceptibility of various groups to harm and that govern their ability to respond (Cutter et al. 2003). Maantay and Maroko make the case that, "certain people may be disproportionately exposed to hazards due to physical factors, like having poor quality housing that inadequately withstands hazard events… but they may also be at a disadvantage due to lack of strong social, financial, or political support structures, and thus suffer greater relative losses, and experience a longer recovery time after a disaster… than the affluent, mainstream, or socially supported" (2009).

According to Cutter et al., one of the barriers to social vulnerability theory and research is the debate on whether it can be quantified or measured for empirical analysis, and subsequently how to do so (2003). Rufat et al. state that over the past decade, social vulnerability indices have emerged as a leading tool to quantify and map human dimensions of hazards vulnerability (2015). These indices are valuable tools for policy formulation and disaster preparedness and response planning (Rufat et al. 2015). However, the authors note that social vulnerability indices exhibit a large degree of uniformity in index construction approaches. This may result in misleading conclusions if pertinent variables are excluded or if weakly influential variables are overrepresented (Rufat et al. 2015). Furthermore, Rufat et al. argue that factors such as social capital, risk perception, and psychosocial dimensions of health are important indicators of flood-risk that typically cannot be computed from national census data, and require qualitative methods, targeted surveys, and participatory approaches to measure (2015).

It has been argued that quantification of the complex nature of social vulnerability is an important and long overdue addition to the hazard mitigation planning and implementation processes, especially in the context of climate change adaptation and disaster risk reduction strategies (Tate et al. 2010). There is increasing momentum for research that measures vulnerability, especially as governments turn their attention to planning for, and responding to, natural hazards (Stafford and Abramowitz 2017). Environmental hazards can be neither eliminated nor controlled, but humans can reduce the risk associated with them by integrating knowledge on the multifaceted dimensions of risk, which include social, demographic, and economic factors (Solangaarachchi et al. 2012).

Several methodologies exist for assessing social vulnerability across different scales and systems. However, the indicator-based approach is common for analyzing patterns in areas that are addressing specific environmental hazards (Mavhura et al. 2017). There are still disagreements in the selection of indicators of social vulnerability. This is due to the fact that natural disasters, and by extension vulnerability, are highly contextual, temporal, spatial, and variable phenomena. Despite this challenge, Chang et al. argue that the indicator approach is ideal for comparative purposes of places (2005). The approach can provide an estimation of the baseline vulnerability at the local level, which is important for policy- and decision-makers in disaster risk reduction (Mavhura et al. 2017). Mavhura et al. conclude that the most important aspect in the selection of indicators is to ensure that the indicators address the research question and test the concepts under operationalization (2017).

Overall, my review of the methods for quantifying social vulnerability informed my decision to use an indicator-based approach in lieu of a social vulnerability index. The following section provides a deeper look at the specific literature on social vulnerability and flood-risk, and serves as the rationale for the selection of variables that address my research questions.

Social Vulnerability and Flood-Risk: Previous Research and Findings

Despite a dearth of literature on the social vulnerability of populations to dam-inundation events, there is abundant research on the social determinants of flood-risk in cases of sea-level rise, climate change, high precipitation, and storm events. From a geographic perspective, coastal cities, inland floodplains, densely populated areas, and regions with more exposure to tropical storms and hurricanes (such as the Northeast, South, and Midwest) experience much higher rates of flooding than others.

Nearly 80 percent of the U.S. population reside in urban areas, which exacerbates flood-risk because sprawling impervious surfaces prevent ground absorption, concentrate urban runoff, and overload water drainage systems during storms. High population densities in flood-prone urban areas can also hinder evacuation due to congestion, limited exit routes, and dense building infrastructure (Donner and Rodriguez 2011).

Considering the social determinants of flood-risk, striking indicators and inequalities along the lines of race, ethnicity, socioeconomic status, age, gender, education, homeowner status, native language, and citizenship emerge. These characteristics are inextricably bound up with location, as socially and economically marginalized groups have the least choice about where to live, and often end up in more hazardous areas where housing costs are lower (Fielding and Burningham 2005).

Chakraborty et al. (2014) and Donner and Rodriguez (2011) find that Black, Latino, Hispanic, and low-income communities are significantly more likely to reside in high flood-risk zones, including 100-year floodplains and flood-prone sections of cities with less structural resilience. It follows that other factors correlated with poverty, including gender, age, and education level are also correlated with higher vulnerability to floods. Moreover, research shows that language barriers contribute significantly to the inadequate dissemination of flood warnings and evacuation announcements, and that fear of deportation influences undocumented migrants and mixed-status families' decision to go to evacuation shelters (Donner and Rodriguez 2011, Maldonado et al. 2015).

In addition to being more vulnerable to floods, socially and economically disadvantaged groups face unequal barriers to recovery. For example, Fielding and Burningham show that low-income people are less likely to have enough financial resources to cover them during an emergency (2005). Furthermore, low-income individuals are more likely to lose their job if they are displaced from their homes, because even temporary relocation can prevent a person from getting to or from work (Fielding and Burningham 2005). These populations tend to work in employment sectors with higher turnover, fewer labor protections, lower job security, and invisible or informal occupations, where missing even a day of work can result in unemployment. This pattern further places a disproportionate economic burden on low-income groups struggling to recover from a flood event or disaster.

Maldonado et al. find that racial and ethnic minorities are less likely than non-Hispanic Caucasians to take certain disaster precautions, like purchasing flood insurance, or installing storm shutters (2015). Additionally, agencies like FEMA and HUD deny post-disaster assistance to foreign-born individuals at higher rates than citizens, regardless if they are green-card holders or legal residents (Maldonado et al. 2015).

Fielding and Burningham summarize that the risk of the initial disaster and speed of recovery from a flood event is often disproportionately borne by the very young, very old, and the disabled. These reasons include dependency and inability to transport themselves to safety zones, the fact that many elderly live alone, and that these groups may not have the same access to evacuation warnings or evacuation centers (2005). Populations younger than 5 older than 65 may also have additional needs in a disaster event, such as refrigerated medications and assisted transportation (Fielding and Burningham 2005).

Chapter 4: Data and Variables

Description of Datasets

To answer the project's proposed research questions, I use the three datasets listed below.

Table 2: Summary of Datasets

Data Source	Publisher	Data Year(s)
National Inventory of Dams	U.S. Army Corps of Engineers	2015
Dam Inundation Maps	California Office of Emergency Services	2017
American Community Survey	U.S. Census Bureau American Fact Finder	2012 – 2016

The National Inventory of Dams

The main source of dam data comes from the 2016 U.S. Army Corp of Engineers' National Inventory of Dams (NID). Free access to this dataset is limited to relevant government agencies and employees. However, I was able to purchase this dataset through the ProPublica Data Store with a Graduate Research Grant provided by the UCLA Luskin Center for Innovation. The 2016 NID uses information collected through 2015 on 90,580 dams in the United States. According to the NID, any dam that exceeds 25 feet in height and 15 acre-feet in storage, exceeds 6 feet in height and 50 acre-feet in storage, or is classified as a High or Significant Hazard is included in the NID. The comprehensive dataset includes 71 variables of the physical, structural, regulatory, operating, and geographic characteristics of these dams.

Table 3: Selected NID Variables

Variable	Description
Downstream Hazard Potential	Code indicating the potential hazard to the downstream area resulting from failure or misoperation of the dam or facilities. Low (L), Significant (S), or High (H).
Year Completed	Year (four digits) when the original main dam structure was completed.
Inspection Date	Date of the most recent inspection of the dam prior to the transmittal of the data by the submitting agency.
Inspection Frequency	The scheduled frequency interval for periodic inspections, in years.

For the purposes of this project, I investigate several variables from the NID. These include dam size (NID Storage), age (Year Completed), and inspection compliance (ratio of Inspection Date to Inspection Frequency). Additionally, the variable "Downstream Hazard Status," determines the subset of dams I need to answer research questions 2, 3, and 4. The California Division of Safety of Dams assigns a hazard status based on the potential downstream impacts to life and property should the dam fail when operating with a full reservoir (2017). Furthermore, the hazard status is separate from the condition of the dam or its appurtenant structures (DSOD 2017). FEMA's publication "Federal Guidelines for Inundation Mapping of Flood Risks Associated with Dam Incidents and Failures" defines the criteria for downstream hazard status (Beadenkopf et al. 2013).

The downstream hazard of a dam falls into one of three categories of increasing severity: Low, Significant, and High. A dam with a High Hazard Potential (HHP) status means that the failure or misoperation of the dam will result in significant loss of life, property destruction, or environmental damage (USACE 2016). The state of California has a higher number and proportion of hazardous dams than most other states in the nation, with 53 percent (833 of 1,585) classified as HHP. To compare this percentage to states with a similar number of dams, consider that just 5 percent of Wyoming's dams (97 of 1,617) and 14 percent of Illinois's dams (231 of 1,607) are High Hazard Potential. Out of 1,736 total dams, Colorado has 425 HHP dams (or 25 percent). Among other West Coast states, about 17 percent of Oregon's dams (146 of 869) and 31 percent of Washington's dams are HHP (243 of 784). The only state with similar number and proportion of hazardous dams is Pennsylvania, where 809 of 1,525 dams are high hazard (53 percent).

The 2016 NID data includes a disclaimer that the 2015 hazard and condition status for each dam is not included in the dataset, for reasons of protecting national security and critical infrastructures (NID 2016). However, the dataset includes both the 2002 and 2013 inventory of the nation's dams, with the 2002 dataset reflecting the hazard status of each dam. The USACE warns that the hazard potential assigned to 2002 dams may have changed in recent years, if substantial repairs, construction, or restrictions occurred in that time period. To bolster the validity of isolating the High Hazard Potential dams in California and reflect the most accurate hazard status given these limitations, I cross-reference the HHP dams from the 2002 NID with a 2017 publication from the California Division of Safety of Dams. This publication, titled "Dams within Jurisdiction of the State of California," is also based on the 2015 NID (2017). It republishes 17 of the NID's 71 variables, including the hazard rating. The DSOD has jurisdiction over about 79 percent of the state's dams (1,249 of 1,585), and the combination and crosschecking of these two sources together represent the most comprehensive list of hazardous dams available.

Dam Inundation Boundary Maps

The second data source I use in my project is a compiled package of dam inundation maps obtained through the California Office of Emergency Services (CalOES) via a Public Records Act request. This data arrived through the U.S. Postal Service on a CD-ROM drive, containing the GIS shapefiles of 564 dam inundation zones. The dam inundation mapping program began in response to the Sylmar earthquake on February 9, 1971, which caused severe damage to the Upper and Lower Van Norman Dams and threatened to cause extensive damage to life and property had dam failure occurred (CalOES 2018). The California Code of Regulations §335 dictates that "inundation maps shall be prepared for dams and critical appurtenant structures regulated by the state, except dams classified by the department as low hazard as described in §335.4" ("Emergency Regulations" 2018). Thus, inundation maps for all dams with Significant and High Hazard Potential status within the jurisdiction of the DWR DSOD are included in this dataset (581 of 1,249). The DSOD permits waivers to this requirement provided no risk to life or property exists (CalOES 2018).

CalOES conveys that these maps approximate the maximum water flow resulting from a complete dam failure, and therefore portray a catastrophic failure of the dam as opposed to the failure of a critical appurtenant structure such as a spillway (De Alba 2018). These maps are prepared by civil engineers on behalf of dam owners, as required by California Code of Regulations §335.8 and §335.12 ("Emergency Regulations" 2018). The main underlying assumption for determining each inundation zone is that the amount of water in the dam is at the safe operating capacity at the time of failure (De Alba 2018). Refer to Appendix F for a full list of dam inundation boundary maps included in this project.

The American Community Survey

The final dataset I use is the American Community Survey, which underpins the analysis of social vulnerability to dam-induced flood risk. This data is publicly available, and I downloaded it through the United States Census Bureau American Fact Finder website. The American Community Survey "is a nationwide, continuous survey designed to provide communities with reliable and timely demographic, housing, social, and economic data every year" (U.S. Census Bureau 2017). I use the 2012-2016 five-year estimates for all census block groups in California. The census block group (CBG) is the smallest geographic scale that the data is available. To select the social vulnerability variables for analysis, I drew on previous literature and academic research on the demographic and socioeconomic determinants of flood-risk. These include race, ethnicity, age, gender, income, ability, employment status, housing tenure, car ownership, educational attainment, and citizenship.

Across these 11 social vulnerability categories, I analyzed 30 specific variables. In addition to seven variables for race and ethnicity, I include three distinct measures of income in order to gain a deeper understanding of relative and absolute poverty in California. The rationale for this stems from social vulnerability and flood-risk literature that identifies income among the most significant indicators of flood hazard exposure (Fielding and Burningham 2005). Though I use an indicator-based approach to analyzing social vulnerability, the two best-known and widelyused social vulnerability indexes incorporate several variables of wealth, income, and poverty for similar reasons.[2]

Absolute poverty is measured according to the official U.S. poverty line. This income-based threshold fluctuates depending on family size, household combination, and the annual Consumer Price Index (Fritzell et al. 2015). For example, in 2016 a family of four with a total household income at or below $24,339 was considered poor (Semega et al. 2017, 43). The major drawback to this measure is that it fails to consider place-to-place differences in the cost of living (e.g., transportation, housing), does not adjust for state and local difference in taxes, and ignores in-kind income such as housing vouchers or food stamps (Lichter and Schafft 2016, 15). A relative measure of poverty is the ratio of the household's income to the surrounding area's median income. Relative poverty measures account for the place-specific differences that absolute measures fail to. The Area Median Income is typically at the scale of the county or the Metropolitan Statistical Area.

There is wide variation in local taxes and housing and transportation costs across the cities and counties of California. To reveal the spatial patterns and nuances of poverty, I chose seven variables to assess the median income, absolute poverty rate, and relative poverty rate for each census block group. The Median Household Income variable allows for an initial interpretation and comparison of income. The variable is measured at the census block group level, and is the

[2] University of Southern Carolina Hazards and Vulnerability Research Institute developed the Social Vulnerability Index (SoVI). It uses principle components analysis to synthesize 29 socioeconomic variables from the American Community Survey and create a county-level vulnerability "score." Five of these 29 variables are categorized as "Wealth" indicators and together explain nearly 16 percent of the variance in the index (2013). The Center for Disease Control Agency for Toxic Substances and Disease Registry developed the Social Vulnerability Index (SVI). It uses 15 variables from the Decennial Census to create a single tract-level percentile rank for vulnerability. Four of the 15 variables are categorized as "Socioeconomic Status."

median dollar amount of all household incomes within the block group. CBGs with lower median household incomes can reveal the geographic distribution or concentration low-income households.

The three variables “V9ExtrmLowInc” “V9VeryLowInc” and “V9LowInc” provide information on the number of households experiencing relative poverty by CBG. These income categories are used by the U.S. Department of Housing and Urban Development (HUD) to determine eligibility for the Section 8 Housing Choice Voucher Program (HCD 2017). Households are Low Income if they earn 80 percent of the Area Median Income (AMI), Very Low Income if they earn 50 percent of the AMI, and Extremely Low Income if they earn 30 percent of the AMI. To capture the number of households experiencing absolute poverty, I included the three variables “V10PctBlw50” “V10PctBlw100” and “V10Pctlw150.” These account for the number of individuals earning at or below 50 percent, 100 percent, or 150 percent of the federal poverty threshold.

Table 4: Selected Social Vulnerability Variables

Variable Category ACS Table	Variable Name	Description
Age B01001	V1Pct_14_65	Percent of dependent age population, defined as younger than 14 or older than 65.
	V1Pct_14_85	Percent of dependent age population, defined as younger than 14 or older than 85.
Automobile B25044	V2Pct_NoAuto	Percent of households with no vehicle available.
Citizenship B99051	V3PctCitizen	Percent of the population born in the United States.
	V3PctForeignBorn	Percent of the population born outside the United States.

Disability C21007	V4PctDis	Percent of the population aged 18 or above with a disability.
	V4PctDis65	Percent of the population aged 65 or above with a disability.
Education B15003	V5Pct_No_HS	Percent of the population aged 25 or above with no high school degree or GED.
	V5Pct_HS_Deg	Percent of the population aged 25 or above whose highest educational attainment is a high school degree or GED.
	V5Pct_Abv_HS	Percent of the population aged 25 or above whose highest educational attainment is at least a 2- or 4-year degree.
Employment B23025	V6PctUNEMP	Percent of population aged 16 or above in the civilian labor force that are unemployed.
Ethnicity B03003	V7PctHISP	Percent of the population that are Hispanic or Latino.
	V7PctNotHISP	Percent of the population that are not Hispanic or Latino.
Gender B11001	V8PctFHH	Percent of female-headed households (no partner present).
	V8PctMHH	Percent of male-headed households (no partner present).
Income B19013 (V9) C17002 (V10)	V9ExtrmLowInc	Number of "Extremely Low Income" households. Defined by HUD as earning 30 percent of the Median Area Income.
	V9VeryLowInc	Number of "Very Low Income" households. Defined by HUD as earning 50 percent of the Median Area Income.
	V9LowInc	Number of "Low Income" households. Defined by HUD as earning 80 percent of the Median Area Income.
	V9MEDHHINC	Median household income in the past 12 months (in 2016 inflation-adjusted dollars) of the Census Block Group.
	V10PctBlw50	Percent of the population with income at or below 50 percent of the federal poverty line.
	V10PctBlw100	Percent of the population with income at or below the federal poverty line.
	V10Pctlw150	Percent of the population with income at or below 150 percent of the federal poverty line.
	V11PctWhite	Percent of the population that is White alone.

Race B02001	V11PctNonWhite	Percent of the population that is Nonwhite.
	V11PctBlack	Percent of the population that is Black or African American alone.
	V11PctIndigenous	Percent of the population that is American Indian and Alaska Native alone.
	V11PctAsian	Percent of the population that is Asian alone.
	V11PctPacific	Percent of the population that is Native Hawaiian and Other Pacific Islander alone.
Tenure B25003	V12PctRenter	Percent of the population that rents their housing unit.
	V12PctOwner	Percent of the population that owns their housing unit.

Data Limitations

There are unique limitations to each data set that are dependent on a number of factors related to their respective methods for collection and representation. The glaring limitation of the National Inventory of Dams data is the suppression of the most up-to-date hazard status of dams. Though I use the methodology of validating the 2002 NID dataset with hazard potential information supplied by the California DSOD, there is potential omission of HHP dams for the 336 (of 1,585) dams that are not under the jurisdiction of the state.

Considering the set of 564 dam inundation maps, some acknowledgement of the approximation of the inundation zone is necessary. First, since civil engineers prepare the maps on behalf of dam owners, there is variation in the modelling software, methods, and assumptions used to determine each inundation boundary. Second, the main assumption for each map is that the amount of water at the time of dam failure is within the safe operating capacity of the dam (De Alba 2018). One issue with this assumption is that capacity restrictions or limitations are imposed as necessary when structural or safety problems are identified. Another issue, demonstrated by the Oroville Dam Spillway Failure, is that the water level of a reservoir can rise well above the safe operating capacity in a short time period under certain climatic conditions and weather events.

Taken together this means that some inundation maps may over or under-approximate the flood zone boundary, and do not reflect current reservoir levels “on the ground.” Finally, the sample size of dam inundation boundary shapefiles is constrained to 581 because the California Water Code does not require every dam to create an inundation zone map. The sample size if further limited to 564 zones because 5 of shapefiles were missing data and could not be projected and an additional 12 could not be matched with existing dam from the NID.

Finally, the ACS is a survey, and thus has the potential to contain a number of errors stemming from issues of sample size, data entry and imputation error, and the nature or phrasing of survey questions. Sampling error is the difference between an estimate based on a sample and the corresponding value that obtained if the entire population were surveyed (Census Bureau 2017, 10). The Census Bureau states that sampling error in the ACS data "arises due to the use of probability sampling, which is necessary to ensure the integrity and representativeness of sample survey results" (2017, 9).

Non-sampling error can occur if survey data is inputted incorrectly, when a variable is weighted inaccurately, or during the data editing and cleaning process. For example, the “hot-deck” imputation method used to generate values for missing fields and nonresponses can be erroneous because it replicates the answer of an existing survey taker with similar demographic or socioeconomic characteristics (Census Bureau 2017, 12). The Research and Training Center on Disability in Rural Communities describes the issues with survey results from rural counties, which include smaller sample sizes, higher margins of error, and an “urban bias” in design of survey questions (2017). Regarding ACS estimates for populations with disabilities, they state, “The high margins of error [from small sample sizes] make data less reliable at smaller geographies (e.g. counties) and forces researchers to aggregate the data to increase data validity. This limits the ability to analyze county level disability data, particularly for subgroups like race and ethnicity” (2017, 7).

The disabled population estimates are also complex because “disability is a dynamic concept that changes over time as one’s health improves or declines, as technology advances, and as social structures adapts. As such, disability is a continuum… Various cut-offs are used to allow for a simpler understanding of the concept, the most common of which is the dichotomous ‘With a disability’ / ‘No disability’ differential” (U.S. Census Bureau 2018). Weathers compares disability data from six nation-wide population and health surveys, and concludes that “The ACS population and prevalence rate estimates are lower than estimates from datasets that use a larger set of questions to estimate the size of the population with disabilities and higher than estimates from datasets that use a smaller set of questions” (2005, 28). This indicates that the number questions and the nature of the questions asked can cause an under- or over-estimate of disabled individuals.

However, in 2008, the Census Bureau conducted a conceptual and empirical overhaul of the ACS disability questions, to the extent that they do not recommend any comparisons of post-2008 disability data to previous years. A recent study comparing the 2012 ACS disability estimates with the 2011 National Health Interview Survey affirms that ACS questions identify a representative sample of the population with hearing, cognitive, ambulatory, self-care, and independent living difficulties (Altman et al. 2017, 489). The authors assert that their results do not support the argument that the ACS questions result in a population sample that is biased (i.e., that misses an important segment of the population with disabilities) (2017, 490). Thus, I assume the results of my statistical analyses concerning individuals with disabilities to be an unbiased and representative snapshot of this population.

The wording of survey questions and range of acceptable potential responses can be a limitation for other estimates as well. For example, after the 2000 Decennial Census the Bureau changed the question regarding race by adding a sixth category, “Some Other Race,” and began allowing respondents to select more than one race. Brooks claims, “This change, while meant to allow for more inclusiveness, made it difficult to accurately calculate racial and ethnic trends” (2008, 2). Autry reports that these shifts in racial classifications raise questions about how people interpret the same question differently (2017). For example, how can researchers accurately evaluate demographic trends when people’s perception of their racial background changes? (2017). A 2015 study by the Pew Research Center found at least 9.8 million people reported a different racial or ethnic background on the 2010 Decennial Census than they did in the 2000 census (Autry 2017). To address this in my research, I include variables for the five major race categories of White, Black or African American, American Indian or Alaskan Native, Asian, and Native Hawaiian or Pacific Islander, as well as a calculated variable Nonwhite. The Nonwhite variable captures these four nonwhite populations, as well as individuals who identify as “Some other race alone,” and “Two or more races.”

Misinformation and nonresponses on the part of the survey taker also influences the accuracy of ACS data. Individuals may be unable to respond to question because they are unsure of the potential answer, misunderstand the question due to language barriers or question phrasing, are in poor health, or have another impairment impeding their ability to complete the survey as accurately as possible. Other factors for nonresponse and measurement error include disinterest and lack of time (Meyer et al. 2015). Individuals might experience internalized biases and social stigmas that influence their answers. For example, Meyer et al. concludes that between 25 and 36 percent of survey takers either failed to report or significantly underreported income from transfer benefits and social programs such as the Temporary Assistance for Needy Families, Supplemental Nutrition Assistance Program, or Supplemental Security Income (2015). Meyers cites societal stigma against social safety net recipients as a reason answers are mis-reported, such as anti-poor rhetoric that ignores structural influences and blames individuals for their economic status (2015).

Survey takers may intentionally leave questions blank or report incorrect information because of privacy concerns or unease about how unease about how local, state, or federal government officials might use certain survey answers. For example, question 8 of the ACS asks whether respondents were born in the United States or were born abroad. Though the ACS does not ask specifically about immigration status, Passel et al. show that citizenship and legal status is strongly associated with country of birth and the number of years a person has lived in the U.S. (2006; Van Hook and Bachmeir 2013). By comparing the responses to this question with the Office of Immigration Statistic's official estimates of the undocumented foreign-born population, Van Hook and Bachmeir found significant underreporting and nonresponse among all immigrants with less than five years of U.S. residence, among Mexican men of all ages and durations of residence, and among Mexican women ages 40 and older (2013, 12). Therefore, I expect the results of my statistical analysis of foreign-born populations to be an under-represented and incomplete estimate.

Despite the limitations of the NID, dam inundation maps, and ACS survey data, these three datasets represent the best available data for the purposes of this investigation.

Chapter 5: Methods

Research Design

This research uses quantitative methods and follows four main steps, including identification of vulnerable groups, data acquisition, data editing and geoprocessing, and statistical analysis. I modelled the research design after previous, recent studies of social vulnerability and flood risk, similar to the methods of Lawal and Arakoyu (2015).

The geographic focus of this research project is the state of California. More specifically, the boundaries of analysis are dam inundation zones across the state. The selected population, and units of analysis, are individuals and households within census block group either inside or outside these dam flood zones.

The instruments I use to measure outcomes in this study are Geographic Information Systems (GIS) and Statistical Package for the Social Sciences (SPSS) software. Within the GIS platform, I utilize several geoprocessing tools to identify populations living within or outside of dam flood zones. I use SPSS to conduct comparison of means tests and multiple regression analyses to identify the relationship between social vulnerability characteristics, dam inundation zones, and certain dam characteristics including reservoir size, age, and inspection frequency ratio.

The main questions of this study are as follows:

1) Are socially vulnerable households more likely to live within dam flood zones than outside of them in California?
    a. Statistical Test: Comparison of means with a two-tailed independent samples test
        i. Test Variables: Selected social vulnerability characteristics
        ii. Grouping Variable: Within (1) or outside (0) all dam flood zones.

2) Are socially vulnerable households more likely to live within HHP dam flood zones than outside of them in California?
    a. Statistical Test: Comparison of means with a two-tailed independent samples test
        i. Test Variables: Selected social vulnerability characteristics
        ii. Grouping Variable: Within (1) or outside (0) HHP dam flood zones.

3) Which factors of household social vulnerability are significantly correlated with living in a dam flood zone? Do these differ from factors significantly correlated with living in an HHP dam flood zone?
    a. Statistical Test: Multiple linear regression
        i. Independent Variables: Selected social vulnerability characteristics
        ii. Dependent Variable: Within (1) or outside (0) HHP dam flood zones.

4) Is there a relationship between social vulnerability and the HHP dam characteristics of age and inspection compliance?
    a. Do HHP dams built more than 50 ago have higher proportions of socially vulnerable households within their inundation zones than HHP dams built less than 50 years ago?
        i. Statistical Test: Comparison of means with a two-tailed independent samples test
            1. Test Variables: Selected social vulnerability characteristics
            2. Grouping Variable: Dam Age ≥ 50 years (1) or < 50 years (0).

    b. Do HHP dams with failed inspection compliance have higher proportions of socially vulnerable households within their inundation zones than HHP dams in compliance?
        i. Statistical Test: Comparison of means with a two-tailed independent samples test
            1. Test Variables: Selected social vulnerability characteristics
            2. Grouping Variable: Fail (1) or Pass (0).

Research Procedure

As stated above, the procedure of this project's methods follows 1) identification of vulnerable groups, 2) data acquisition, 3) data editing and geoprocessing, and 4) statistical analysis.

Identification of Vulnerable Groups

To identify the characteristics of socially vulnerable groups, I draw on previous flood-risk and social vulnerability literature. This process resulted in the identification of 12 variables of social vulnerability, described in detail in the Data and Variables section.

Data Acquisition

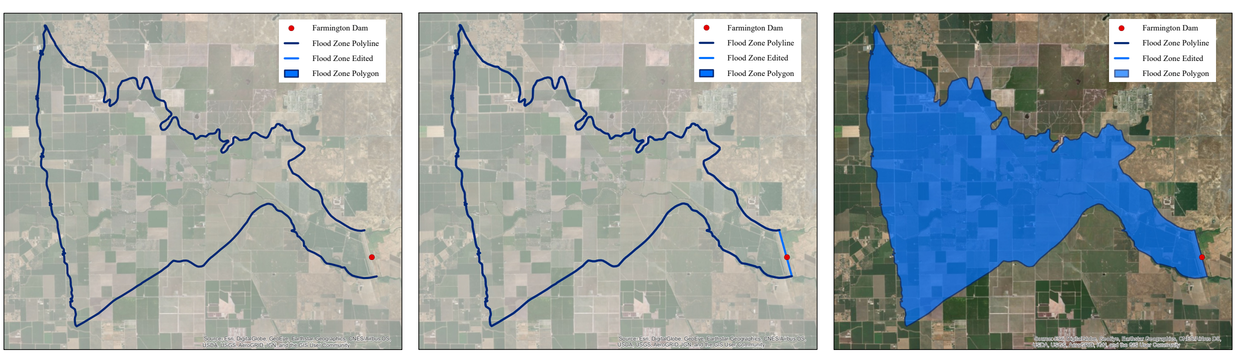
I obtained the first dataset, the National Inventory of Dams, on February 1, 2018 through the ProPublica Data Store. The second dataset containing geospatial shapefiles for 564 dam inundation zones in California arrived via U.S. mail on January 11, 2018. I downloaded the third dataset, containing 30 variables of social vulnerability selected from the American Community Survey, on January 24, 2018.

Data Editing and Geoprocessing

Once I had access to all three datasets, I began the process of data projection, editing, and geoprocessing. I loaded the National Inventory of Dams data into GIS and spatially projected the file based on the latitudes and longitudes included for each dam in California. This resulted in a point shapefile of the data, showing the geographic location and each of the 71 attributes from the NID.

The American Community Survey data was also straightforward to project in GIS software. After downloading the tables for the 30 selected social vulnerability characteristics, I combined all the data into a single excel spreadsheet. I then downloaded the Census Block Group geographic boundary shapefile from the U.S. Census Bureau website. Once I projected this shapefile in GIS, I joined it with the selected ACS variables based on the unique 17-character Geographic Identification Number (GEOID_Data). This resulted in a spatial representation of all 30 social vulnerability variables for each census block group in California.

Next, I projected all dam inundation boundary shapefiles within GIS. This step required a significant amount of geoprocessing and attribute editing because many shapefiles were not in the right format to perform spatial analyses on. For example, to select census block groups within dam flood zones, I ran an Intersect function, which requires all inundation boundaries to be polygon shapefiles. However, the data I received contained 373 shapefiles in polygon format and 191 in polyline format (not counting the 17 shapefiles that I excluded because they were unable to be geospatially projected). Converting polyline flood zones to a polygon format took a degree of manual geographic editing to create a completely closed shape. I took care to alter the original polyline shape as little as possible, though I had to make some assumptions in cases of ambiguity. The common ambiguity I came across was an open-ended shape at the start and end of the inundation zone. In these cases, I enclosed the shape without adding any curvature.



Once all 564 dam inundation boundary shapefiles were in the polygon format, I joined them with the National Inventory of Dams point data shapefile, based on the field Dam Name. Thus, each dam inundation boundary also contained the 71 variables of the NID. I then merged all 564 dam flood zones into a single shapefile, keeping the boundaries and NID attribute information intact. I replicated this process for HHP dams by selecting and merging the 481 flood zones attached to hazardous dams. The result was one shapefile that contained all dam flood zones and one shapefile that contained only HHP dam flood zones.

The final step of GIS analysis was to differentiate the census block groups that fall within dam flood zones from those outside of them. This process produces the data necessary to perform statistical analyses comparing the social vulnerability characteristics of people living within or outside of the inundation areas. Most dam inundation zones cross portions of census block groups, where only a certain percent of the block group falls within the flood zone. To address this, I created a copy of the ACS social vulnerability shapefile using the Make Feature Layer tool in ArcToolbox. This tool allows for an area-weighted, proportional result when running geoprocessing functions that overlay two shapefile layers with different spatial boundaries.

Using the shapefile outputted from the Make Feature Layer tool and the shapefile with all 564 dam flood zones, I ran the Intersect tool. This tool returns a shapefile containing the whole or partial census block groups that fall within dam inundation boundaries. After running this function, I had a shapefile reflecting proportionalities in the social vulnerability variables for intersected census block groups. For example, consider a CBG where 100 households do not own a car and 25 percent of the block group falls within a dam flood zone. After running Intersect, the output shapefile would show that 25 households in that CBG do not own a car. I replicated this process using the Symmetrical Difference tool, which is the inverse of the Intersect tool. In other words, the Symmetrical Difference function shows all the census block groups that are outside of a dam inundation zone. The same assumptions for ensuring proportionality applied to this step as well.

At the end of this process, I had one shapefile with CBGs within all 564 dam inundation zones and one shapefile with CBGs outside these zones. I ran these steps again for HHP dam flood zones. The result was a third shapefile with CBGs within the 481 HHP dam flood inundation zones and a fourth shapefile with CBGs outside these zones. The Intersect and Symmetrical Difference geoprocessing functions split many of the 23,212 total census block groups into multiple parts, which explains the high number of CBGs within or outside dam flood zones.

Table 5: Number of CBGs for Selected Shapefiles	
CA Census Block Groups	23,212
CBGs Within All Dam Flood Zones	49,414
CBGs Outside All Dam Flood Zones	17,473
CBGs Within HHP Dam Flood Zones	38,927
CBGs Outside HHP Dam Flood Zones	17,500

Statistical Analysis

The final step of the statistical analysis for this project was to export the data from GIS to an excel format, so it could then be uploaded into SPSS. I used the GIS conversion tool "Table to

Excel" for the four flood zone shapefiles. After opening each table in excel, I added a new field reflect the variable "In Flood Zone." A value of 1 indicates census block groups within dam inundation zones, and a value of 0 indicates block groups outside of zones. The excel tables were then combined. Next, I added new fields calculate the percentages of each social vulnerability characteristic in each census block group. The first finalized spreadsheet, "All Dam Flood Zones," contained the census block groups within and outside 564 inundation zones in California. The second finalized spreadsheet, "HHP Dam Flood Zones," contained the census block groups within and outside 481 HHP inundation zones in California. Both included the 30 selected social vulnerability variables and 71 NID variables by census block group.

After uploading these two datasets into SPSS, I completed a number of steps to normalize the independent variables and account for any missing or null values. To compute missing values, I selected all variables measured at the scale level and recoded them into the same variables by replacing "System- or user-missing" values with -9999. I selected this value because it does not normally appear in any of the data. I then entered this value in the "Discrete missing values" column for all relevant variables, which ensures the exclusion of missing values from the statistical analyses and regressions.

Second, I normalized all of the independent variables to the best of my ability. This is an important step because non-normalized variables included in the independent samples tests or multiple linear regressions can influence the validity, character, and interpretation of the results. The independent variables for multiple regressions are the 30 social vulnerability characteristics identified previously. For each, I applied a square root, natural logarithmic, or arcsine transformation. I then performed the Kolmogorov-Smirnov test for normality and compared the skew, kurtosis, K-S test statistic, and histogram of the original variable against the three transformed variables. Out of these four variable iterations, I selected the one that had skew, kurtosis, and Kolmogorov-Smirnov test statistic values closest to 0.[3] When multiple variable iterations had similarly skew, kurtosis, or K-S values, I referred to the histograms to determine which one had a distribution closest to the normal distribution curve. While none of the original or transformed social vulnerability variables had perfectly normal distributions, the ones selected to use in statistical tests are as close to a normal distribution as possible. Refer to Appendix A for a complete list of normalized variables and histograms for all dam inundation zones and for HHP dam inundation zones.

I used two different statistical tests to answer the four research questions guiding my project. For research questions 1, 2, and 4, I performed independent samples t-tests. The test variables were the 30 normalized social vulnerability variables. The grouping variables included "In Flood Zone," "Dam Age," and "Inspection Compliance." I used a 95 percent confidence interval threshold for determining statistically significant differences in means. Test variables with missing or null values were excluded analysis-by-analysis. The sig. value for Levene's Test for Equality of Variances determined which values I include in the summary tables in Chapter 6: Results and Findings. After identifying the means for the normalized test variables, I then back-

[3] Skewness is the extent to which a distribution of values deviates from symmetry around the mean. A value of zero means the distribution is symmetric. A skew value of +/- 1 is considered an acceptable range for most normality tests (Cutting 2017). Kurtosis is a measure of the "peakedness" or "flatness" of a distribution. A kurtosis value near zero indicates the shape is close to normal, while a negative value indicates a more peaked distribution, and a positive value indicates a flatter distribution. A kurtosis value of +/- 2 is considered an acceptable range for most normality tests (Cutting 2017). The Kolmogorov-Smirnov test statistic (D) is based on the largest vertical difference between the theoretical distribution (if the data were normal) and the empirical cumulative distribution function of the variable. A smaller K-S value implies the empirical distribution of the data is closer to a normal distribution. Larger values indicate the data do not follow normal distribution (Minitlab 2017).

transformed the values based on normalization method. The back-transformed values for each social vulnerability variable are listed in the summary tables in Chapter 6, while the complete outputs for each independent samples t-test are located in either Appendix B (RQ 1), Appendix C (RQ 2) or Appendix D (RQ 4).

I ran two multiple linear regressions to answer research question 3. The dependent variable was the indicator "In Flood Zone." Before selecting independent variables for the regression models, I assessed the multicollinearity among the 30 normalized social vulnerability variables. I ran the multicollinearity test for both datasets, "All Dam Flood Zones" and "HHP Dam Flood Zones." Based on these results, I excluded certain variables that had high and statistically significant Pearson Correlation values (typically 0.8 and above).

Despite the difference in the number of flood zones between the datasets "All Dam Flood Zones" (564) and the "HHP Dam Flood Zones" (481), the multicollinearity tests revealed similar highly correlated variables. The variables "V5PctAbvHS," V5PctNoHS," "V9MHHINC," "V10PctBlw100," and "V10PctBlw150" had high, statistically significant correlations with other indicators, and were excluded from the regressions. Furthermore, I excluded one of two variables for categories that were inverses of each other, such as Hispanic or Latino / Not Hispanic Latino, White / Nonwhite, and Citizen / Foreign Born. The total number of possible independent variables was limited to 21 of the selected 30 social vulnerability characteristics.

I performed the multiple linear regression multiple times for both "All Dam Flood Zones" and "HHP Dam Flood Zones." I used a 95 percent confidence interval threshold to determine statistically significant variables and coefficients. Furthermore, I generated collinearity statistics for all regression model iterations. This calculates the variance inflation factor (VIF) of each variable. The general rule of thumb is that a variable with a VIF value less than 1 or greater than 10 is significantly correlated with another variable included in the model (IDRE 2018). As such, I excluded a number of additional variables that had high VIFs (typically a value of 4 or more). Finally, I examined the p-value of the independent variables in the model to identify those that were not statistically significant. While testing different combinations of independent variables, I paid attention to the inclusion or exclusion of these in relation to their effect on the R-Square value. The final regression models therefore reflect the combination of normalized social vulnerability variables that result in the highest R-Square value, accounting for multicollinearity. Refer to Appendix D for the final outputs of all multiple linear regression models.[4]

[4] Due to my own statistical analysis limitations, I was unable to fully back-transform the normalized variables in the model. Thus, when discussing the regression results I rely on the standardized coefficients to provide a baseline for interpreting the independent variables that have the highest degree of influence.

Chapter 6: Results and Findings

In this section, I present the results of the statistical analyses performed for each research question. In order to present these findings in a clear and concise way, I exclude the number of cases and standard deviations from the summary tables below. I omit the significance values for research question 4b) for similar reasons, though statistically significant results are still demarcated with a "*" symbol. This information is listed in the full statistical outputs for each research question located in Appendix B (RQ 1), Appendix C (RQ 2), Appendix D (RQ 3), and Appendix E (RQ 4).

On a technical note, I narratively distinguish between the absolute and relative changes for social vulnerability variables included in the independent samples two-tail t-tests. The absolute differences in means are discussed as percentage point increases or decreases and are meant to convey how the proportions of the variables compare based on the test factor. I use the percentage change between means, or the relative difference, to present another way of interpreting the magnitude of the difference. For example, the average proportion of the households with no automobile is 4 percent within dam inundation zones and 4.4 percent outside of them. While the absolute difference in means is 0.4 percent, the relative difference is 9.3 percent. I also describe the relative difference in terms of likelihood, i.e., households with no automobile are 9.3 percent more likely to live outside of dam flood zones than within them. This descriptive choice of words does not reflect a calculated likelihood or probability ratio.

Finally, RQ 4 compares social vulnerability variables that are solely located within HHP dam flood zones. To avoid repeating this lengthy distinction so many times, I use the phrase "near" interchangeably. For example, the phrase “renters are more likely to live within flood zones of HHP dams that are 50 or more years old” is equivalent to “renters are more likely to live near older dams.”

Results for Research Question 1

Are socially vulnerable households more likely to live within dam flood zones than outside of them in California?

Table 6: Comparison of Social Vulnerability Means for All Dam Flood Zones

	Within Zone	Outside Zone			Sig.*
	Mean	Mean	Difference in Means	Percent Change	
V1Pct_14_65	33.08%	32.82%	0.25%	0.77%	0.002
V1Pct_14_85	20.31%	19.96%	0.35%	1.77%	0.000
V2Pct_NoAuto	3.96%	4.37%	-0.40%	-9.25%	0.000
V3PctCitizen	82.59%	78.06%	4.53%	5.80%	0.000
V3PctForeignBorn	17.11%	21.59%	-4.49%	-20.78%	0.000
V4PctDis	14.09%	12.26%	1.83%	14.91%	0.000
V4PctDis65	36.42%	34.34%	2.08%	6.07%	0.000
V5Pct_No_HS	12.90%	12.02%	0.88%	7.28%	0.000
V5Pct_HS_Deg	22.66%	19.81%	2.85%	14.38%	0.000
V5Pct_Abv_HS	34.23%	38.83%	-4.59%	-11.83%	0.000
V6PctUNEMP	8.60%	7.17%	1.43%	19.96%	0.000
V7PctHISP	24.72%	26.65%	-1.93%	-7.23%	0.000
V7PctNotHISP	74.47%	72.35%	2.13%	2.94%	0.000
V8PctFHH	11.42%	10.90%	0.51%	4.72%	0.000
V8PctMHH	4.50%	4.02%	0.49%	12.12%	0.000
V9MEDHHINC	$57,711	$66,151	-$8,440	-12.76%	0.000
V9ExtrmLow	1.00%	1.00%	0.00%	0.00%	0.014
V9VeryLowInc	7.00%	7.00%	0.00%	0.00%	**0.721**
V9LowInc	33.00%	29.00%	4.00%	13.79%	0.000
V10PctBlw50	5.61%	4.67%	0.94%	20.07%	0.000
V10PctBlw100	14.39%	11.60%	2.79%	24.08%	0.000
V10PctBlw150	24.37%	19.90%	4.47%	22.48%	0.000
V11PctWhite	69.84%	68.32%	1.53%	2.23%	0.000
V11PctNonwhite	29.45%	30.88%	-1.43%	-4.62%	0.000
V11PctBlack	3.01%	2.67%	0.34%	12.61%	0.000
V11PctIndigenous	0.39%	0.20%	0.19%	98.41%	0.000
V11PctAsian	6.81%	8.24%	-1.44%	-17.42%	0.000
V11PctPacific	0.09%	0.04%	0.05%	122.01%	0.000
V12PctRenter	37.54%	37.85%	-0.31%	-0.81%	**0.201**
V12PctOwner	61.32%	60.94%	0.38%	0.62%	**0.120**

*p-value < 0.05 is significant - bolded p-value indicates no statistically significant difference in means

I performed an independent samples t-test for 30 social vulnerability variables, with the grouping variable "In Flood Zone." The grouping variable is a categorical indicator where 1 is assigned to values within dam flood zones, and 0 is assigned to values outside of them. The results show 27 of the 30 variables have statistically significant differences in means. The non-significant differences in means are Very Low Income households and individuals who either rent or own their homes. In total, 22 characteristics of individual and household social vulnerability are more likely to be located in dam flood zones.

Of these 22 variables, the highest differences in means include U.S. citizenship (4.5 percent), the absolute poverty threshold of at or below 150 percent of the federal poverty line (4.5 percent), and the relative poverty measure of low-income populations (4 percent). Contrastingly, the highest differences in means for variables located outside of dam flood zones are foreign-born individuals (4.5 percent) and Californians with at least a 2- or 4-year degree (4.6 percent).

There is a large disparity in median household income by location. For households within dam flood zones the median income is $57,711, compared to $66,151 those households outside zones. This means that households earning around $57,700 are nearly 12.8 percent more likely to be in a dam inundation zone than households earning more than $66,150 are. Among other income indicators, households experiencing absolute or relative poverty are also more likely to be in flood zones. This includes households earning at or below 50 and 100 percent of the federal poverty threshold (20 and 24 percent more likely) and Low Income households earning below 80 percent of the Area Median Income (13.8 percent more likely).

Several additional demographic and socioeconomic characteristics appear to be at higher risk for potential dam-induced flood disasters. For example, there are 14.9 percent more disabled individuals and almost 20 percent more unemployed individuals in dam flood zones. Higher proportions of age-dependent populations, U.S. citizens, people whose highest educational attainment is a high school degree, female or male single parents, and homeowners also live in these zones.

Race and ethnicity by location have some notable distinctions. Although there are slight differences in the average proportions of American Indian or Native Alaskan (0.2 percent) and Native Hawaiian or Pacific Islanders (less than 0.1 percent), these represent a 98.4 percent and 122 percent increase if these groups live within inundation areas. White and Black and African Americans have higher population proportions within zones, while Asian-identifying individuals are 17.4 more likely to live outside of zones. Finally, foreign-born and Hispanic or Latino individuals and households with no available car are less likely to live in a dam flood zones by 20.8 percent, 7.2 percent, and 9.3 percent, respectively.

Results for Research Question 2

Are socially vulnerable households more likely to live within HHP dam flood zones than outside of them in California?

Table 7: Comparison of Social Vulnerability Means for HHP Dam Flood Zones

	Within Zone Mean	Outside Zone Mean	Difference in Means	Percent Change	Sig.
V1Pct_14_65	33.08%	32.83%	0.26%	0.78%	0.002
V1Pct_14_85	20.66%	19.96%	0.70%	3.51%	0.000
V2Pct_NoAuto	4.01%	4.37%	-0.35%	-8.12%	0.000
V3PctCitizen	80.98%	78.05%	2.92%	3.75%	0.000

V3PctForeignBorn	18.71%	21.60%	-2.89%	-13.37%	0.000
V4PctDis	13.48%	12.26%	1.23%	9.99%	0.000
V4PctDis65	36.06%	34.34%	1.72%	5.00%	0.000
V5Pct_No_HS	13.52%	12.02%	1.50%	12.49%	0.000
V5Pct_HS_Deg	22.38%	19.81%	2.57%	12.97%	0.000
V5Pct_Abv_HS	34.06%	38.84%	-4.78%	-12.31%	0.000
V6PctUNEMP	8.10%	7.17%	0.93%	12.99%	0.000
V7PctHISP	27.16%	26.63%	0.52%	1.96%	0.020
V7PctNotHISP	71.94%	72.36%	-0.42%	-0.58%	**0.072**
V8PctFHH	11.52%	10.90%	0.62%	5.70%	0.000
V8PctMHH	4.36%	4.01%	0.35%	8.68%	0.000
V9MEDHHINC	$60,232	$66,171	-$5,940	-8.98%	0.000
V9ExtrmLow	1.02%	0.86%	0.16%	18.63%	**0.069**
V9VeryLowInc	6.76%	6.72%	0.04%	0.57%	**0.868**
V9LowInc	30.66%	28.88%	1.77%	6.14%	0.000
V10PctBlw50	5.24%	4.67%	0.57%	12.27%	0.000
V10PctBlw100	13.26%	11.59%	1.66%	14.32%	0.000
V10PctBlw150	22.88%	19.89%	2.99%	15.01%	0.000
V11PctWhite	68.98%	68.30%	0.68%	1.00%	0.001
V11PctNonwhite	30.31%	30.90%	-0.58%	-1.89%	0.004
V11PctBlack	3.08%	2.67%	0.41%	15.32%	0.000
V11PctIndigenous	0.35%	0.20%	0.15%	78.88%	0.000
V11PctAsian	7.23%	8.26%	-1.02%	-12.39%	0.000
V11PctPacific	0.07%	0.04%	0.03%	80.26%	0.000
V12PctRenter	38.48%	37.84%	0.64%	1.69%	0.010
V12PctOwner	60.39%	60.95%	-0.55%	-0.91%	0.029

*p-value < 0.05 is significant - bolded p-value indicates no statistically significant difference in means

I performed an independent samples t-test for 30 social vulnerability variables, with the grouping variable “In Flood Zone.” The grouping variable is a categorical indicator where 1 is assigned to values within HHP dam flood zones, and 0 is assigned to values outside of them. The results show that 27 out of 30 variables have statistically differences in means, and that 22 variables are more likely to occur in HHP zones. The non-significant results for this question are proportions of non-Hispanic individuals, Extremely Low Income households, and Very Low Income households.

The characteristics with noticeable differences between means are located outside of HHP inundation areas, such as the number of people with at least a 2- or 4-year degree (4.8 percent difference) and median household income ($5,940 difference). These variables also have strikingly lower likelihoods of being in HHP dam flood zones: The average college educated person is 12.3 percent more likely to live outside such areas, while households outside these areas earn about 9 percent more median income ($66,171 compared to $60,232).

The other income indicators examined, such as the absolute and relative poverty thresholds, have higher proportions located within hazardous dam flood boundaries. These differences in means are small. Consider the average population at or below 50, 100, and 150 percent of the federal poverty line (0.6, 1.7, and 3 percent difference) and households considered Extremely Low, Very Low, and Low Income (0.2, less than 0.1, and 1.8 percent difference). However the difference in means for Extremely Low and Very Low Income individuals are not statistically significant.

The results indicate that age-dependent populations, U.S. Citizens, disabled individuals, people whose highest educational attainment is a high school degree, unemployed individuals, female and male single parents, and non-homeowners are more likely to live in HHP inundation zones. The differences between race and ethnicity shows similar patterns among flood areas for all 564 dams and the 481 HHP dams. Namely, that higher proportions of Hispanic (0.5 percent), White (0.7 percent), Black and African American (0.4 percent), American Indian or Native Alaskan (0.2 percent), and Native Hawaiian or Pacific Islanders (less than 0.1 percent) live within HHP zones and higher proportions of Asian populations (1 percent) live outside these zones. Finally, foreign-born and non-Hispanic or Latino individuals and households with no available car are less likely to live in a dam flood zone by 13.4 percent, 0.6 percent, and 8.1 percent, respectively.

Results for Research Question 3

Which factors of household social vulnerability are significantly correlated with living in a dam flood zone? Do these differ from factors significantly correlated with living in an HHP dam flood zone?

Table 8: Multiple Linear Regression for All Dam Flood Zones					
Model	R	R-Square	Adjusted R Square	Std. Error of the Estimate	Collinearity Diagnostic Condition Index
	0.216	0.047	0.046	.430	33.099
	Unstandardized Coefficients	Std. Error	Standardized Coefficients	Sig.	VIF
	0.617	0.013		0.000	
V1Pct_14_65	-0.134	0.029	-0.026	0.000	2.067
V2Pct_NoAuto	-0.235	0.015	-0.083	0.000	1.789
V3PctForeignBorn	-0.411	0.014	**-0.164**	0.000	2.025
V4PctDis	0.205	0.023	0.047	0.000	1.825
V5Pct_HS_Deg	0.370	0.021	**0.083**	0.000	1.457
V6PctUNEMP	0.153	0.017	0.040	0.000	1.364
V8PctFHH	-0.078	0.015	-0.024	0.000	1.577
V8PctMHH	0.077	0.014	0.023	0.000	1.218
V9VeryLowInc	-0.023	0.008	-0.013	0.004	1.367
V9LowInc	0.029	0.005	0.030	0.000	1.750
V10PctBlw50	0.055	0.016	0.017	0.001	1.627
V11PctBlack	0.069	0.012	0.026	0.000	1.351
V11PctIndigenous	0.172	0.021	0.033	0.000	1.166
V11PctAsian	0.159	0.011	**0.074**	0.000	1.725
V11PctPacific	0.301	0.028	0.043	0.000	1.077
V12PctRenter	0.086	0.011	0.042	0.000	2.057

$p < 0.05$

Refer to the Statistical Analysis subsection in Chapter 5: Methods for a full description of the testing parameters, assumptions, and process for this statistical test.

The multiple linear regression test shows that 16 social vulnerability variables are statistically significant predictors of being located within a dam inundation zone in California. The model has an R-square value of 0.047. This means that taken together, the 16 independent variables explain about 4.7 percent of the variation in the dependent variable "In Flood Zone." In other words, about 95.3 percent of the locational outcome of living within a dam flood zone is due to other factors. Due to the low R-square value, it is unlikely that the linear equation derived from the coefficients of the independent values creates a best-fit prediction curve for the data points.

More importantly, this model conveys the values of interest for answering research question 3. The positive coefficients represent the demographic and socioeconomic variables correlated with living in a dam flood zone. These 11 variables include individuals with disabilities, people with a high school level education, unemployment, male-headed households, households earning 80 percent of the Median Area Income, individuals with incomes at or below 50 percent of the federal poverty threshold, and renters. Furthermore, people who identify as Black, American Indian and Native Alaskan, Asian, and Native Hawaiian and Pacific Islander have statistically significant positive coefficients. Of these, people whose highest level of education is a high school degree and Asian-identifying individuals appear to have the greatest influence in the model (with standardized coefficients of 0.083 and 0.074, respectively).

The negative variables in the model are statistically significant predictors of living outside of dam inundation zones. These include age-dependent populations, households with no automobile, foreign-born individuals, female-headed households, and people who earn 50 percent of the Median Area Income. The negative variable with the most influence in the model is individuals born in a country other than the U.S., with a standardized coefficient of -0.164.

Another way to interpret the results of the multiple regression model is that for a variable with a positive coefficient, a census block group with a higher percentage of the given variable's population is more likely fall within a dam flood zone. Positive variables with larger standardized coefficients are also more likely to predict location in these zones. For example, a CGB with a 30 percent population of Asian-identifying people is more likely to be in a flood zone than a CBG with a 30 percent population of Black-identifying people (standardized coefficients of 0.074 and 0.026, respectively.

Table 9: Multiple Linear Regression for HHP Dam Flood Zones					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Collinearity Diagnostic Condition Index
	0.187	0.035	0.035	.454	29.499
	Unstandardized Coefficients	Std. Error	Standardized Coefficients	Sig.	VIF
	0.535	0.014		0.000	
V1Pct_14_65	-0.139	0.032	-0.026	0.000	2.137
V2Pct_NoAuto	-0.202	0.015	-0.070	0.000	1.656
V3PctForeignBorn	-0.357	0.019	**-0.133**	0.000	2.876
V4PctDis	0.206	0.024	0.046	0.000	1.656
V5Pct_HS_Deg	0.405	0.023	**0.088**	0.000	1.472
V6PctUNEMP	0.122	0.018	0.030	0.000	1.242
V7PctHisp	0.071	0.014	0.035	0.000	2.798
V8PctFHH	-0.082	0.017	-0.025	0.000	1.576
V11PctBlack	0.068	0.013	0.024	0.000	1.292
V11PctIndigenous	0.214	0.024	0.040	0.000	1.128
V11PctAsian	0.140	0.014	0.062	0.000	2.108
V11PctPacific	0.277	0.033	0.036	0.000	1.074
V12PctRenter	0.094	0.012	0.044	0.000	1.811

$p < 0.05$

Refer to the Statistical Analysis subsection in Chapter 5: Methods for a full description of the testing parameters, assumptions, and process for this statistical test.

The multiple linear regression model includes 13 statistically significant predictors of being located within a High Hazard Potential dam flood zone. The model has an R-square value of

0.035, meaning the independent variables explain about 3.5 percent of the variation in the dependent variable "In Flood Zone." In other words, about 96.5 percent of the dependent variable is explained by other factors.

The statistically significant independent variables in this model are strikingly similar to the model for all dam inundation zones. The main difference is that the variables Very Low Income, Low Income, and male-headed households are not correlated with living in an HHP flood zone. Additionally, the model includes the variable for Hispanic and Latino individuals, while the model for all dam flood zones does not. This may be an important distinction.

For both regression models, the variables for age-dependent populations, households with no automobile, female-headed households, and foreign-born individuals have negative coefficients. These are therefore statistically significant predictors of living outside of dam flood zones. Another similarity between the two models are the indicators with the strongest negative and positive influence in the regression equation. For both, the variable with the highest positive standardized coefficient is the percentage of the population whose highest educational attainment is a high school degree (0.083 for all dams and 0.088 for HHP dams). On the other hand, the variable with the strongest negative standardized coefficient is the proportion of the foreign-born population (-0.164 for all dams and -0.133 for HHP dams).

To summarize, the independent variables with positive coefficients found in both regression models include individuals with disabilities, people with high school degrees, unemployed, renters, and people who identify as Black, American Indian and Native Alaskan, Asian, and

Native Hawaiian and Pacific Islander. Though the magnitude of the standardized coefficients for these variables differs between models, these 8 independent variables are significantly correlated with living in the flood zones of all dams and HHP dams.

Results for Research Question 4

4a) Is there a relationship between social vulnerability and the HHP dam characteristics of age, reservoir size, and inspection compliance?

Table 10: Comparison of Social Vulnerability Means by Age for HHP Dam Flood Zones

	< 50 Years Mean	≥ 50 Years Mean	Difference in Means	Percent Change	Sig.
V1Pct_14_65	34.30%	32.93%	-1.37%	-3.99%	0.000
V1Pct_14_85	20.54%	2.67%	-1.13%	-5.22%	0.000
V2Pct_NoAuto	3.21%	4.12%	0.91%	28.18%	0.000
V3PctCitizen	82.43%	80.79%	-1.64%	-1.99%	0.000
V3PctForeignBorn	17.38%	18.89%	1.51%	8.67%	0.000
V4PctDis	13.59%	13.47%	-0.13%	-0.92%	**0.273**
V4PctDis65	35.72%	36.10%	0.38%	1.07%	**0.191**
V5Pct_No_HS	13.94%	13.47%	-0.47%	-3.35%	0.037
V5Pct_HS_Deg	23.17%	22.28%	-0.90%	-3.87%	0.000
V5Pct_Abv_HS	31.42%	34.39%	2.97%	9.46%	0.000
V6PctUNEMP	8.54%	8.04%	-0.50%	-5.86%	0.000
V7PctHISP	31.51%	26.65%	-4.86%	-15.42%	0.000
V7PctNotHISP	67.58%	72.46%	4.88%	7.22%	0.000
V8PctFHH	11.29%	11.56%	0.27%	2.40%	**0.084**
V8PctMHH	4.38%	4.36%	-0.02%	-0.38%	**0.840**
V9MEDHHINC	$62,611	$59,940	-$2,671	-4.27%	0.000
V9ExtrmLow	1.00%	1.00%	0.00%	0.00%	**0.061**
V9VeryLowInc	6.00%	7.00%	1.00%	16.67%	**0.283**
V9LowInc	30.00%	31.00%	1.00%	3.33%	**0.506**
V10PctBlw50	4.87%	5.29%	0.42%	8.70%	0.000
V10PctBlw100	12.18%	13.40%	1.22%	9.98%	0.000
V10PctBlw150	21.53%	23.06%	1.53%	7.10%	0.000
V11PctWhite	73.48%	68.40%	-5.08%	-6.91%	0.000
V11PctNonwhite	26.00%	30.89%	4.89%	18.81%	0.000
V11PctBlack	2.52%	3.15%	0.64%	25.24%	0.000
V11PctIndigenous	0.28%	0.36%	0.08%	26.77%	0.000
V11PctAsian	5.11%	7.53%	2.42%	47.29%	0.000
V11PctPacific	0.04%	0.08%	0.03%	72.73%	0.000
V12PctRenter	34.89%	38.95%	4.06%	11.63%	0.000
V12PctOwner	64.25%	59.90%	-4.34%	-6.76%	0.000

*p-value < 0.05 is significant - bolded p-value indicates no statistically significant difference in means

I performed an independent samples t-test for 30 social vulnerability variables, with the grouping variable "Dam Age." The grouping variable is a categorical indicator where 1 is assigned to values within flood zones of HHP dams 50 years or older, and 0 is assigned to values within flood zones of HHP dams less than 50 years old. The results indicate that 24 of the 30 social vulnerability variables have statistically significant differences in means. Among the non-significant variables are the proportions of disabled individuals, single mothers and fathers, and the relative poverty categories Extremely Low, Very Low, and Low Income households. Furthermore, 12 variables are more likely to live in HHP dam zones less than 50 years old, compared to 18 variables that are more likely to live zones 50 years or older.

Of these 18 variables, the highest differences in means include non-Hispanic or Latino individuals (4.9 percent), renters (4.1 percent), and non-White identifying persons (4.9 percent). Additionally, households with no available car, Californians with at least a 2- or 4-year degree, and foreign-born individuals, are significantly more likely to live within flood zones of older HHP dams (28 percent, 9.5 percent, and 8.7 percent respectively). Both female-headed households and disabled individuals over the age of 65 are more likely to be in older zones but these percentages are relatively small and not statistically significant.

Racial minorities and low-income households and individuals are more likely to live in older flood zones. This includes those who identify as Black (25.24 percent), American Indian and Native Alaskan (26.77 percent), Asian (47.29 percent), and Native Hawaiian and Pacific Islander (72.73 percent). The difference in means for people with incomes at or below 50, 100, and 150 percent of the federal poverty line is 0.4 percent, 1.2 percent, and 1.5 percent. Median income also follows this pattern, with households in older zones earning $59,940 and those in younger zones earning $62,611 (4.3 percent difference). Though this trend appears to hold true for relative poverty indicators, these results are not statistically significant.

The variables with the largest differences in means in younger HHP inundation zones are Hispanic or Latino individuals (4.9 percent), homeowners (4.3 percent) and White people (5.1 percent). Unemployed individuals, U.S. Citizens, male-headed households, people with or without high school degrees, and age-dependent populations are also more likely to be found in younger in flood zones.

4b) Do HHP dams with failed inspection compliance have higher proportions of socially vulnerable households within their inundation zones than HHP dams in compliance

Table 11: Comparison of Social Vulnerability Means by Inspection Compliance for HHP Dam Flood Zones

	Fail	Pass			Sig.
	Mean	Mean	Difference in Means	Percent Change	
V1Pct_14_65	32.35%	33.75%	-1.39%	-4.13%	0.000
V1Pct_14_85	20.56%	2.76%	-0.20%	-0.94%	0.011
V2Pct_NoAuto	4.90%	3.29%	1.61%	48.99%	0.000
V3PctCitizen	79.96%	81.87%	-1.91%	-2.33%	0.000
V3PctForeignBorn	19.76%	17.79%	1.97%	11.05%	0.000
V4PctDis	13.32%	13.63%	-0.31%	-2.26%	0.000
V4PctDis65	37.25%	34.99%	2.26%	6.46%	0.000
V5Pct_No_HS	12.98%	14.02%	-1.04%	-7.39%	0.000
V5Pct_HS_Deg	22.01%	22.71%	-0.70%	-3.07%	0.000
V5Pct_Abv_HS	35.22%	33.02%	2.21%	6.69%	0.000
V6PctUNEMP	8.28%	7.93%	0.35%	4.45%	0.000
V7PctHISP	26.30%	27.94%	-1.65%	-5.89%	0.000
V7PctNotHISP	72.90%	71.07%	1.83%	2.57%	0.000
V8PctFHH	12.12%	11.00%	1.13%	10.26%	0.000
V8PctMHH	4.36%	4.37%	-0.01%	-0.29%	**0.817**
V9MEDHHINC	$58,221	$62,131	-$3,910	-6.29%	0.000
V9ExtrmLow	2.00%	0.00%	2.00%	200.00%	0.000
V9VeryLowInc	9.00%	5.00%	4.00%	80.00%	0.000
V9LowInc	33.00%	28.00%	5.00%	17.86%	0.000
V10PctBlw50	5.61%	4.92%	0.69%	14.08%	0.000
V10PctBlw100	14.12%	12.50%	1.62%	12.95%	0.000
V10PctBlw150	23.99%	21.90%	2.09%	9.53%	0.000

V11PctWhite	65.77%	71.78%	-6.01%	-8.37%	0.000
V11PctNonwhite	33.49%	27.57%	5.92%	21.46%	0.000
V11PctBlack	5.11%	1.68%	3.43%	203.62%	0.000
V11PctIndigenous	0.24%	0.47%	-0.24%	-50.10%	0.000
V11PctAsian	8.13%	6.47%	1.66%	25.69%	0.000
V11PctPacific	0.11%	0.04%	0.07%	156.92%	0.000
V12PctRenter	42.89%	34.69%	8.20%	23.63%	0.000
V12PctOwner	55.86%	64.34%	-8.48%	-13.18%	0.000

*p-value < 0.05 is significant - bolded p-value indicates no statistically significant difference in means

I performed an independent samples t-test for 30 social vulnerability variables, with the grouping variable "Inspection Compliance." The grouping variable is a categorical indicator where 1 is assigned to values within flood zones of HHP dams that failed to be inspected within the required frequency ("Fail), and 0 is assigned to values within flood zones of HHP dams that have been inspected within required frequency ("Pass").

The test shows that 29 of the 30 variables have statistically significant differences in means between dams failing and passing inspection compliance. The non-significant result is the variable "Percentage of Male-Headed Households." Furthermore, 19 variables have higher population proportions within flood zones of HHP dams that failed compliance, compared to 11 that have higher proportions within zones of dams passing compliance.

Several variables have large absolute differences in population proportions when compared across inspection compliance categories. For example, Very Low Income households, Low Income households, and renters have higher proportions within flood zones of HHP dams failing compliance by 4.2 percent, 5 percent, and 8.2 percent. Conversely, the highest differences in means for variables located in zones of HHP dams passing compliance are White people (6 percent) and homeowners (8.4 percent).

Certain demographic and socioeconomic variables have staggering relative differences between the average amount of people located near dams failing compliance compared to those near dams passing compliance. In terms of racial categories, individuals who identify as Black, Native Hawaiian and Pacific Islander, and Asian are more likely to be within "Fail" dam flood zones by 203.6 percent, 156.9 percent, and 25.7 percent, respectively.

The same trend applies to Extremely Low Income households (200 percent) and households with no automobile (49 percent). Other variables that are more likely to be located within flood zones of dams failing compliance are include foreign-born, unemployed, and non-Hispanic or Latino individuals, as well as people 65 years or older with disabilities, female-headed households, and people with at least a 2- or 4-year degree.

It appears that indicators of income and absolute poverty follow this pattern as well. Households with lower median incomes are more likely to be near "Fail" dams ($58,221) than "Pass" dams ($62,131) by 6.3 percent. Similarly, the proportions of individuals earning at or below 50, 100, and 150 percent of the federal poverty threshold are higher in flood zones of dams failing compliance (0.7 percent, 1.6 percent, and 2.1 percent difference in means).

Variables more likely to be within "Pass" flood zones include those who identify as American Indian and Native Alaskan (50.1 percent), Hispanic and Latino individuals (5.9 percent), age-dependent populations (4.1 percent), U.S. Citizens (2.3 percent), and individuals with disabilities (2.3 percent). The proportion of people whose highest educational attainment is a high school degree or below is also higher in flood zones of HHP dams passing compliance (0.7 percent difference in means).

Chapter 7: Discussion

The Geography of Social Vulnerability and Hazardous Dams

The goal of the first research question is to gain an initial understanding of the demographic and socioeconomic differences between populations that live within dam inundation zones and populations that live outside such zones. The second research question has similar motivations, but is concerned with parsing out these patterns for High Hazard Potential dams. By comparing the findings of these two questions, I hope to uncover the aspects of social vulnerability that fall disproportionately within dam flood zones.

Considering the results for the first and second research questions, the broader social vulnerability categories of automobile ownership, citizenship, disability, education, employment, ethnicity, head-of-household gender, income, and race have statistically significant differences in means by location. While age-dependency has a very small difference, the proportions are essentially the same. Renters, homeowners, and white people are also fairly equally located within and outside dam flood zones.

Specifically, individuals and households are disproportionately located within dam flood zones if they are U.S. Citizens, live with a disability, are less educated, are unemployed, are single parents, have lower median household incomes, live at, below, or near the federal poverty line, and identify as either Black and African American, American Indian and Native Alaskan, or Native Hawaiian and Pacific Islander. While the magnitude of the respective means differ slightly, all 12 of social vulnerability variables are also disproportionately located within the flood zones of hazardous dams.

The similarities of these demographic and socioeconomic factors, regardless of the hazard potential of the dam, may be explained in part by the dam inundation maps themselves. There are 564 total dam inundation zones and 481 HHP dam inundation zones. Comparing the maps of these two datasets reveals that the 83 non-HHP flood zones are attached to dams with relatively small reservoirs, and thus have smaller inundation coverages. This means that although there is a difference in the total inundation area between all and HHP flood zones, it is small. HHP flood zones by nature cover the largest areas, as it is one of the factors that determines the hazard classification.

By this account, it makes sense that the same social vulnerability characteristics are disproportionately located in both all dam flood zones and HHP dam flood zones. This also implies that any difference in this pattern is worthy of further examination. Notably, the only variable that diverges from this pattern is ethnicity. For example, Hispanic or Latino individuals are more likely to live outside all dam flood zones (7.2 percent) but are more likely to live within HHP dam flood zones (2 percent). This could be due to spatially concentrated populations of Hispanic or Latino individuals within the inundation areas of hazardous dams.

The results of the multiple linear regression models support the explanation that there are smaller differences in the inundation extent of the two flood zone maps than expected. Of the 13 social vulnerability variables correlated with HHP dam flood zones, 12 are also correlated with all dam flood zones. Additionally, the 12 statistically significant independent variables found in both regression models have standardized coefficients with comparable magnitudes and signifiers.

The only independent variable in the HHP regression model not found in the regression for all dam flood zones is Hispanic or Latino. This further supports the explanation that Hispanic and Latino populations have a distinct spatial geography, which is significantly correlated with being located inside hazardous dam inundation zones.

In both regression outputs, the variables for education (percent with a high school degree) and race (percent Asian) have the greatest positive influence on the model, while citizenship (percent foreign-born) has the greatest negative influence on the model. This partially supports the findings of the independent samples tests which reveal that people with lower levels of educational attainment (earning a high school degree) are more likely to be in all- and HHP-dam flood zones, and foreign-born individuals are less likely to be in such zones.

Surprisingly, both comparison of means tests show higher proportions of Asian populations located outside of dam flood zones, though the regression results indicate that this variable is positively correlated with location inside zones. The multiple regression analysis confirms this is a statistically significant predictor of location, but contradicts the directionality of the independent samples tests. This contradiction might be explained by the influence of the citizenship variable. The variables for foreign-born and Asian individuals have higher population proportions located outside all- and HHP-flood zones. Though these variables have opposite directionalities in the regression equations, the standardized coefficients show the foreign-born variable has more than twice the influence on the model than the variable for Asian populations (-0.164 versus 0.074 for all zones, and -0.133 versus 0.062 for HHP zones).

If the two variables are correlated, the positive influence of the Asian population variable on the regression model could be negated if a significant share of foreign-born individuals are also Asian. Indeed, the collinearity matrices show these variables are moderately correlated (0.544 for all zones versus 0.500 for HPP zones). Information of the demographic trends of immigration to California further supports this explanation. In recent years, Asian immigration to California has outpaced Hispanic and Latino immigration (Garofoli 2012, Reese 2015). Census data confirms that 39 percent of the foreign-born population are Asian (Census Bureau 2016).

Hazardous Dams, Flood-Risk, and Dimensions of Vulnerability in California

The final research question comes from a desire to understand how social vulnerability variables within High Hazard Potential dam flood zones differ depending on certain physical and politically-influenced characteristics of hazardous dams. Since an HHP dam failure would cause significant environmental harm, property damage, and loss of human life, the patterns revealed in these statistical analyses shed further light on individuals and households that are at higher risk for dam-induced flood event.

To examine differences in the proportions of social vulnerability based on the age of the dam, I selected an age threshold of 50 years for the independent samples tests. This threshold comes from the fact that the average useful life of a dam is just 50 years, after which the deterioration of dam components steeply rises and impacts the physical and structural integrity of the dam (Ho et al. 2017). Thus, any demographic or socioeconomic variables disproportionately located within inundation areas of HHP dams older than 50 years are at a greater risk for dam failure and flooding.

The social vulnerability categories of automobile ownership, citizenship, education, ethnicity, income, race, and housing tenure have statistically significant differences in means by location. Specifically, individuals and households are disproportionately located in hazardous dam flood zones over 50 years old if they are foreign-born, have higher levels of educational attainment, are not Hispanic or Latino, have lower median household incomes, live at, below, or near the federal poverty line, are renters, and identify as either Black and African American, American Indian and Native Alaskan, or Native Hawaiian and Pacific Islander.

Several of these variables present an interesting avenue for inquiry. Consider that people with at least a 2- or 4-year and non-Hispanic or Latino individuals are more likely to live within older HHP dam flood zones. Intriguingly, the results of the previous independent samples test for these variables shows the opposite trend. In the absence of the dam age grouping variable, people with at least a 2- or 4-year degree and non-Hispanic or Latino individuals are less likely to live in HHP-dam zones by 12.3 percent and 0.6 percent. The multiple regression model also demonstrates that lower educational attainment (percent with a high school degree) and Hispanic or Latino ethnicity are statistically significant predictors of residing in HHP-dam flood zones. Taken together, the discrepancy in these patterns is explained by the age of the dam (50 or more years old).

A possible explanation for this phenomena lies in the history of dam construction and the nature of urbanization in the state of California. Spillman et al. explains that many urban dams were originally surrounded by undeveloped agricultural land (2017). Over time, populations grew, city limits expanded, suburbs exploded, and land costs and constraints meant that homes, businesses, public buildings, roads and critical infrastructures were built up around many dams and reservoirs (Spillman et al. 2017).

Through the processes of urbanization, suburbanization, and city sprawl, many reservoirs are now surrounded by development. Urban, suburban, and peri-urban dams and reservoirs are often viewed as highly desirable environmental amenities rather than environmental hazards or sites of flood-risk (SLRC 2017). The collinearity matrices for variables in HHP dam flood zones indicate strong correlations between higher educational attainment and income (0.691) and non-Hispanic or Latino populations (0.686). Previous social vulnerability research shows that less educated, lower-income, and Hispanic or Latino populations face significant barriers to locational choice and housing, which is a causal factor of flood-risk (Donner and Rodriguez 2011, Maldonado et al. 2015). In the absence of such barriers, these two variables may indicate that highly educated and non-Hispanic or Latino individuals choose to live within the inundation zones of older High Hazard Potential dams.

The last characteristic of High Hazard Potential dams I was interested in examining is inspection compliance. I calculated this variable from information in the National Inventory of Dams, including the required inspection frequencies for each dam, the most recent inspection date, and the date the inspection was reported to the NID (2016). I was able to determine which dams were successfully inspected in the required about of time (usually annually), and which dams had failed inspection compliance. Inspections are integral to discovering physical problems and structural weaknesses of dams. Failing to inspect dams within the frequency required by the

DWR Division of Safety of Dams increases the chance that a serious issue will go unnoticed or fixed, which could potentially lead to dam failure. Inspection compliance is highly dependent on certain political, economic, and regulatory machinations, including the amount of money the state legislature allocates for dam safety, maintenance, and repair programs.

Thus, the patterns revealed in this statistical test can show which social vulnerability factors may be disproportionately exposed to a dam-induced flood disaster. The overall social vulnerability categories of automobile ownership, citizenship, disability, education, employment, ethnicity, gender of the head-householder, income, race, and housing tenure have statistically significant differences in means by location.

Specifically, individuals and households are disproportionately located in the flood zones of hazardous dams with failed inspection compliance if they do not own a car, are foreign-born, are older than the age of 65 and live with a disability, have higher levels of educational attainment, are unemployed, are non-Hispanic or Latino, are a female-headed household, have a lower medium household income, live at, below, or near the federal poverty line, are renters, and identify as either Black and African American, Asian, or Native Hawaiian and Pacific Islander.

The results of the previous multiple regression test establishes that several social vulnerability variables are statistically significant predictors of living in the flood zone of a High Hazard Potential dam. The regression results and the independent samples test for inspection compliance both find unemployed individuals, renters, those who identify as Black and African American or Native Hawaiian and Pacific Islander to be more likely to live in a hazardous dam inundation area. This means that individuals and households with these social vulnerability characteristics are more likely to be located within an HHP zone, and are more likely live near a hazardous dam that has not been inspected within the required frequency.

Chapter 8: Why Give a Dam(n)?

The state of California has 1,585 dams. These infrastructures directly and indirectly influence important aspects of everyday life, from storing and supplying the water we drink, to irrigating the food we eat, to generating the electricity we use to power our homes. Dams are crucial for flood control, fire protection, debris control, and drought resilience. However, dams are also significant environmental hazards, and increase the flood-risk for communities and populations located within their inundation zones. Recognizing these flood-risks, both the National Inventory of Dams and the California Division of Safety of Dams assign a downstream hazard classification to each dam in the state. High Hazard Potential dams are those defined as causing significant loss of life, property destruction, and environmental damage in an event of dam failure (2016, 2016).

California's dams are aging and lack adequate funding for safety, maintenance, and repair programs. In 2015, nearly 44 percent of dams had not been inspected within the required timeframe and frequency (Spillman et al. 2017). Furthermore, dams are acutely vulnerable to both seismic activity and climate change. As evidenced by the Oroville Dam Spillway Failure in February 2017, even dams with satisfactory condition ratings can begin to fail from a combination of physical, structural, political, economic, and climatic factors. The events leading up to the spillway failure exemplify the current shortfalls in policy, planning, and action for managing large-scale water infrastructure and safeguarding the public from avoidable environmental hazards.

In this context, I am interested in uncovering the answer to the fundamental question – Who is the most vulnerable to dam-induced flooding in California?

My research project analyzes variables of social vulnerability for individuals and households located in the flood zones of High Hazard Potential dams in California. I perform a series of geostatistical analyses, independent samples tests, and multiple linear regressions in pursuance of four distinct research questions. The overarching goal is to determine which social vulnerability characteristics are disproportionately located within hazardous dam inundation areas, and examine whether these demographic and socioeconomic factors are statistically significant predictors of location to dam-hazards.

From previous literature analyzing social vulnerability and flood-risk in cases of sea-level rise, climate change, high precipitation, and storm events, I identified 11 broad social vulnerability categories. Among these categories of age, automobile ownership, citizenship, disability, education, employment, ethnicity, head-householder gender, income, race, and housing tenure, I selected 30 specific demographic and socioeconomic variables.

Results from independent samples t-tests show that individuals and households are disproportionately located within hazardous dam flood zones if they are U.S. Citizens, live with a disability, are less educated, are unemployed, are single parents, have lower median household incomes, live at, below, or near the federal poverty line, and identify as either Black and African American, American Indian and Native Alaskan, or Native Hawaiian and Pacific Islander.

Furthermore, people whose highest educational attainment is a high school degree, unemployed individuals, those living with disabilities, Hispanic or Latino individuals, female-headed households, renters, and people who identify as Black and African American, American Indian and Native Alaskan, Asian, and Native Hawaiian and Pacific Islander represent variables of social vulnerability that are statistically significant predictors of living within a hazardous dam flood zone.

Comparing the means of social vulnerability variables by the grouping factor “Dam Age” reveal that people who lack car ownership, foreign-born individuals, people with at least a 2- or 4-year degree, non-Hispanic or Latino, female-headed households, living at, below, or near the federal poverty threshold, renters, and those who identify as White, as Black and African American, American Indian and Native Alaskan, Asian, and Native Hawaiian and Pacific Islander are more likely to live in HHP dam flood zones aged 50 years or older.

Finally, the independent samples test for social vulnerability and the grouping factor “Inspection Compliance” show that those lacking car ownership, foreign-born individuals, people aged 65 or older living with a disability, individuals with at least a 2- or 4-year degree, non-Hispanic or Latino, unemployment, living at, below, or near the federal poverty threshold, renters, and those who identify as Black and African American, Asian, and Native Hawaiian and Pacific Islander are more likely to live in HHP dam flood zones with failed inspection compliance.

Emergency and disaster planners depend on knowledge of socially vulnerable populations to ensure sufficient disaster preparedness and response policies in a given place. For example, a community with a high percentage of older adults will require a different type of emergency response in terms of warning, evacuation, and assistance. Failing to account for the spatial patterns and geographic concentrations of socially vulnerable populations in the planning process can have devastating consequences.

This project reveals the spatial and social characteristics of vulnerability to dam-induced flood hazards in California. Planners and policymakers can use this information to improve existing disaster management and response plans by incorporating targeted and specific strategies to reduce the flood-risk of highly vulnerable populations. Furthermore, it provides the information necessary for planners and policymakers to address the existing social and spatial inequalities in dam inundation zones to create a more environmentally just California.

Appendix A: Data Normalization

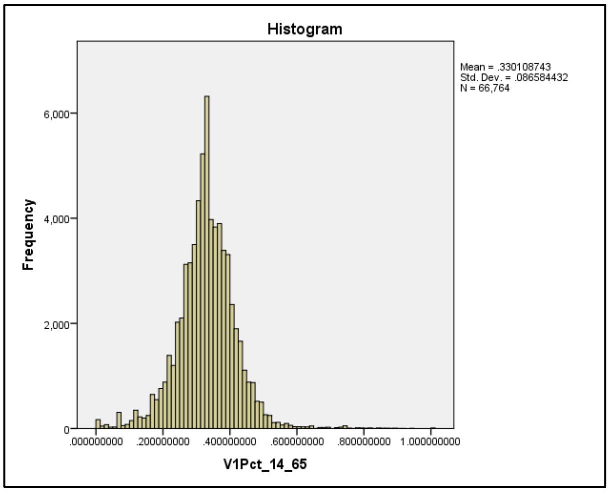
Normalized Variables for All Dam Flood Zones

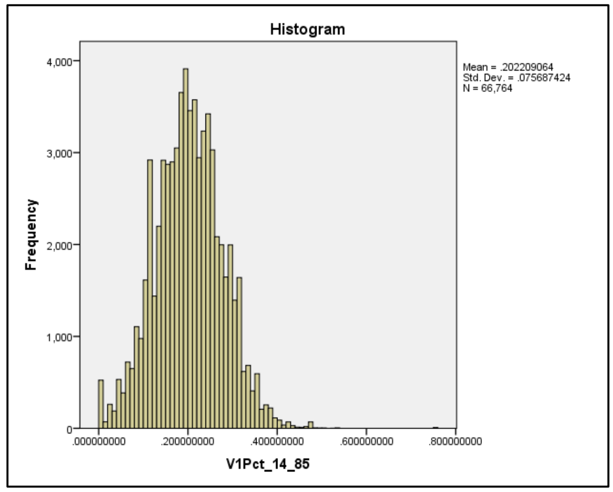
Variable	Data Normalization Method	Skew and Kurtosis Before Normalization	Skew and Kurtosis After Normalization	Kolmogorov-Smirnov Statistic	K-S Test Sig. Value
V1Pct_14_65	None	Skew: 0.221 Kurtosis: 3.724	N/A	0.050	0.000
V1Pct_14_85	None	Skew: 0.092 Kurtosis: 0.371	N/A	0.016	0.000
V2Pct_NoAuto	Square root	Skew: 2.858 Kurtosis: 12.723	Skew: 0.688 Kurtosis: 0.467	0.115	0.000
V3PctCitizen	Arcsin	Skew: -0.649 Kurtosis: -0.102	Skew: 0.100 Kurtosis: -0.582	0.037	0.000
V3PctForeignBorn	Square root	Skew: 0.649 Kurtosis: -0.102	Skew: -0.188 Kurtosis: -0.595	0.039	0.000
V4PctDis	Square root	Skew: 1.084 Kurtosis: 2.269	Skew: 0.088 Kurtosis: 0.541	0.027	0.000
V4PctDis65	Natural log	Skew: 0.546 Kurtosis: 0.696	Skew: 0.086 Kurtosis: 0.168	0.031	0.000
V5Pct_No_HS	Square root	Skew: 1.297 Kurtosis: 1.374	Skew: 0.257 Kurtosis: -0.398	0.053	0.000
V5Pct_HS_Deg	None	Skew: 0.177 Kurtosis: -0.168	N/A	0.027	0.000
V5Pct_Abv_HS	Square root	Skew: 0.420 Kurtosis: -0.615	Skew: -0.211 Kurtosis: -0.417	0.032	0.000
V6PctUNEMP	Square root	Skew: 1.572 Kurtosis: 4.437	Skew: -0.090 Kurtosis: 0.764	0.043	0.000

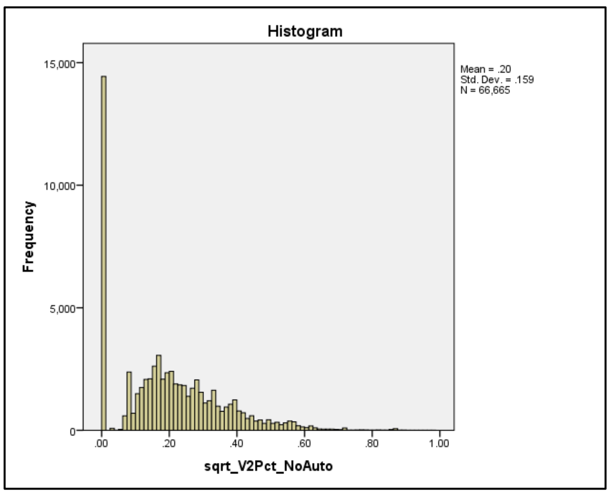
V7PctHISP	Square root	Skew: 0.978 Kurtosis: 0.061	Skew: 0.196 Kurtosis: -0.612	0.051	0.000
V7PctNotHISP	Arcsin	Skew: -0.978 Kurtosis: 0.061	Skew: -0.344 Kurtosis: -0.522	0.063	0.000
V8PctFHH	Square root	Skew: 1.247 Kurtosis: 2.224	Skew: -0.144 Kurtosis: 0.407	0.041	0.000
V8PctMHH	Square root	Skew: 1.409 Kurtosis: 3.661	Skew: -0.102 Kurtosis: -0.598	0.135	0.000
V9ExtrmLowInc	N/A	N/A	N/A	N/A	N/A
V9VeryLowInc	N/A	N/A	N/A	N/A	N/A
V9LowInc	N/A	N/A	N/A	N/A	N/A
V9MEDHHINC	Natural log	Skew: 1.154 Kurtosis: 1.876	Skew: -0.226 Kurtosis: -0.134	0.032	0.000
V10PctBlw50	Square root	Skew: 2.440 Kurtosis: 9.180	Skew: 0.507 Kurtosis: 0.606	0.044	0.000
V10PctBlw100	Square root	Skew: 1.283 Kurtosis: 1.609	Skew: 0.240 Kurtosis: -0.319	0.048	0.000
V10Pctlw150	Square root	Skew: 0.770 Kurtosis: -0.82	Skew: 0.000 Kurtosis: -0.566	0.032	0.000
V11PctWhite	Arcsin	Skew: -0.552 Kurtosis: -0.533	Skew: 0.007 Kurtosis: -0.647	0.034	0.000
V11PctNonWhite	Square root	Skew: -0.816 Kurtosis: 0.023	Skew: -0.137 Kurtosis: -0.636	0.037	0.000
V11PctBlack	Square root	Skew: 3.180 Kurtosis: 14.722	Skew: 1.002 Kurtosis: 0.832	0.151	0.000
V11PctIndigenous	Square root	Skew: 12.378 Kurtosis: 258.162	Skew: 2.217 Kurtosis: 9.011	0.322	0.000
V11PctAsian	Square root	Skew: 2.076 Kurtosis: 4.862	Skew: 0.620 Kurtosis: -0.091	0.095	0.000
V11PctPacific	Square root	Skew: 6.428 Kurtosis: 63.082	Skew: 2.832 Kurtosis: 9.003	0.460	0.000

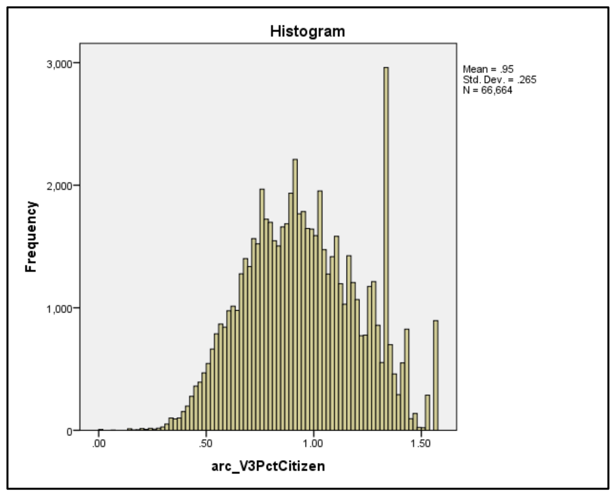
V12PctRenter	Square root	Skew: 0.496 Kurtosis: -0.791	Skew: -0.120 Kurtosis: -0.687	0.043	0.000
V12PctOwner	Arcsin	Skew: -0.496 Kurtosis: -0.791	Skew: -0.035 Kurtosis: -0.737	0.048	0.000
V13MEDINCCNTY	N/A	N/A	N/A	N/A	N/A

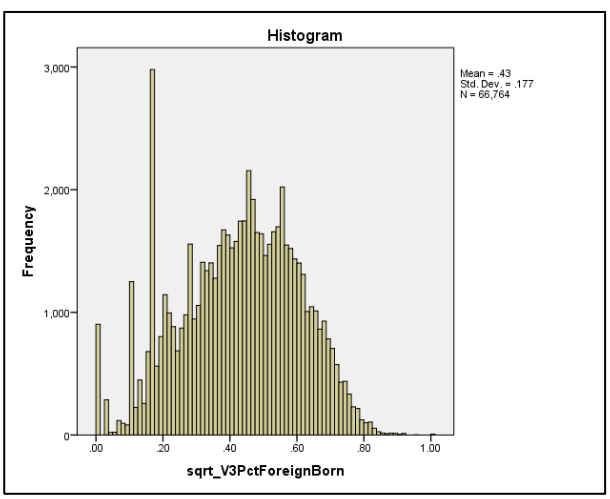
Histograms for Each Social Vulnerability Variable After Normalization

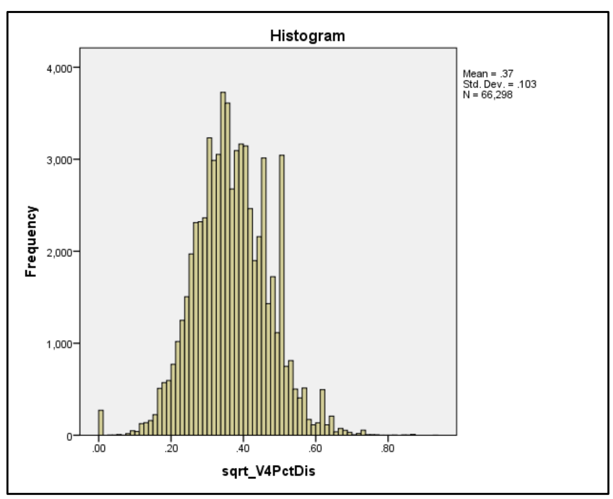


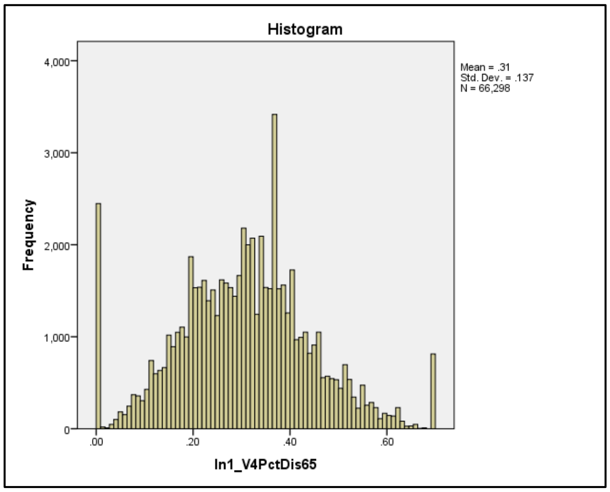











Histogram
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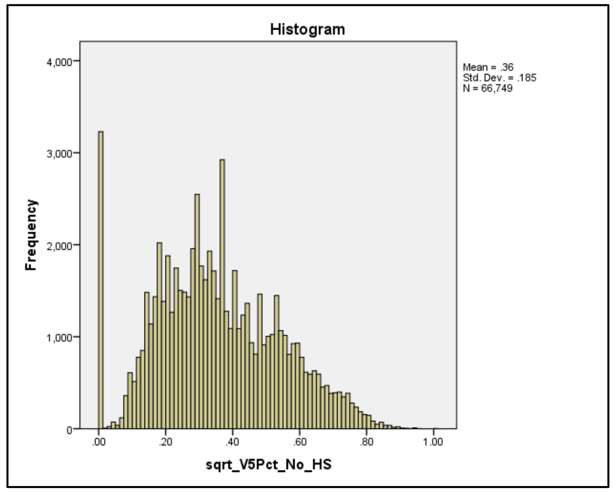
Std. Dev. = .137
N = 66,298
Frequency
ln1_V4PctDis65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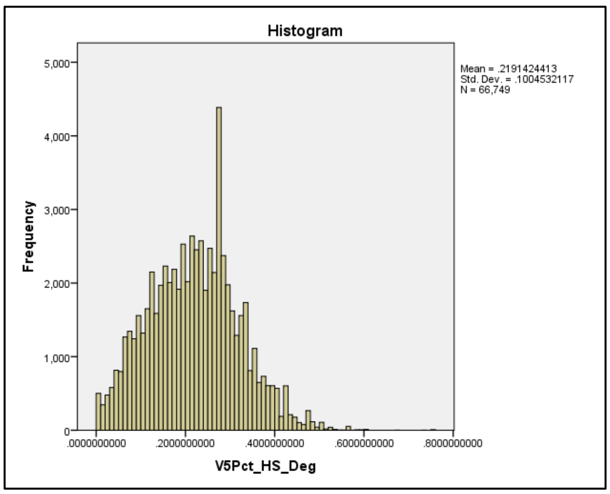
N = 66,749
Frequency
sqrt_V5Pct_No_HS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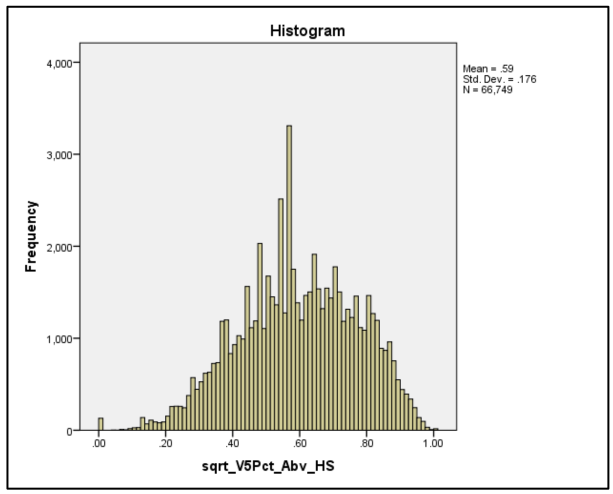
Std. Dev. = .1004532117
N = 66,749
Frequency
V5Pct_HS_Deg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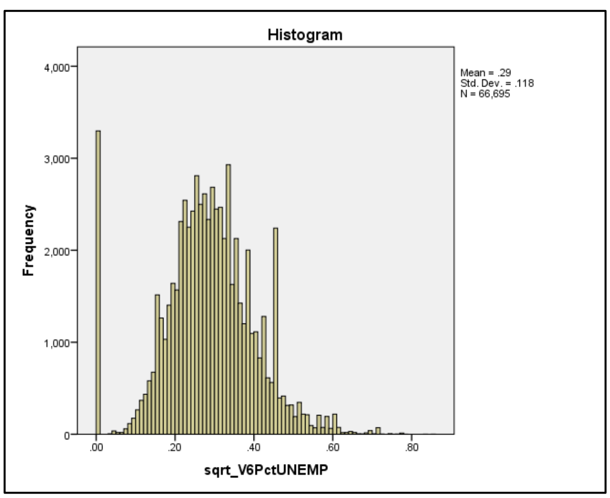
Std. Dev. = .176
N = 66,749
Frequency
sqrt_V5Pct_Abv_HS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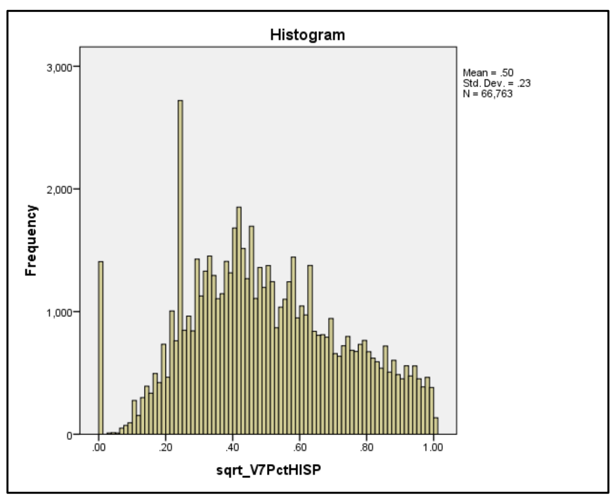
Std. Dev. = .118
N = 66,695
Frequency
sqrt_V6PctUNEMP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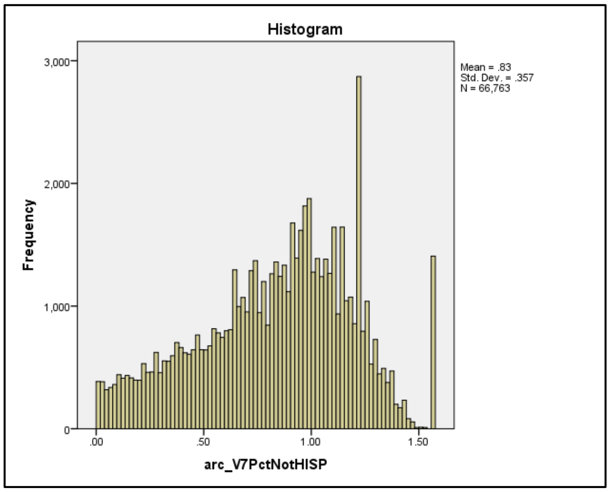
N = 66,763
Frequency
sqrt_V7PctHISP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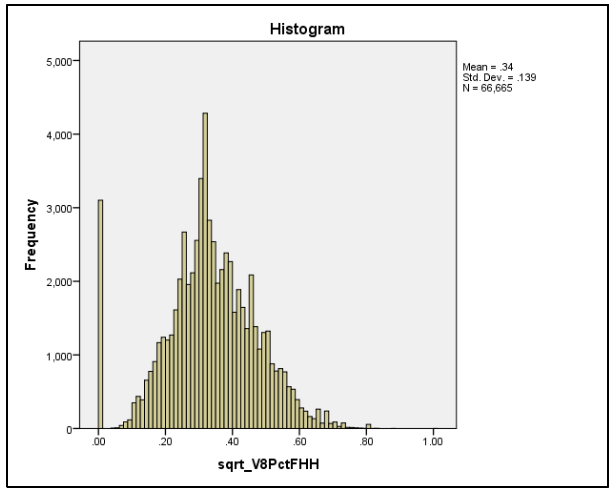
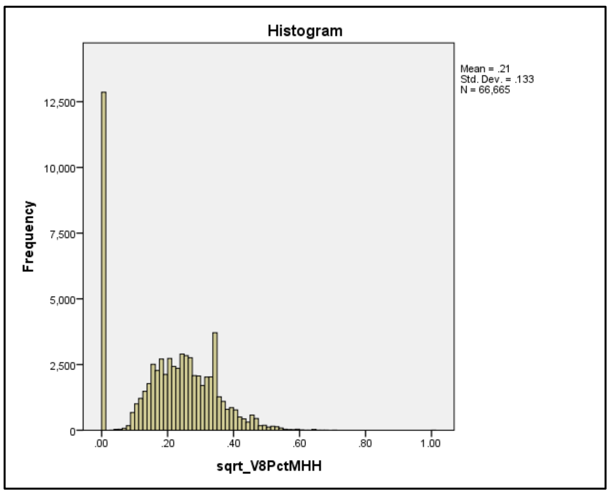
Mean = .83
Std. Dev. = .357
N = 66,763
Frequency
arc_V7PctNotHISP


Histogram
Mean = .34
Std. Dev. = .139
N = 66,665
Frequency
sqrt_V8PctFHH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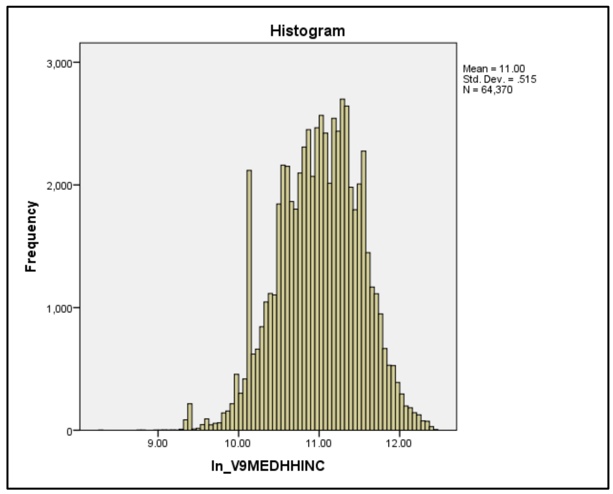
Mean = .21
Std. Dev. = .133
N = 66,665
Frequency
sqrt_V8PctMHH


Histogram
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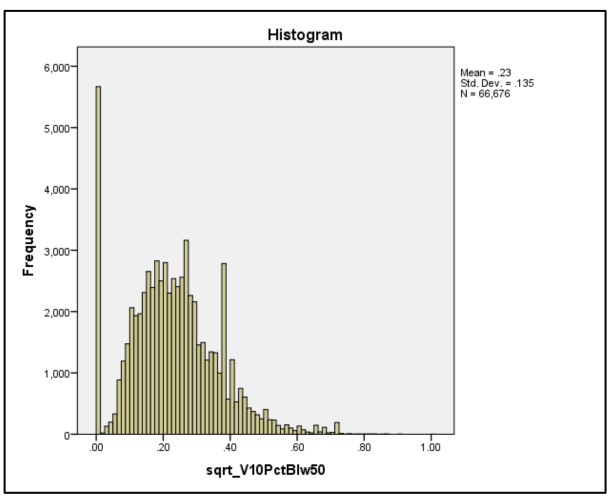
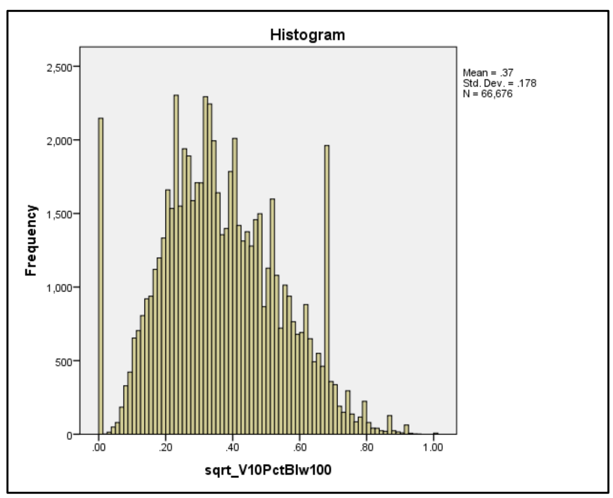
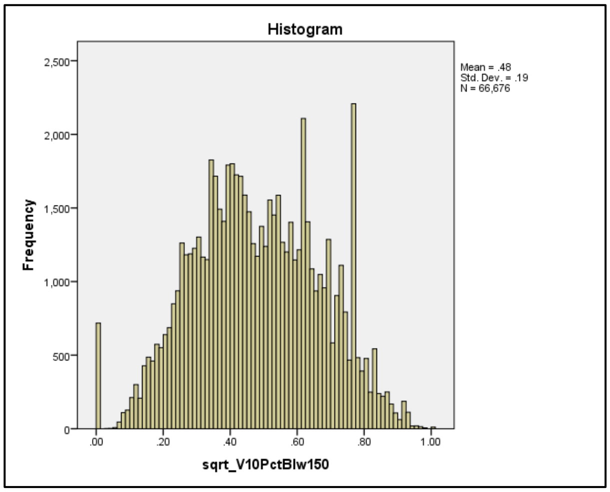
Std. Dev. = .515
N = 64,370
Frequency
ln_V9MEDHHINC


Histogram
Mean = .23
Std. Dev. = .135
N = 66,676
Frequency
sqrt_V10PctBlw50


Histogram
Mean = .37
Std. Dev. = .178
N = 66,676
Frequency
sqrt_V10PctBlw100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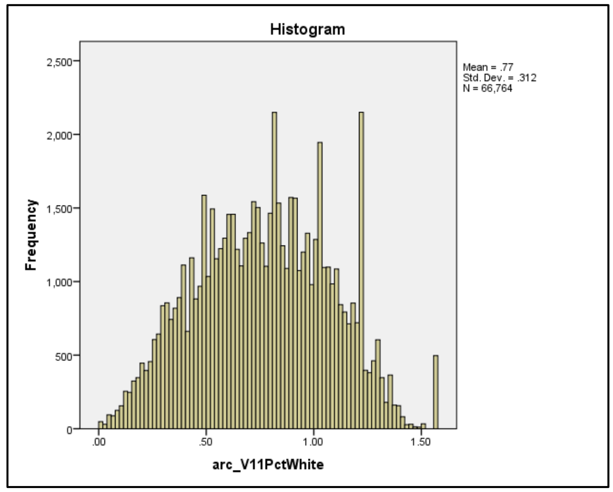
Std. Dev. = .19
N = 66,676
Frequency
sqrt_V10PctBlw150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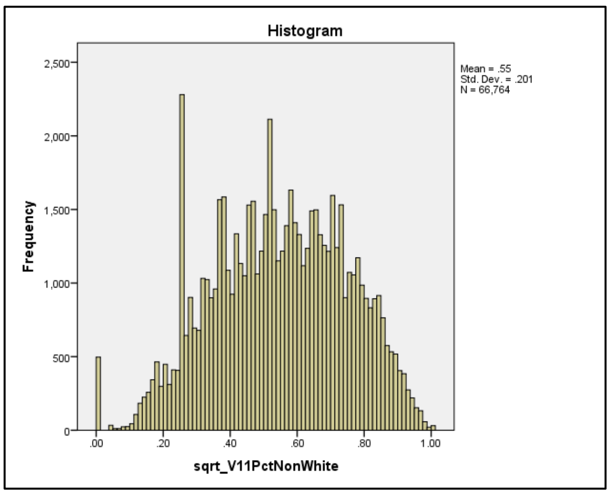
Std. Dev. = .312
N = 66,764
Frequency
arc_V11PctWhite


Histogram
Mean = .55
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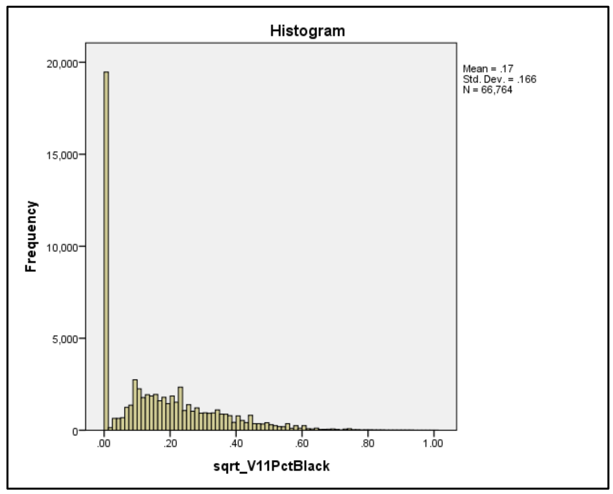
N = 66,764
Frequency
sqrt_V11PctNonWhite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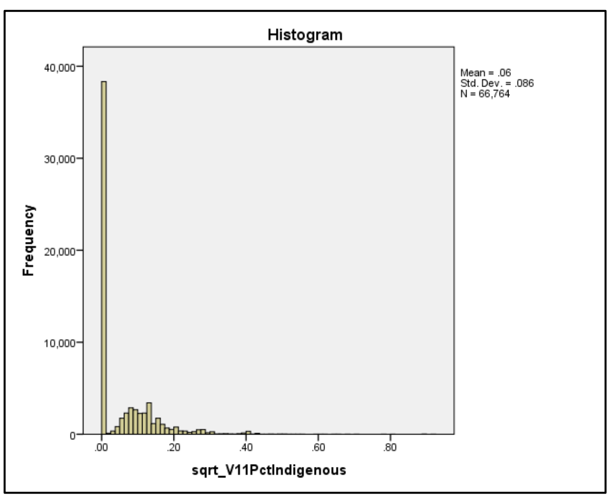
Std. Dev. = .166
N = 66,764
Frequency
sqrt_V11PctBlack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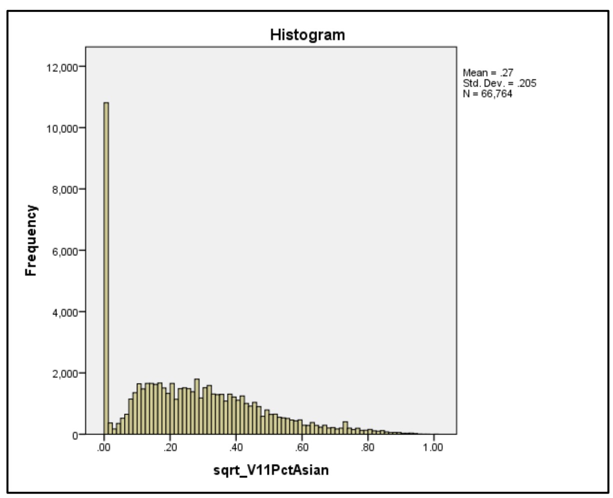
Mean = .06
Std. Dev. = .086
N = 66,764
Frequency
sqrt_V11PctIndigenous


Histogram
Mean = .27
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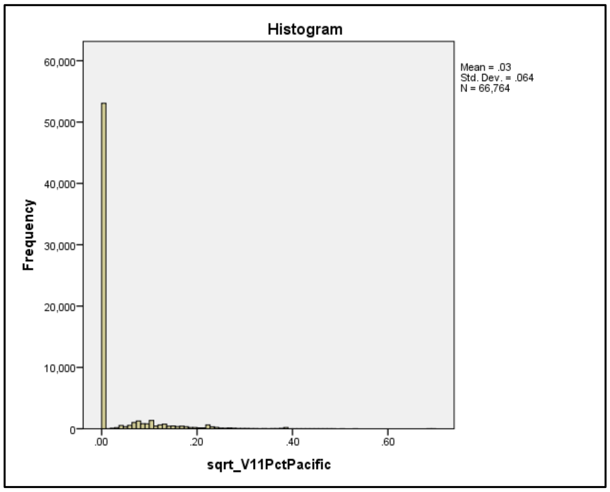
N = 66,764
Frequency
sqrt_V11PctAsian


Histogram
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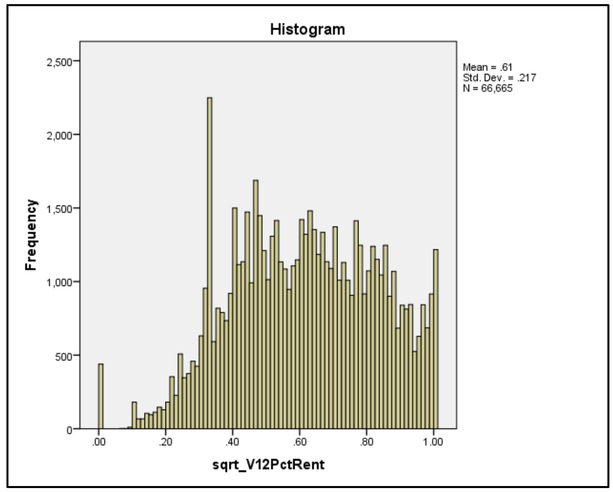
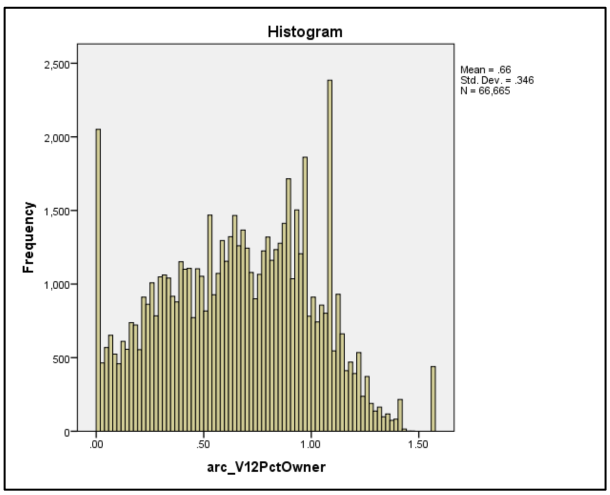
Std. Dev. = .064
N = 66,764
Frequency
sqrt_V11PctPacific


Histogram
Mean = .61
Std. Dev. = .217
N = 66,665
Frequency
sqrt_V12PctRent


Histogram
Mean = .66
Std. Dev. = .346
N = 66,665
Frequency
arc_V12PctOwner

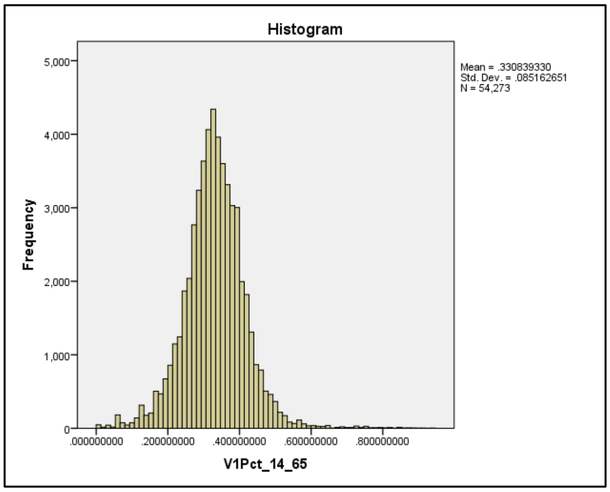
Normalized Variables for HHP Dam Flood Zones

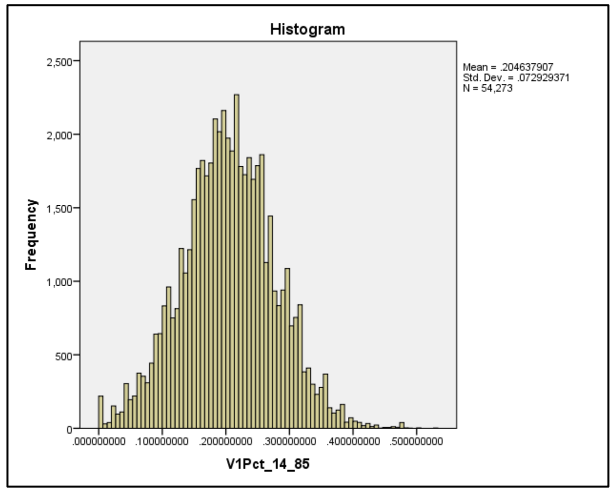
Variable	Data Normalization Method	Skew and Kurtosis Before Normalization	Skew and Kurtosis After Normalization	Kolmogorov-Smirnov Statistic	K-S Test Sig. Value
V1Pct_14_65	None	Skew: 0.339 Kurtosis: 3.235	N/A	0.042	0.000
V1Pct_14_85	None	Skew: 0.047 Kurtosis: 0.137	N/A	0.013	0.000
V2Pct_NoAuto	Square root	Skew: 2.848 Kurtosis: 13.249	Skew: 0.622 Kurtosis: 0.366	0.125	0.000
V3PctCitizen	Arcsin	Skew: -0.595 Kurtosis: -0.196	Skew: 0.155 Kurtosis: -0.430	0.027	0.000
V3PctForeignBorn	Square root	Skew: 0.595 Kurtosis: -0.196	Skew: -0.249 Kurtosis: -0.415	0.032	0.000
V4PctDis	Square root	Skew: 1.155 Kurtosis: 2.377	Skew: 0.127 Kurtosis: 0.698	0.027	0.000
V4PctDis65	Natural log	Skew: 0.506 Kurtosis: 0.565	Skew: 0.065 Kurtosis: 0.099	0.024	0.000
V5Pct_No_HS	Square root	Skew: 1.238 Kurtosis: 1.083	Skew: 0.253 Kurtosis: -0.474	0.053	0.000
V5Pct_HS_Deg	None	Skew: 0.169 Kurtosis: -0.307	N/A	0.023	0.000
V5Pct_Abv_HS	Square root	Skew: 0.368 Kurtosis: -0.709	Skew: -0.234 Kurtosis: -0.513	0.037	0.000
V6PctUNEMP	Square root	Skew: 1.579 Kurtosis: 4.632	Skew: -0.111 Kurtosis: 0.876	0.043	0.000
V7PctHISP	Square root	Skew: 0.880 Kurtosis: -0.202	Skew: 0.165 Kurtosis: -0.708	0.051	0.000
V7PctNotHISP	Arcsin	Skew: -0.880 Kurtosis: -0.202	Skew: -0.309 Kurtosis: -0.637	0.061	0.000

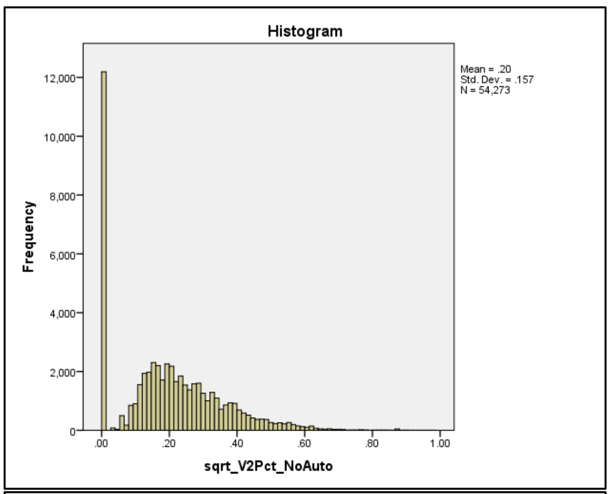
V8PctFHH	Square root	Skew: 1.154 Kurtosis: 1.790	Skew: -0.144 Kurtosis: 0.276	0.035	0.000
V8PctMHH	Square root	Skew: 1.1439 Kurtosis: 2.845	Skew: -0.064 Kurtosis: -0.489	0.126	0.000
V9ExtrmLowInc	N/A	N/A	N/A	N/A	N/A
V9VeryLowInc	N/A	N/A	N/A	N/A	N/A
V9LowInc	N/A	N/A	N/A	N/A	N/A
V9MEDHHINC	Natural log	Skew: 1.176 Kurtosis: 1.963	Skew: -0.242 Kurtosis: 0.053	0.026	0.000
V10PctBlw50	Square root	Skew: 2.288 Kurtosis: 8.042	Skew: 0.476 Kurtosis: 0.450	0.043	0.000
V10PctBlw100	Square root	Skew: 1.426 Kurtosis: 2.399	Skew: 0.289 Kurtosis: -0.153	0.046	0.000
V10Pctlw150	Square root	Skew: 0.901 Kurtosis: 0.308	Skew: 0.085 Kurtosis: -0.484	0.032	0.000
V11PctWhite	Arcsin	Skew: -0.558 Kurtosis: -0.509	Skew: -0.005 Kurtosis: -0.604	0.033	0.000
V11PctNonWhite	Square root	Skew: 0.558 Kurtosis: -0.509	Skew: -0.129 Kurtosis: -0.588	0.034	0.000
V11PctBlack	Square root	Skew: 3.407 Kurtosis: 16.959	Skew: 1.044 Kurtosis: 1.134	0.145	0.000
V11PctIndigenous	Square root	Skew: 13.123 Kurtosis: 271.713	Skew: 2.406 Kurtosis: 10.709	0.332	0.000
V11PctAsian	Square root	Skew: 2.067 Kurtosis: 4.723	Skew: 0.649 Kurtosis: 0.003	0.086	0.000
V11PctPacific	Square root	Skew: 7.160 Kurtosis: 80.789	Skew: 3.025 Kurtosis: 10.642	0.465	0.000
V12PctRenter	Square root	Skew: 0.456 Kurtosis: -0.798	Skew: -0.181 Kurtosis: -0.603	0.043	0.000
V12PctOwner	Arcsin	Skew: -0.456 Kurtosis: -0.798	Skew: 0.023 Kurtosis: -0.678	0.037	0.000

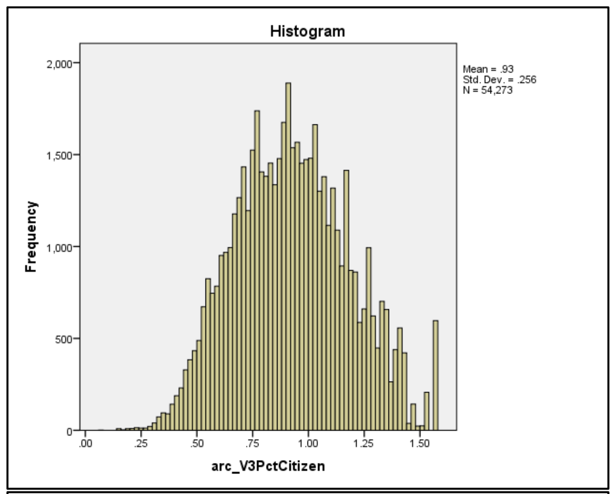
V13MEDINCCNTY	N/A	N/A	N/A	N/A	N/A

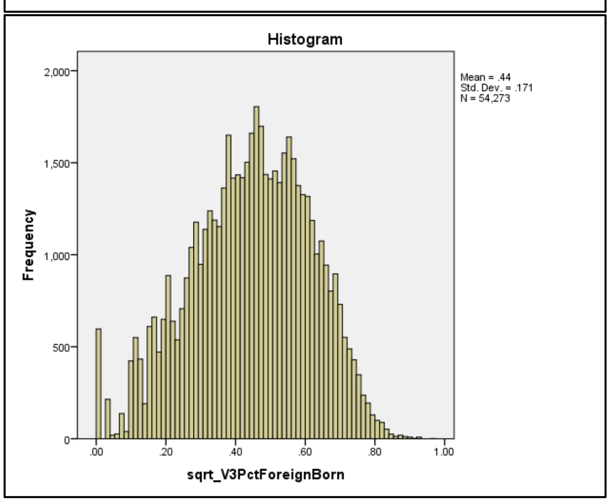
Histograms for Each Social Vulnerability Variable After Normalization

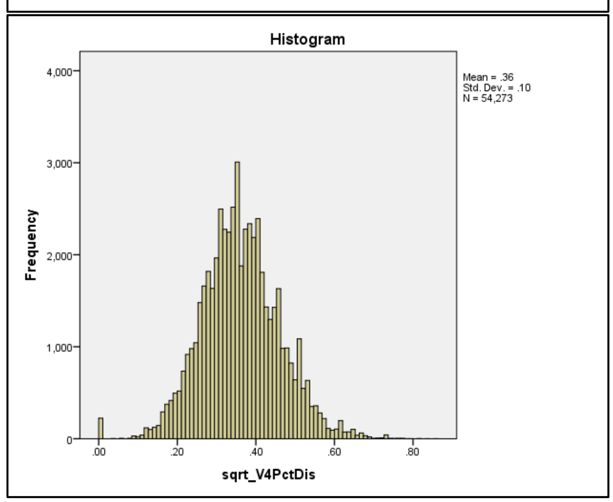


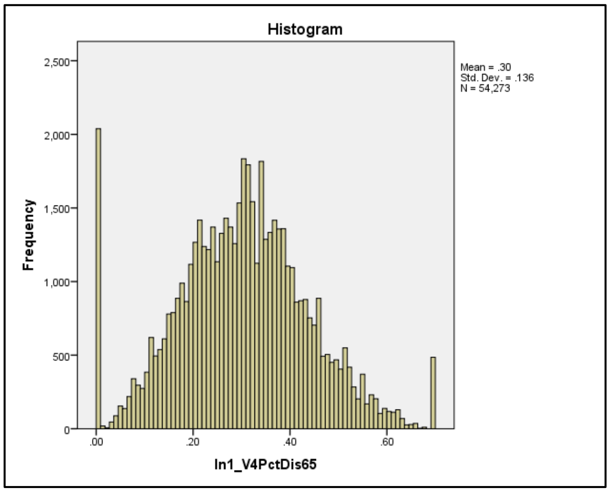


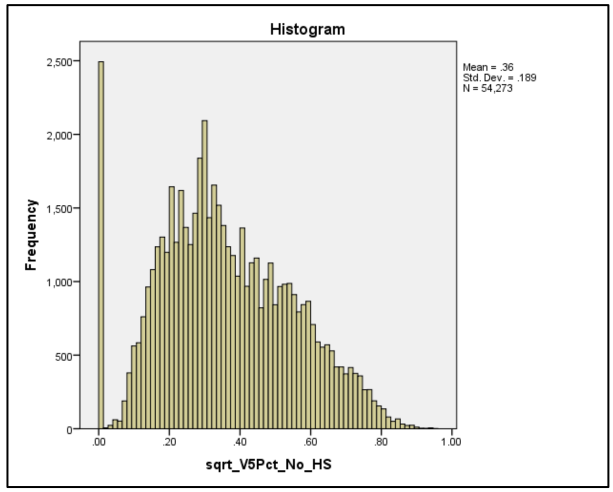


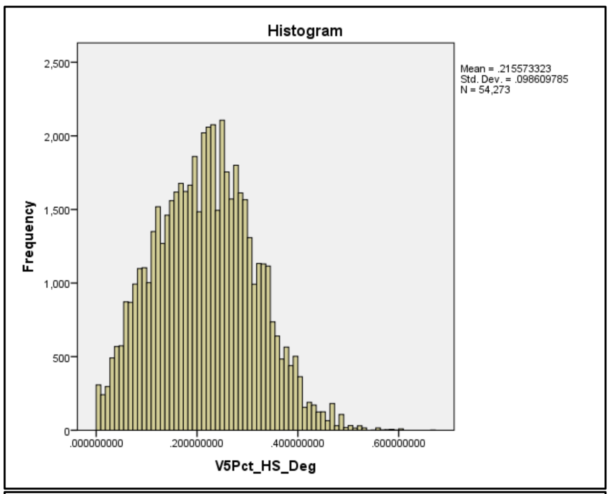


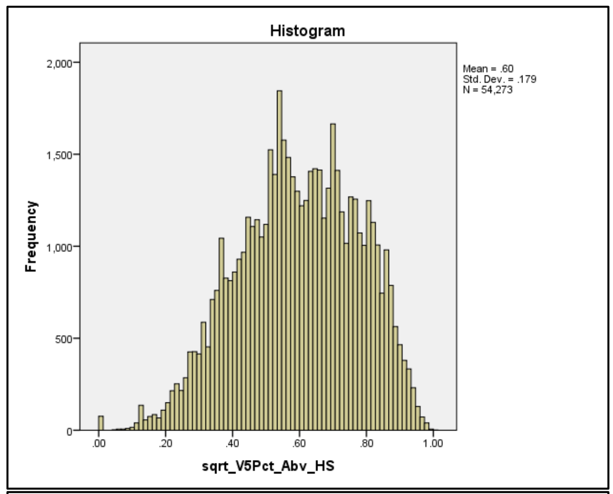


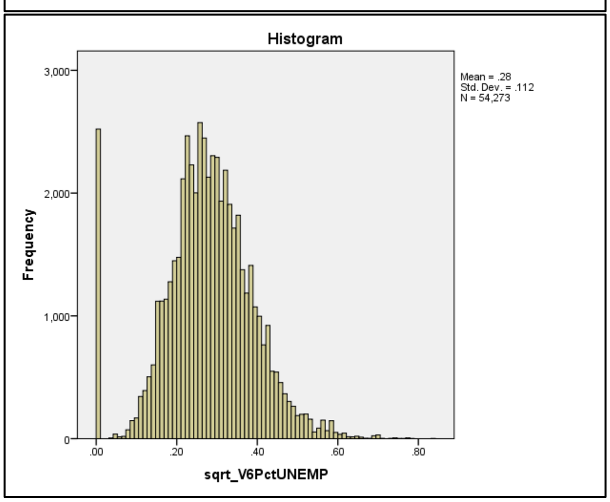


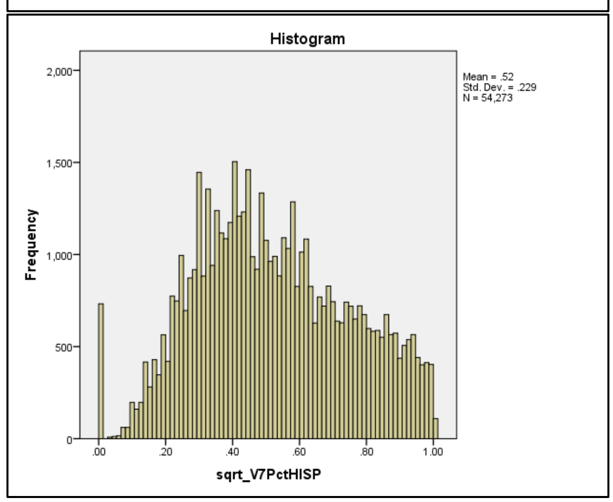

Histogram
Mean = .30
Std. Dev. = .136
N = 54,273
Frequency
ln1_V4PctDis65

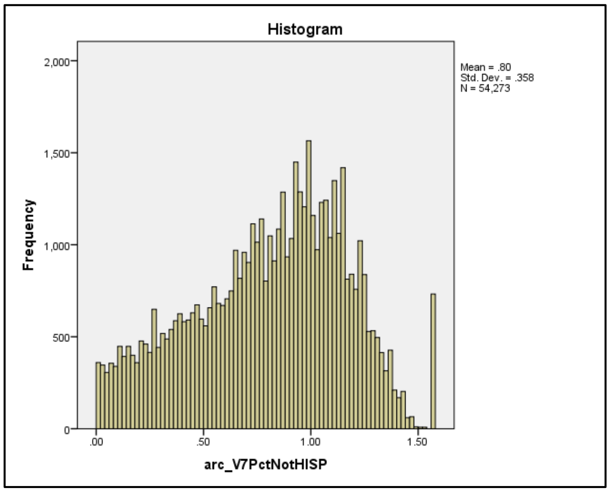

Histogram
Mean = .36
Std. Dev. = .189
N = 54,273
Frequency
sqrt_V5Pct_No_HS

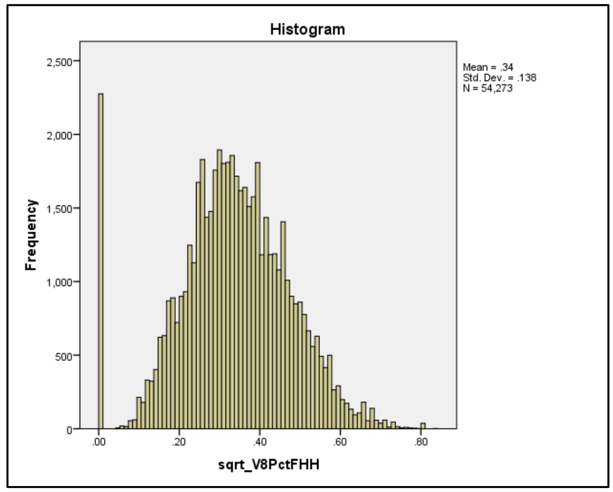

Histogram
Mean = .215573323
Std. Dev. = .098609785
N = 54,273
Frequency
V5Pct_HS_Deg

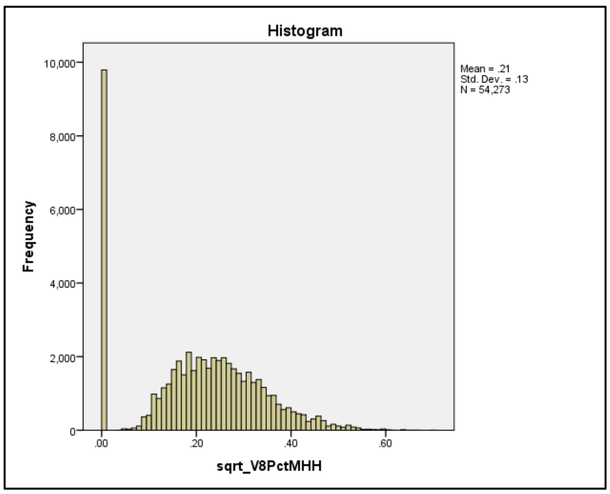

Histogram
Mean = .60
Std. Dev. = .179
N = 54,273
Frequency
sqrt_V5Pct_Abv_HS

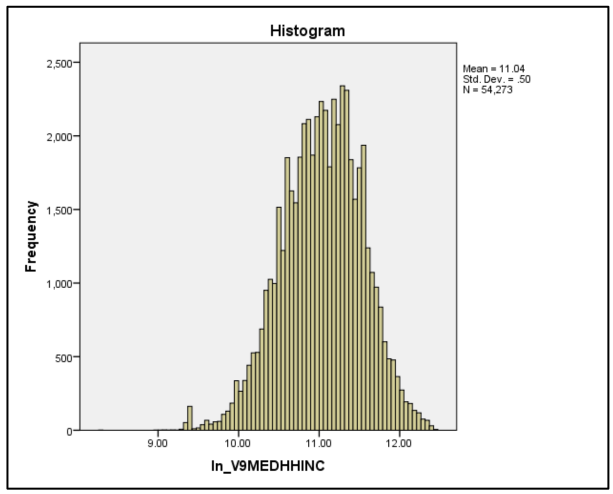

Histogram
Mean = .28
Std. Dev. = .112
N = 54,273
Frequency
sqrt_V6PctUNEMP

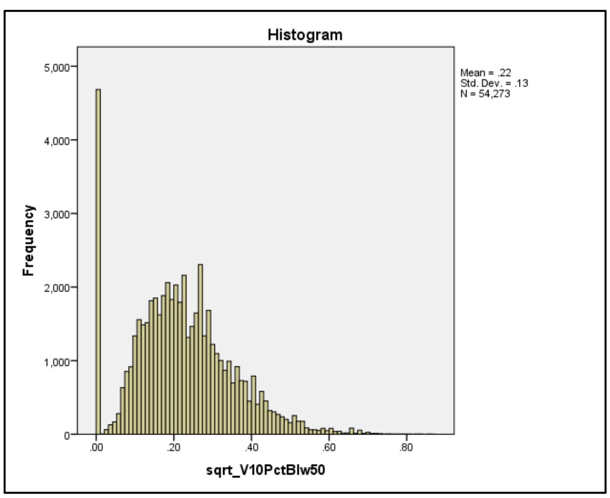

Histogram
Mean = .52
Std. Dev. = .229
N = 54,273
Frequency
sqrt_V7PctHISP

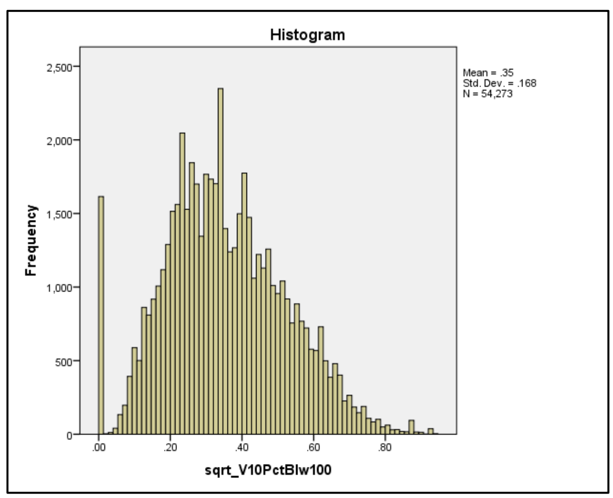

Histogram
Mean = .80
Std. Dev. = .358
N = 54,273
Frequency
arc_V7PctNotHISP

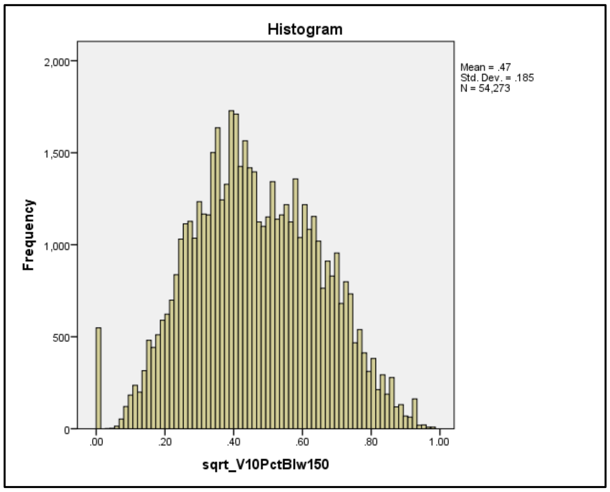

Histogram
Mean = .34
Std. Dev. = .138
N = 54,273
Frequency
sqrt_V8PctFHH

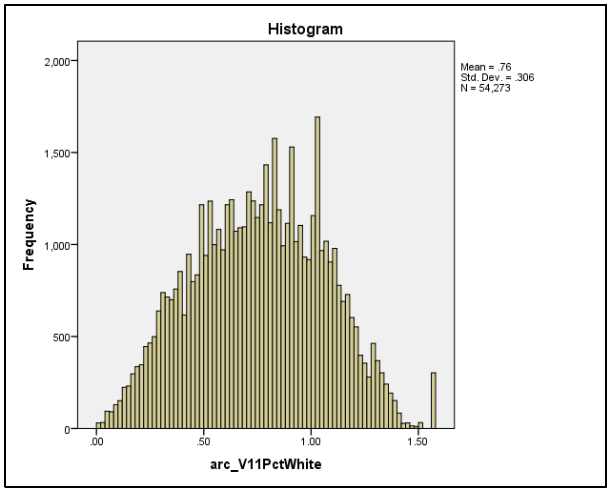

Histogram
Mean = .21
Std. Dev. = .13
N = 54,273
Frequency
sqrt_V8PctMHH

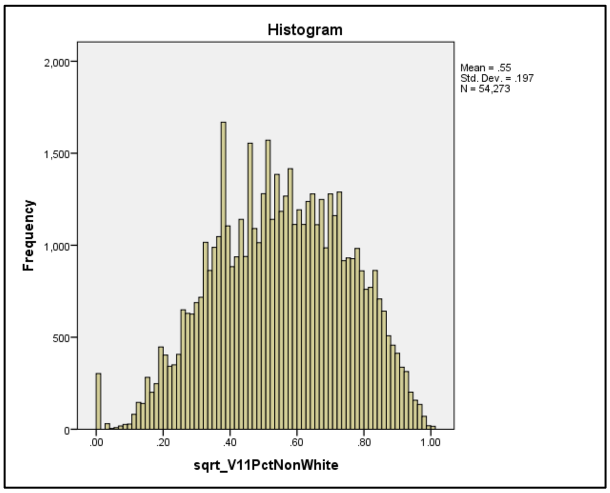

Histogram
Mean = 11.04
Std. Dev. = .50
N = 54,273
Frequency
ln_V9MEDHHINC

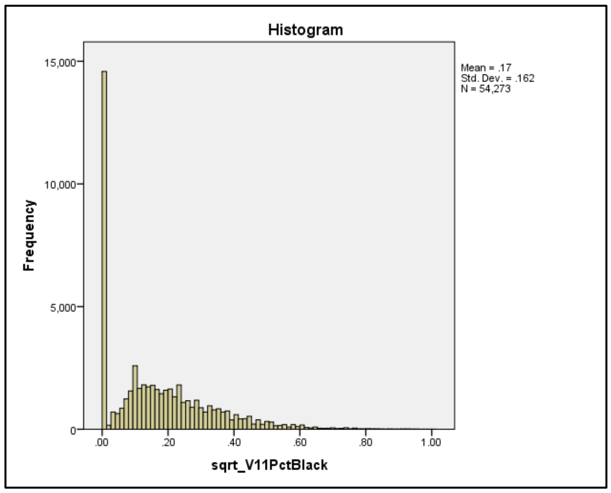

Histogram
Mean = .22
Std. Dev. = .13
N = 54,273
Frequency
sqrt_V10PctBlw50

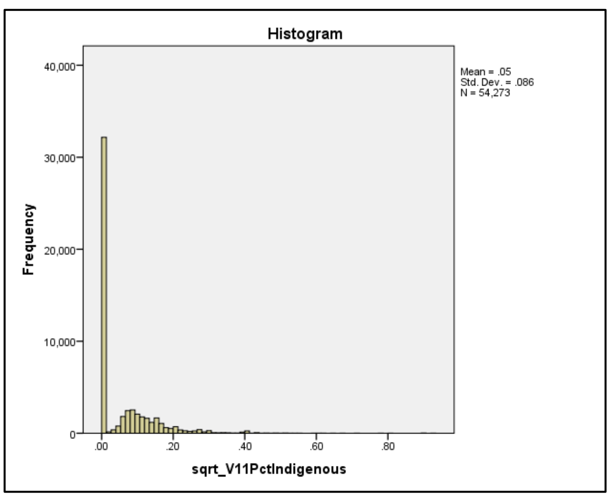

Histogram
Mean = .35
Std. Dev. = .168
N = 54,273
Frequency
sqrt_V10PctBlw100

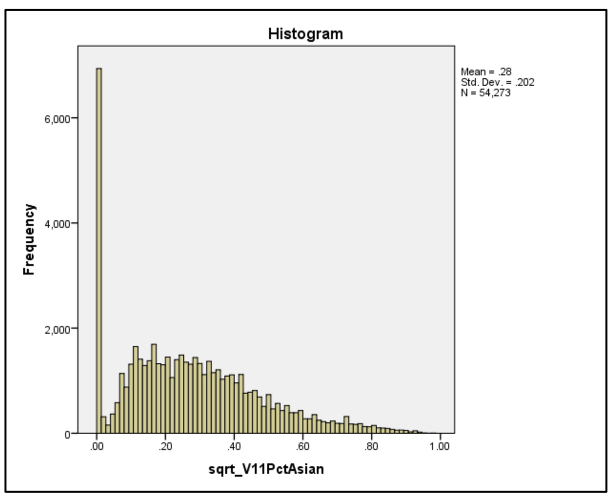

Histogram
Mean = .47
Std. Dev. = .185
N = 54,273
Frequency
sqrt_V10PctBlw150

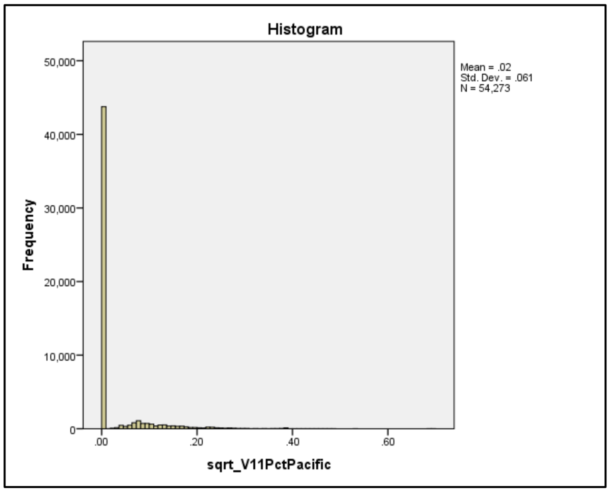

Histogram
Mean = .76
Std. Dev. = .306
N = 54,273
Frequency
arc_V11PctWhite

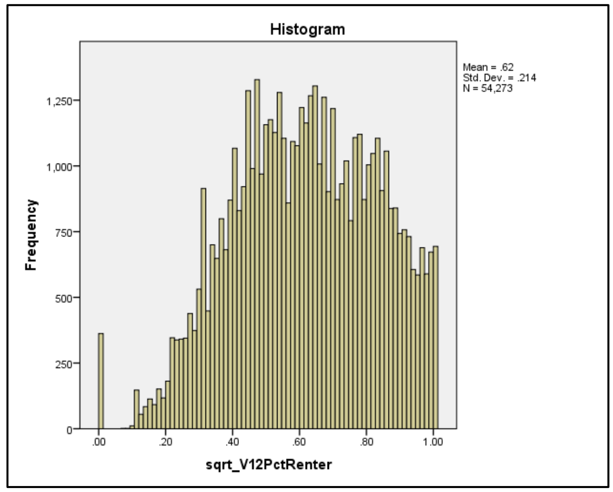

Histogram
Mean = .55
Std. Dev. = .197
N = 54,273
Frequency
sqrt_V11PctNonWhite

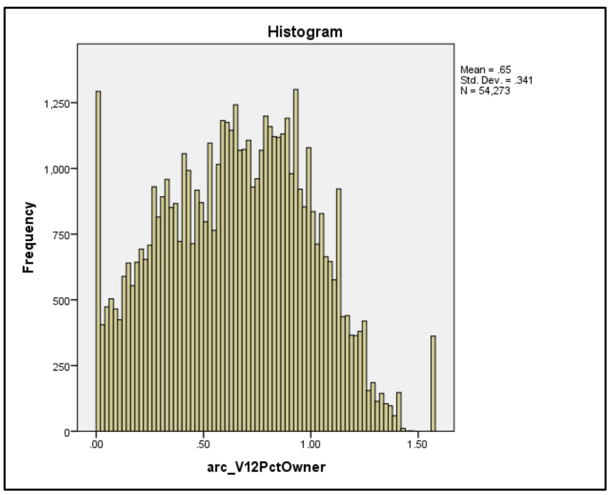

Histogram
Mean = .17
Std. Dev. = .162
N = 54,273
Frequency
sqrt_V11PctBlack


Histogram
Mean = .05
Std. Dev. = .086
N = 54,273
Frequency
sqrt_V11PctIndigenous


Histogram
Mean = .28
Std. Dev. = .202
N = 54,273
Frequency
sqrt_V11PctAsian


Histogram
Mean = .02
Std. Dev. = .061
N = 54,273
Frequency
sqrt_V11PctPacific


Histogram
Mean = .62
Std. Dev. = .214
N = 54,273
Frequency
sqrt_V12PctRenter


Histogram
Mean = .65
Std. Dev. = .341
N = 54,273
Frequency
arc_V12PctOwner

Appendix B: Statistical Analyses for Research Question 1

Independent Samples Tests of Social Vulnerability Variables in All Dam Flood Zones

Group Statistics

	In_Flood_Zone	N	Mean	Std. Deviation	Std. Error Mean
V1Pct_14_65	0	17405	.3282392326	.0953295172	.0007225874
	1	49359	.3307679711	.0832730576	.0003748188
V1Pct_14_85	0	17405	.1995972115	.0751032263	.0005692743
	1	49359	.2031300571	.0758716693	.0003415045
sqrt_V2Pct_NoAuto	0	17360	.2090	.16730	.00127
	1	49305	.1991	.15559	.00070
arc_V3PctCitizen	0	17405	.8957	.25179	.00191
	1	49359	.9718	.26620	.00120
sqrt_V3PctForeignBorn	0	17405	.4647	.16709	.00127
	1	49359	.4136	.17903	.00081
sqrt_V4PctDis	0	17366	.3501	.10239	.00078
	1	49310	.3753	.10359	.00047
ln1_V4PctDis65	0	17225	.2952	.13850	.00106
	1	49073	.3106	.13685	.00062
sqrt_V5Pct_No_HS	0	17402	.3467	.19703	.00149
	1	49347	.3591	.18099	.00081
V5Pct_HS_Deg	0	17402	.1980784167	.1008149848	.0007642325
	1	49347	.2265705759	.0992659457	.0004468584
sqrt_V5Pct_Abv_HS	0	17402	.6231	.18672	.00142
	1	49347	.5851	.17098	.00077
sqrt_V6PctUNEMP	0	17371	.2677	.11759	.00089
	1	49324	.2932	.11800	.00053
sqrt_V7PctHISP	0	17404	.5162	.24031	.00182
	1	49359	.4972	.22546	.00101
arc_V7PctNotHISP	0	17404	.8088	.37505	.00284
	1	49359	.8401	.34960	.00157
sqrt_V8PctFHH	0	17360	.3302	.14394	.00109
	1	49305	.3379	.13724	.00062
sqrt_V8PctMHH	0	17360	.2004	.13316	.00101
	1	49305	.2122	.13277	.00060
ln_V9MEDHHINC	0	16877	11.0997	.51868	.00399
	1	47493	10.9632	.50939	.00234
V9ExtrmLow	0	16877	.01	.092	.001
	1	47493	.01	.103	.000
V9VeryLowI	0	16877	.07	.251	.002
	1	47493	.07	.252	.001
V9LowInc	0	16877	.29	.453	.003
	1	47493	.33	.470	.002
sqrt_V10PctBlw50	0	17366	.2162	.13373	.00101
	1	49310	.2369	.13543	.00061
sqrt_V10PctBlw100	0	17366	.3406	.16974	.00129
	1	49310	.3794	.17957	.00081
sqrt_V10PctBlw150	0	17366	.4461	.19069	.00145
	1	49310	.4937	.18801	.00085
arc_V11PctWhite	0	17405	.7521	.31828	.00241
	1	49359	.7732	.30908	.00139
sqrt_V11PctNonWhite	0	17405	.5557	.20410	.00155
	1	49359	.5427	.19992	.00090
sqrt_V11PctBlack	0	17405	.1635	.17191	.00130
	1	49359	.1735	.16338	.00074
sqrt_V11PctIndigenous	0	17405	.0443	.07607	.00058
	1	49359	.0624	.08906	.00040
sqrt_V11PctAsian	0	17405	.2871	.21481	.00163
	1	49359	.2609	.20037	.00090
sqrt_V11PctPacific	0	17405	.0200	.05572	.00042
	1	49359	.0298	.06639	.00030
sqrt_V12PctRenter	0	17360	.6152	.22407	.00170
	1	49305	.6127	.21487	.00097
arc_V12PctOwner	0	17360	.6553	.35592	.00270
	1	49305	.6601	.34288	.00154

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
V1Pct_14_65	Equal variances assumed	253.524	.000	-3.313	66762	.001	-.002528739	.0007632351	-.004024679	-.001032799
	Equal variances not assumed			-3.106	27331.994	**.002**	**-.002528739**	.0008140158	-.004124250	-.000933227
V1Pct_14_85	Equal variances assumed	13.844	.000	-5.296	66762	.000	-.003532846	.0006670936	-.004840348	-.002225343
	Equal variances not assumed			-5.322	30778.903	**.000**	**-.003532846**	.0006638513	-.004834021	-.002231670
sqrt_V2Pct_NoAuto	Equal variances assumed	105.859	.000	7.085	66663	.000	.00992	.00140	.00718	.01267
	Equal variances not assumed			6.843	28607.370	**.000**	**.00992**	.00145	.00708	.01277
arc_V3PctCitizen	Equal variances assumed	146.133	.000	-32.859	66762	.000	-.07604	.00231	-.08058	-.07151
	Equal variances not assumed			-33.744	32069.221	**.000**	**-.07604**	.00225	-.08046	-.07163
sqrt_V3PctForeignBorn	Equal variances assumed	209.496	.000	32.886	66762	.000	.05102	.00155	.04798	.05406
	Equal variances not assumed			33.988	32469.376	**.000**	**.05102**	.00150	.04808	.05396
sqrt_V4PctDis	Equal variances assumed	37.551	.000	-27.603	66674	.000	-.02516	.00091	-.02694	-.02337
	Equal variances not assumed			-27.758	30735.795	**.000**	**-.02516**	.00091	-.02693	-.02338
ln1_V4PctDis65	Equal variances assumed	13.024	.000	-12.635	66296	.000	-.01536	.00122	-.01774	-.01298
	Equal variances not assumed			-12.562	29821.781	**.000**	**-.01536**	.00122	-.01776	-.01296
sqrt_V5Pct_No_HS	Equal variances assumed	278.747	.000	-7.611	66747	.000	-.01243	.00163	-.01564	-.00923
	Equal variances not assumed			-7.308	28410.406	**.000**	**-.01243**	.00170	-.01577	-.00910
V5Pct_HS_Deg	Equal variances assumed	15.593	.000	-32.423	66747	.000	-.028492159	.0008787514	-.030214511	-.026769807
	Equal variances not assumed			-32.184	30093.111	**.000**	**-.028492159**	.0008852874	-.030227360	-.026756959
sqrt_V5Pct_Abv_HS	Equal variances assumed	356.438	.000	24.640	66747	.000	.03806	.00154	.03504	.04109
	Equal variances not assumed			23.625	28340.319	**.000**	**.03806**	.00161	.03491	.04122
sqrt_V6PctUNEMP	Equal variances assumed	.081	**.776**	-24.477	66693	**.000**	**-.02546**	.00104	-.02750	-.02342
	Equal variances not assumed			-24.517	30521.844	.000	-.02546	.00104	-.02749	-.02342
sqrt_V7PctHISP	Equal variances assumed	222.268	.000	9.414	66761	.000	.01904	.00202	.01508	.02300
	Equal variances not assumed			9.131	28900.428	**.000**	**.01904**	.00209	.01495	.02313
arc_V7PctNotHISP	Equal variances assumed	254.179	.000	-9.958	66761	.000	-.03129	.00314	-.03745	-.02513
	Equal variances not assumed			-9.629	28749.068	**.000**	**-.03129**	.00325	-.03766	-.02492
sqrt_V8PctFHH	Equal variances assumed	125.554	.000	-6.289	66663	.000	-.00772	.00123	-.01012	-.00531
	Equal variances not assumed			-6.147	29196.761	**.000**	**-.00772**	.00126	-.01018	-.00526
sqrt_V8PctMHH	Equal variances assumed	.548	**.459**	-10.071	66663	**.000**	**-.01181**	.00117	-.01411	-.00951
	Equal variances not assumed			-10.057	30330.932	.000	-.01181	.00117	-.01411	-.00951
ln_V9MEDHHINC	Equal variances assumed	1.708	**.191**	29.748	64368	**.000**	**.13645**	.00459	.12746	.14544
	Equal variances not assumed			29.494	29207.553	.000	.13645	.00463	.12738	.14552
V9ExtrmLow	Equal variances assumed	22.027	.000	-2.344	64368	.019	-.002	.001	-.004	.000
	Equal variances not assumed			-2.468	32793.878	**.014**	**-.002**	.001	-.004	.000
V9VeryLowI	Equal variances assumed	.510	**.475**	-.357	64368	**.721**	**-.001**	.002	-.005	.004
	Equal variances not assumed			-.358	29813.397	.720	-.001	.002	-.005	.004
V9LowInc	Equal variances assumed	387.740	.000	-9.381	64368	.000	-.039	.004	-.047	-.031
	Equal variances not assumed			-9.539	30615.616	**.000**	**-.039**	.004	-.047	-.031
sqrt_V10PctBlw50	Equal variances assumed	3.738	**.053**	-17.384	66674	**.000**	**-.02071**	.00119	-.02304	-.01837
	Equal variances not assumed			-17.490	30762.613	.000	-.02071	.00118	-.02303	-.01839
sqrt_V10PctBlw100	Equal variances assumed	98.982	.000	-24.810	66674	.000	-.03876	.00156	-.04182	-.03570
	Equal variances not assumed			-25.488	32001.225	**.000**	**-.03876**	.00152	-.04174	-.03578
sqrt_V10PctBlw150	Equal variances assumed	.237	**.626**	-28.540	66674	**.000**	**-.04753**	.00167	-.05079	-.04426
	Equal variances not assumed			-28.347	30048.895	.000	-.04753	.00168	-.05081	-.04424
arc_V11PctWhite	Equal variances assumed	5.108	.024	-7.681	66762	.000	-.02109	.00275	-.02647	-.01571
	Equal variances not assumed			-7.574	29743.502	**.000**	**-.02109**	.00278	-.02655	-.01563
sqrt_V11PctNonWhite	Equal variances assumed	.870	**.351**	7.378	66762	**.000**	**.01307**	.00177	.00960	.01655
	Equal variances not assumed			7.305	29963.000	.000	.01307	.00179	.00957	.01658
sqrt_V11PctBlack	Equal variances assumed	.585	**.444**	-6.875	66762	**.000**	**-.01004**	.00146	-.01290	-.00718
	Equal variances not assumed			-6.709	29211.134	.000	-.01004	.00150	-.01297	-.00711
sqrt_V11PctIndigenous	Equal variances assumed	517.524	.000	-23.907	66762	.000	-.01810	.00076	-.01958	-.01661
	Equal variances not assumed			-25.769	35381.074	**.000**	**-.01810**	.00070	-.01947	-.01672
sqrt_V11PctAsian	Equal variances assumed	61.396	.000	14.531	66762	.000	.02616	.00180	.02263	.02969
	Equal variances not assumed			14.055	28766.792	**.000**	**.02616**	.00186	.02251	.02981
sqrt_V11PctPacific	Equal variances assumed	926.893	.000	-17.367	66762	.000	-.00976	.00056	-.01087	-.00866
	Equal variances not assumed			-18.874	36009.739	**.000**	**-.00976**	.00052	-.01078	-.00875
sqrt_V12PctRenter	Equal variances assumed	45.221	.000	1.305	66663	.192	.00250	.00192	-.00126	.00626
	Equal variances not assumed			1.279	29337.264	**.201**	**.00250**	.00196	-.00133	.00634
arc_V12PctOwner	Equal variances assumed	43.184	.000	-1.582	66663	.114	-.00484	.00306	-.01083	.00116
	Equal variances not assumed			-1.554	29450.120	**.120**	**-.00484**	.00311	-.01093	.00126

Appendix C: Statistical Analyses for Research Question 2

Independent Samples Tests of Social Vulnerability Variables in HHP Dam Flood Zones

Group Statistics

	In_Flood_Zone	N	Mean	Std. Deviation	Std. Error Mean
V1Pct_14_65	0	17432	.3282635938	.0953003503	.0007218067
	1	38876	.3308354217	.0845075377	.0004286025
V1Pct_14_85	0	17432	.1996354763	.0750858485	.0005687016
	1	38876	.2066373638	.0747894427	.0003793146
sqrt_V2Pct_NoAuto	0	17387	.2090	.16728	.00127
	1	38833	.2003	.15577	.00079
arc_V3PctCitizen	0	17432	.8955	.25184	.00191
	1	38876	.9438	.25917	.00131
sqrt_V3PctForeignBorn	0	17432	.4648	.16712	.00127
	1	38876	.4326	.17384	.00088
sqrt_V4PctDis	0	17393	.3501	.10239	.00078
	1	38838	.3672	.10206	.00052
ln1_V4PctDis65	0	17252	.2952	.13847	.00105
	1	38663	.3079	.13780	.00070
sqrt_V5Pct_No_HS	0	17429	.3466	.19700	.00149
	1	38864	.3677	.18592	.00094
V5Pct_HS_Deg	0	17429	.1980685937	.1008423243	.0007638474
	1	38864	.2237632508	.0991305879	.0005028448
sqrt_V5Pct_Abv_HS	0	17429	.6232	.18674	.00141
	1	38864	.5836	.17579	.00089
sqrt_V6PctUNEMP	0	17398	.2677	.11756	.00089
	1	38852	.2845	.11449	.00058
sqrt_V7PctHISP	0	17431	.5161	.24029	.00182
	1	38876	.5211	.22684	.00115
arc_V7PctNotHISP	0	17431	.8090	.37501	.00284
	1	38876	.8030	.35367	.00179
sqrt_V8PctFHH	0	17387	.3302	.14389	.00109
	1	38833	.3395	.13946	.00071
sqrt_V8PctMHH	0	17387	.2004	.13315	.00101
	1	38833	.2089	.13149	.00067
ln_V9MEDHHINC	0	16903	11.1000	.51860	.00399
	1	37637	11.0060	.48915	.00252
V9ExtrmLow	0	16903	.01	.092	.001
	1	37637	.01	.100	.001
V9VeryLowI	0	16903	.07	.250	.002
	1	37637	.07	.251	.001
V9LowInc	0	16903	.29	.453	.003
	1	37637	.31	.461	.002
sqrt_V10PctBlw50	0	17393	.2161	.13368	.00101
	1	38838	.2290	.13376	.00068
sqrt_V10PctBlw100	0	17393	.3405	.16969	.00129
	1	38838	.3641	.17161	.00087
sqrt_V10PctBlw150	0	17393	.4460	.19067	.00145
	1	38838	.4783	.18508	.00094
arc_V11PctWhite	0	17432	.7519	.31829	.00241
	1	38876	.7613	.30300	.00154
sqrt_V11PctNonWhite	0	17432	.5559	.20410	.00155
	1	38876	.5506	.19555	.00099
sqrt_V11PctBlack	0	17432	.1634	.17182	.00130
	1	38876	.1755	.15987	.00081
sqrt_V11PctIndigenous	0	17432	.0443	.07605	.00058
	1	38876	.0592	.08972	.00046
sqrt_V11PctAsian	0	17432	.2874	.21497	.00163
	1	38876	.2690	.19697	.00100
sqrt_V11PctPacific	0	17432	.0200	.05573	.00042
	1	38876	.0269	.06270	.00032
sqrt_V12PctRenter	0	17387	.6152	.22408	.00170
	1	38833	.6204	.21231	.00108
arc_V12PctOwner	0	17387	.6554	.35595	.00270
	1	38833	.6484	.33873	.00172

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
V1Pct_14_65	Equal variances assumed	133.789	.000	-3.207	56306	.001	-.002571828	.0008020577	-.004143865	-.000999790
	Equal variances not assumed			-3.064	30206.148	**.002**	**-.002571828**	.0008394671	-.004217218	-.000926437
V1Pct_14_85	Equal variances assumed	.073	**.787**	-10.258	56306	**.000**	**-.007001888**	.0006825653	-.008339719	-.005664056
	Equal variances not assumed			-10.243	33423.689	.000	-.007001888	.0006835942	-.008341756	-.005662019
sqrt_V2Pct_NoAuto	Equal variances assumed	94.585	.000	5.959	56218	.000	.00867	.00145	.00582	.01152
	Equal variances not assumed			5.799	31388.370	**.000**	**.00867**	.00149	.00574	.01160
arc_V3PctCitizen	Equal variances assumed	24.790	.000	-20.595	56306	.000	-.04823	.00234	-.05282	-.04364
	Equal variances not assumed			-20.822	34436.106	**.000**	**-.04823**	.00232	-.05277	-.04369
sqrt_V3PctForeignBorn	Equal variances assumed	43.582	.000	20.562	56306	.000	.03220	.00157	.02913	.03527
	Equal variances not assumed			20.873	34777.633	**.000**	**.03220**	.00154	.02917	.03522
sqrt_V4PctDis	Equal variances assumed	1.453	**.228**	-18.321	56229	**.000**	**-.01708**	.00093	-.01890	-.01525
	Equal variances not assumed			-18.299	33356.259	.000	-.01708	.00093	-.01891	-.01525
ln1_V4PctDis65	Equal variances assumed	7.489	.006	-10.043	55913	.000	-.01269	.00126	-.01517	-.01021
	Equal variances not assumed			-10.024	32991.281	**.000**	**-.01269**	.00127	-.01517	-.01021
sqrt_V5Pct_No_HS	Equal variances assumed	98.144	.000	-12.170	56291	.000	-.02102	.00173	-.02440	-.01763
	Equal variances not assumed			-11.905	31852.833	**.000**	**-.02102**	.00177	-.02448	-.01756
V5Pct_HS_Deg	Equal variances assumed	14.772	.000	-28.281	56291	.000	-.025694657	.0009085612	-.027475442	-.023913872
	Equal variances not assumed			-28.097	33025.075	**.000**	**-.025694657**	.0009145030	-.027487115	-.023902199
sqrt_V5Pct_Abv_HS	Equal variances assumed	152.479	.000	24.249	56291	.000	.03962	.00163	.03642	.04283
	Equal variances not assumed			23.698	31781.611	**.000**	**.03962**	.00167	.03635	.04290
sqrt_V6PctUNEMP	Equal variances assumed	23.584	.000	-16.007	56248	.000	-.01686	.00105	-.01892	-.01479
	Equal variances not assumed			-15.846	32672.743	**.000**	**-.01686**	.00106	-.01894	-.01477
sqrt_V7PctHISP	Equal variances assumed	149.908	.000	-2.384	56305	.017	-.00502	.00211	-.00915	-.00089
	Equal variances not assumed			-2.333	31861.764	**.020**	**-.00502**	.00215	-.00924	-.00080
arc_V7PctNotHISP	Equal variances assumed	148.583	.000	1.837	56305	.066	.00603	.00329	-.00040	.01247
	Equal variances not assumed			1.796	31834.086	**.072**	**.00603**	.00336	-.00055	.01262
sqrt_V8PctFHH	Equal variances assumed	36.693	.000	-7.216	56218	.000	-.00927	.00129	-.01179	-.00676
	Equal variances not assumed			-7.130	32511.432	**.000**	**-.00927**	.00130	-.01182	-.00672
sqrt_V8PctMHH	Equal variances assumed	16.599	.000	-7.071	56218	.000	-.00852	.00120	-.01088	-.00616
	Equal variances not assumed			-7.037	33060.962	**.000**	**-.00852**	.00121	-.01089	-.00615
ln_V9MEDHHINC	Equal variances assumed	78.366	.000	20.377	54538	.000	.09405	.00462	.08500	.10309
	Equal variances not assumed			19.930	30891.765	**.000**	**.09405**	.00472	.08480	.10330
V9ExtrmLow	Equal variances assumed	12.443	.000	-1.762	54538	.078	-.002	.001	-.003	.000
	Equal variances not assumed			-1.820	35192.155	**.069**	**-.002**	.001	-.003	.000
V9VeryLowI	Equal variances assumed	.111	.740	-.166	54538	.868	.000	.002	-.005	.004
	Equal variances not assumed			-.166	32622.878	.868	.000	.002	-.005	.004
V9LowInc	Equal variances assumed	72.123	.000	-4.176	54538	.000	-.018	.004	-.026	-.009
	Equal variances not assumed			-4.204	33057.617	**.000**	**-.018**	.004	-.026	-.009
sqrt_V10PctBlw50	Equal variances assumed	.770	**.380**	-10.550	56229	**.000**	**-.01287**	.00122	-.01526	-.01048
	Equal variances not assumed			-10.552	33471.442	.000	-.01287	.00122	-.01526	-.01048
sqrt_V10PctBlw100	Equal variances assumed	1.753	**.185**	-15.105	56229	**.000**	**-.02357**	.00156	-.02663	-.02051
	Equal variances not assumed			-15.171	33798.962	.000	-.02357	.00155	-.02661	-.02052
sqrt_V10PctBlw150	Equal variances assumed	18.081	.000	-18.952	56229	.000	-.03230	.00170	-.03564	-.02896
	Equal variances not assumed			-18.738	32569.110	**.000**	**-.03230**	.00172	-.03568	-.02892
arc_V11PctWhite	Equal variances assumed	38.667	.000	-3.341	56306	.001	-.00937	.00281	-.01487	-.00387
	Equal variances not assumed			-3.279	32098.582	**.001**	**-.00937**	.00286	-.01498	-.00377
sqrt_V11PctNonWhite	Equal variances assumed	28.238	.000	2.919	56306	.004	.00527	.00181	.00173	.00882
	Equal variances not assumed			2.872	32282.137	**.004**	**.00527**	.00184	.00167	.00887
sqrt_V11PctBlack	Equal variances assumed	13.713	.000	-8.093	56306	.000	-.01207	.00149	-.01500	-.00915
	Equal variances not assumed			-7.874	31463.924	**.000**	**-.01207**	.00153	-.01508	-.00907
sqrt_V11PctIndigenous	Equal variances assumed	423.443	.000	-19.119	56306	.000	-.01494	.00078	-.01647	-.01341
	Equal variances not assumed			-20.352	39144.248	**.000**	**-.01494**	.00073	-.01638	-.01350
sqrt_V11PctAsian	Equal variances assumed	137.739	.000	9.955	56306	.000	.01840	.00185	.01477	.02202
	Equal variances not assumed			9.630	31052.797	**.000**	**.01840**	.00191	.01465	.02214
sqrt_V11PctPacific	Equal variances assumed	448.460	.000	-12.409	56306	.000	-.00686	.00055	-.00794	-.00577
	Equal variances not assumed			-12.976	37423.832	**.000**	**-.00686**	.00053	-.00789	-.00582
sqrt_V12PctRenter	Equal variances assumed	97.857	.000	-2.627	56218	.009	-.00518	.00197	-.00904	-.00132
	Equal variances not assumed			-2.574	31866.689	**.010**	**-.00518**	.00201	-.00912	-.00124
arc_V12PctOwner	Equal variances assumed	90.733	.000	2.219	56218	.026	.00697	.00314	.00081	.01313
	Equal variances not assumed			2.178	31988.690	**.029**	**.00697**	.00320	.00070	.01324

Appendix D: Statistical Analyses for Research Question 3

Multiple Linear Regression for Social Vulnerability Variables in All Dam Flood Zones

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.216[a]	.047	.046	.430

a. Predictors: (Constant), sqrt_V12PctRenter, sqrt_V4PctDis, sqrt_V11PctPacific, sqrt_V8PctMHH, sqrt_V11PctIndigenous, V1Pct_14_85, sqrt_V11PctAsian, sqrt_V6PctUNEMP, V9VeryLowI, sqrt_V11PctBlack, V5Pct_HS_Deg, sqrt_V8PctFHH, sqrt_V10PctBlw50, V9LowInc, sqrt_V2Pct_NoAuto, sqrt_V3PctForeignBorn, V1Pct_14_65

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	580.174	17	34.128	184.995	.000[b]
	Residual	11871.277	64350	.184		
	Total	12451.451	64367			

a. Dependent Variable: ln_Flood_Zone

b. Predictors: (Constant), sqrt_V12PctRenter, sqrt_V4PctDis, sqrt_V11PctPacific, sqrt_V8PctMHH, sqrt_V11PctIndigenous, V1Pct_14_85, sqrt_V11PctAsian, sqrt_V6PctUNEMP, V9VeryLowI, sqrt_V11PctBlack, V5Pct_HS_Deg, sqrt_V8PctFHH, sqrt_V10PctBlw50, V9LowInc, sqrt_V2Pct_NoAuto, sqrt_V3PctForeignBorn, V1Pct_14_65

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.617	.013		45.831	.000		
	V1Pct_14_65	-.134	.029	-.026	-4.651	.000	.484	2.067
	V1Pct_14_85	.260	.033	.044	7.930	.000	.484	2.068
	sqrt_V2Pct_NoAuto	-.235	.015	-.083	-16.170	.000	.559	1.789
	sqrt_V3PctForeignBorn	-.411	.014	-.164	-30.021	.000	.494	2.025
	sqrt_V4PctDis	.205	.023	.047	9.124	.000	.548	1.825
	V5Pct_HS_Deg	.370	.021	.083	17.768	.000	.686	1.457
	sqrt_V6PctUNEMP	.153	.017	.040	8.922	.000	.733	1.364
	sqrt_V8PctFHH	-.078	.015	-.024	-5.012	.000	.634	1.577
	sqrt_V8PctMHH	.077	.014	.023	5.395	.000	.821	1.218
	V9VeryLowI	-.023	.008	-.013	-2.909	.004	.732	1.367
	V9LowInc	.029	.005	.030	5.938	.000	.572	1.750
	sqrt_V10PctBlw50	.055	.016	.017	3.368	.001	.615	1.627
	sqrt_V11PctBlack	.069	.012	.026	5.738	.000	.740	1.351
	sqrt_V11PctIndigenous	.172	.021	.033	8.012	.000	.857	1.166
	sqrt_V11PctAsian	.159	.011	.074	14.560	.000	.580	1.725
	sqrt_V11PctPacific	.301	.028	.043	10.769	.000	.929	1.077
	sqrt_V12PctRenter	.086	.011	.042	7.652	.000	.486	2.057

a. Dependent Variable: ln_Flood_Zone

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	V1Pct_14_65	V1Pct_14_85	sqrt_V2Pct_NoAuto	sqrt_V3PctForeignBorn	sqrt_V4PctDis	V5Pct_HS_Deg	sqrt_V6PctUNEMP
1	1	12.840	1.000	.00	.00	.00	.00	.00	.00	.00	.00
	2	1.128	3.374	.00	.00	.00	.01	.00	.00	.00	.00
	3	.877	3.826	.00	.00	.00	.00	.00	.00	.00	.00
	4	.759	4.112	.00	.00	.00	.00	.00	.00	.00	.00
	5	.497	5.082	.00	.00	.00	.00	.00	.00	.00	.00
	6	.382	5.797	.00	.00	.00	.02	.00	.00	.01	.00
	7	.314	6.390	.00	.00	.00	.02	.02	.00	.02	.01
	8	.265	6.956	.00	.00	.00	.41	.00	.00	.00	.00
	9	.206	7.888	.00	.01	.00	.20	.00	.00	.00	.01
	10	.165	8.834	.00	.01	.02	.06	.00	.00	.01	.04
	11	.125	10.129	.00	.00	.12	.01	.01	.04	.19	.10
	12	.115	10.570	.00	.05	.01	.00	.06	.03	.31	.00
	13	.092	11.827	.00	.00	.00	.00	.00	.01	.26	.65
	14	.081	12.603	.01	.00	.04	.13	.11	.00	.01	.01
	15	.069	13.619	.01	.00	.17	.02	.05	.11	.12	.14
	16	.051	15.850	.00	.01	.06	.01	.65	.02	.04	.01
	17	.021	24.595	.05	.47	.46	.03	.04	.74	.03	.00
	18	.012	33.099	.93	.44	.10	.08	.05	.06	.00	.03

a. Dependent Variable: In_Flood_Zone

Collinearity Diagnostics[a]

Model	Dimension	sqrt_V8PctFHH	sqrt_V8PctMHH	V9VeryLowI	V9LowInc	sqrt_V10PctBlw50	sqrt_V11PctBlack	sqrt_V11PctIndigenous	sqrt_V11PctAsian	sqrt_V11PctPacific	sqrt_V12PctRenter
1	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
	2	.00	.00	.37	.07	.00	.00	.01	.01	.01	.00
	3	.00	.00	.00	.00	.00	.03	.14	.01	.52	.00
	4	.00	.00	.00	.01	.00	.01	.34	.03	.37	.00
	5	.00	.01	.33	.34	.01	.02	.18	.04	.01	.00
	6	.00	.01	.19	.04	.00	.51	.12	.00	.05	.00
	7	.00	.00	.01	.14	.00	.24	.11	.25	.00	.00
	8	.00	.21	.04	.09	.01	.04	.01	.03	.02	.01
	9	.01	.65	.01	.11	.00	.00	.00	.01	.00	.00
	10	.00	.01	.00	.05	.62	.01	.00	.04	.00	.00
	11	.07	.01	.00	.00	.06	.01	.04	.09	.00	.03
	12	.15	.04	.00	.05	.01	.05	.00	.01	.01	.02
	13	.05	.00	.00	.00	.17	.02	.00	.03	.00	.00
	14	.24	.00	.02	.00	.04	.01	.01	.17	.00	.25
	15	.40	.03	.00	.00	.01	.02	.01	.00	.00	.02
	16	.01	.01	.00	.01	.05	.04	.01	.26	.00	.33
	17	.04	.01	.01	.01	.01	.00	.00	.00	.00	.00
	18	.02	.01	.01	.08	.00	.00	.00	.01	.00	.36

a. Dependent Varia

Multiple Linear Regression for Social Vulnerability Variables in HHP Dam Flood Zones

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.187[a]	.035	.035	.454

a. Predictors: (Constant), sqrt_V12PctRenter, sqrt_V11PctAsian, V1Pct_14_85, sqrt_V11PctPacific, sqrt_V11PctIndigenous, sqrt_V4PctDis, sqrt_V6PctUNEMP, sqrt_V11PctBlack, V5Pct_HS_Deg, sqrt_V8PctFHH, sqrt_V2Pct_NoAuto, sqrt_V7PctHISP, V1Pct_14_65, sqrt_V3PctForeignBorn

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	417.891	14	29.849	144.741	.000[b]
	Residual	11589.877	56200	.206		
	Total	12007.768	56214			

a. Dependent Variable: In_Flood_Zone

b. Predictors: (Constant), sqrt_V12PctRenter, sqrt_V11PctAsian, V1Pct_14_85, sqrt_V11PctPacific, sqrt_V11PctIndigenous, sqrt_V4PctDis, sqrt_V6PctUNEMP, sqrt_V11PctBlack, V5Pct_HS_Deg, sqrt_V8PctFHH, sqrt_V2Pct_NoAuto, sqrt_V7PctHISP, V1Pct_14_65, sqrt_V3PctForeignBorn

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.535	.014		38.315	.000		
	V1Pct_14_65	-.139	.032	-.026	-4.332	.000	.468	2.137
	V1Pct_14_85	.337	.038	.054	8.964	.000	.467	2.143
	sqrt_V2Pct_NoAuto	-.202	.015	-.070	-13.053	.000	.604	1.656
	sqrt_V3PctForeignBorn	-.357	.019	-.133	-18.955	.000	.348	2.876
	sqrt_V4PctDis	.206	.024	.046	8.548	.000	.604	1.656
	V5Pct_HS_Deg	.405	.023	.088	17.466	.000	.680	1.472
	sqrt_V6PctUNEMP	.122	.018	.030	6.589	.000	.805	1.242
	sqrt_V7PctHISP	.071	.014	.035	5.117	.000	.357	2.798
	sqrt_V8PctFHH	-.082	.017	-.025	-4.777	.000	.635	1.576
	sqrt_V11PctBlack	.068	.013	.024	5.103	.000	.774	1.292
	sqrt_V11PctIndigenous	.214	.024	.040	9.040	.000	.887	1.128
	sqrt_V11PctAsian	.140	.014	.062	10.230	.000	.474	2.108
	sqrt_V11PctPacific	.277	.033	.036	8.466	.000	.931	1.074
	sqrt_V12PctRenter	.094	.012	.044	7.883	.000	.552	1.811

a. Dependent Variable: In_Flood_Zone

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions						
				(Constant)	V1Pct_14_65	V1Pct_14_85	sqrt_V2Pct_NoAuto	sqrt_V3PctForeignBorn	sqrt_V4PctDis	V5Pct_HS_Deg
1	1	11.532	1.000	.00	.00	.00	.00	.00	.00	.00
	2	.859	3.663	.00	.00	.00	.00	.00	.00	.00
	3	.765	3.884	.00	.00	.00	.00	.00	.00	.00
	4	.439	5.127	.00	.00	.00	.10	.00	.00	.00
	5	.384	5.477	.00	.00	.00	.01	.00	.00	.02
	6	.297	6.230	.00	.00	.00	.49	.00	.00	.01
	7	.186	7.864	.00	.03	.00	.01	.04	.04	.00
	8	.132	9.329	.00	.03	.12	.01	.00	.00	.33
	9	.109	10.278	.00	.00	.00	.03	.00	.00	.36
	10	.090	11.332	.01	.00	.02	.06	.04	.01	.01
	11	.077	12.206	.01	.00	.10	.11	.01	.04	.03
	12	.061	13.765	.00	.01	.16	.01	.05	.15	.17
	13	.032	18.844	.00	.07	.05	.00	.56	.17	.06
	14	.022	22.967	.14	.24	.35	.09	.31	.57	.00
	15	.013	29.499	.83	.61	.19	.09	.00	.01	.00

a. Dependent Variable: In_Flood_Zone

Collinearity Diagnostics[a]

Model	Dimension	ns								
		V5Pct_HS_Deg	sqrt_V6PctUNEMP	sqrt_V7PctHISP	sqrt_V8PctFHH	sqrt_V11PctBlack	sqrt_V11PctIndigenous	sqrt_V11PctAsian	sqrt_V11PctPacific	sqrt_V12PctRenter
1	1	.00	.00	.00	.00	.00	.00	.00	.00	.00
	2	.00	.00	.00	.00	.01	.05	.00	.78	.00
	3	.00	.00	.00	.00	.01	.61	.01	.11	.00
	4	.00	.00	.00	.00	.47	.01	.03	.02	.00
	5	.02	.00	.01	.00	.05	.21	.26	.04	.00
	6	.01	.00	.00	.01	.29	.00	.01	.02	.00
	7	.00	.01	.11	.03	.01	.05	.00	.00	.01
	8	.33	.15	.00	.01	.02	.03	.04	.00	.00
	9	.36	.65	.00	.00	.02	.00	.01	.00	.01
	10	.01	.01	.04	.62	.07	.00	.05	.01	.06
	11	.03	.14	.03	.22	.02	.01	.01	.00	.26
	12	.17	.01	.07	.06	.01	.00	.02	.01	.33
	13	.06	.00	.47	.04	.01	.01	.39	.00	.00
	14	.00	.00	.21	.01	.00	.00	.07	.01	.01
	15	.00	.01	.07	.01	.00	.00	.09	.00	.31

a. Dependent Varia

Appendix E: Statistical Analyses for Research Question 4

Independent Samples Tests of Social Vulnerability Variables and Age for HHP Dams

Group Statistics

	Dam_Age_2Cats	N	Mean	Std. Deviation	Std. Error Mean
V1Pct_14_65	0 to 49 Years	4306	.3430099601	.0822952449	.0012541161
	50 or More Years	34549	.3293136547	.0846740975	.0004555466
V1Pct_14_85	0 to 49 Years	4306	.2166990015	.0721190313	.0010990384
	50 or More Years	34549	.2053924568	.0750239578	.0004036289
sqrt_V2Pct_NoAuto	0 to 49 Years	4303	.1793	.14232	.00217
	50 or More Years	34509	.2030	.15720	.00085
arc_V3PctCitizen	0 to 49 Years	4306	.9689	.21193	.00323
	50 or More Years	34549	.9405	.26428	.00142
sqrt_V3PctForeignBorn	0 to 49 Years	4306	.4169	.14268	.00217
	50 or More Years	34549	.4346	.17722	.00095
sqrt_V4PctDis	0 to 49 Years	4303	.3687	.09456	.00144
	50 or More Years	34514	.3670	.10298	.00055
ln1_V4PctDis65	0 to 49 Years	4264	.3054	.13040	.00200
	50 or More Years	34378	.3082	.13870	.00075
sqrt_V5Pct_No_HS	0 to 49 Years	4306	.3733	.18607	.00284
	50 or More Years	34537	.3670	.18592	.00100
V5Pct_HS_Deg	0 to 49 Years	4306	.2317239227	.0917196126	.0013977362
	50 or More Years	34537	.2227622128	.0999713975	.0005379395
sqrt_V5Pct_Abv_HS	0 to 49 Years	4306	.5605	.16714	.00255
	50 or More Years	34537	.5864	.17665	.00095
sqrt_V6PctUNEMP	0 to 49 Years	4303	.2923	.11356	.00173
	50 or More Years	34528	.2836	.11459	.00062
sqrt_V7PctHISP	0 to 49 Years	4306	.5613	.21403	.00326
	50 or More Years	34549	.5162	.22792	.00123
arc_V7PctNotHISP	0 to 49 Years	4306	.7420	.33554	.00511
	50 or More Years	34549	.8104	.35518	.00191
sqrt_V8PctFHH	0 to 49 Years	4303	.3360	.14320	.00218
	50 or More Years	34509	.3400	.13899	.00075
sqrt_V8PctMHH	0 to 49 Years	4303	.2093	.13065	.00199
	50 or More Years	34509	.2089	.13161	.00071
ln_V9MEDHHINC	0 to 49 Years	4140	11.0447	.47602	.00740
	50 or More Years	33477	11.0011	.49061	.00268
V9ExtrmLow	0 to 49 Years	4140	.01	.088	.001
	50 or More Years	33477	.01	.102	.001
V9VeryLowI	0 to 49 Years	4140	.06	.244	.004
	50 or More Years	33477	.07	.252	.001
V9LowInc	0 to 49 Years	4140	.30	.459	.007
	50 or More Years	33477	.31	.461	.003
sqrt_V10PctBlw50	0 to 49 Years	4303	.2206	.12553	.00191
	50 or More Years	34514	.2300	.13474	.00073
sqrt_V10PctBlw100	0 to 49 Years	4303	.3490	.16529	.00252
	50 or More Years	34514	.3660	.17232	.00093
sqrt_V10PctBlw150	0 to 49 Years	4303	.4640	.18119	.00276
	50 or More Years	34514	.4802	.18551	.00100
arc_V11PctWhite	0 to 49 Years	4306	.8253	.28453	.00434
	50 or More Years	34549	.7532	.30426	.00164
sqrt_V11PctNonWhite	0 to 49 Years	4306	.5099	.18585	.00283
	50 or More Years	34549	.5558	.19612	.00106
sqrt_V11PctBlack	0 to 49 Years	4306	.1587	.14483	.00221
	50 or More Years	34549	.1776	.16154	.00087
sqrt_V11PctIndigenous	0 to 49 Years	4306	.0532	.07566	.00115
	50 or More Years	34549	.0599	.09118	.00049
sqrt_V11PctAsian	0 to 49 Years	4306	.2261	.16334	.00249
	50 or More Years	34549	.2744	.20012	.00108
sqrt_V11PctPacific	0 to 49 Years	4306	.0210	.04917	.00075
	50 or More Years	34549	.0276	.06416	.00035
sqrt_V12PctRenter	0 to 49 Years	4303	.5907	.19563	.00298
	50 or More Years	34509	.6241	.21404	.00115
arc_V12PctOwner	0 to 49 Years	4303	.6977	.31039	.00473
	50 or More Years	34509	.6423	.34165	.00184

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
V1Pct_14_65	Equal variances assumed	16.766	.000	10.040	38853	.000	.0136963054	.0013642132	.0110224142	.0163701966
	Equal variances not assumed			10.265	5504.046	**.000**	**.0136963054**	.0013342900	.0110805698	.0163120410
V1Pct_14_85	Equal variances assumed	5.242	.022	9.365	38853	.000	.0113065447	.0012073516	.0089401060	.0136729834
	Equal variances not assumed			9.657	5532.069	**.000**	**.0113065447**	.0011708124	.0090112923	.0136017970
sqrt_V2Pct_NoAuto	Equal variances assumed	69.732	.000	-9.402	38810	.000	-.02365	.00252	-.02859	-.01872
	Equal variances not assumed			-10.157	5693.939	**.000**	**-.02365**	.00233	-.02822	-.01909
arc_V3PctCitizen	Equal variances assumed	356.419	.000	6.780	38853	.000	.02838	.00419	.02018	.03658
	Equal variances not assumed			8.042	6106.810	**.000**	**.02838**	.00353	.02146	.03530
sqrt_V3PctForeignBorn	Equal variances assumed	348.223	.000	-6.315	38853	.000	-.01773	.00281	-.02324	-.01223
	Equal variances not assumed			-7.469	6091.764	**.000**	**-.01773**	.00237	-.02239	-.01308
sqrt_V4PctDis	Equal variances assumed	46.492	.000	1.026	38815	.305	.00169	.00165	-.00154	.00493
	Equal variances not assumed			1.097	5652.760	**.273**	**.00169**	.00154	-.00133	.00472
ln1_V4PctDis65	Equal variances assumed	27.110	.000	-1.247	38640	.212	-.00279	.00224	-.00718	.00160
	Equal variances not assumed			-1.309	5529.997	**.191**	**-.00279**	.00213	-.00697	.00139
sqrt_V5Pct_No_HS	Equal variances assumed	.239	**.625**	2.081	38841	**.037**	**.00625**	.00300	.00036	.01214
	Equal variances not assumed			2.079	5433.004	.038	.00625	.00301	.00036	.01215
V5Pct_HS_Deg	Equal variances assumed	71.963	.000	5.596	38841	.000	.0089617098	.0016014368	.0058228545	.0121005651
	Equal variances not assumed			5.984	5659.295	**.000**	**.0089617098**	.0014976800	.0060256831	.0118977366
sqrt_V5Pct_Abv_HS	Equal variances assumed	45.632	.000	-9.115	38841	.000	-.02587	.00284	-.03143	-.02031
	Equal variances not assumed			-9.516	5574.216	**.000**	**-.02587**	.00272	-.03120	-.02054
sqrt_V6PctUNEMP	Equal variances assumed	1.218	**.270**	4.685	38829	**.000**	**.00867**	.00185	.00504	.01230
	Equal variances not assumed			4.718	5452.149	.000	.00867	.00184	.00507	.01227
sqrt_V7PctHISP	Equal variances assumed	42.122	.000	12.337	38853	.000	.04514	.00366	.03797	.05232
	Equal variances not assumed			12.955	5594.043	**.000**	**.04514**	.00348	.03831	.05197
arc_V7PctNotHISP	Equal variances assumed	32.700	.000	-11.995	38853	.000	-.06844	.00571	-.07962	-.05726
	Equal variances not assumed			-12.538	5577.813	**.000**	**-.06844**	.00546	-.07914	-.05774
sqrt_V8PctFHH	Equal variances assumed	4.792	.029	-1.767	38810	.077	-.00398	.00225	-.00840	.00044
	Equal variances not assumed			-1.726	5362.779	**.084**	**-.00398**	.00231	-.00851	.00054
sqrt_V8PctMHH	Equal variances assumed	.061	**.805**	.202	38810	**.840**	**.00043**	.00213	-.00374	.00460
	Equal variances not assumed			.203	5448.776	.839	.00043	.00211	-.00372	.00457
ln_V9MEDHHINC	Equal variances assumed	8.663	.003	5.415	37615	.000	.04363	.00806	.02784	.05942
	Equal variances not assumed			5.544	5286.566	**.000**	**.04363**	.00787	.02820	.05905
V9ExtrmLow	Equal variances assumed	11.154	.001	-1.666	37615	.096	-.003	.002	-.006	.000
	Equal variances not assumed			-1.873	5619.834	**.061**	**-.003**	.001	-.006	.000
V9VeryLowI	Equal variances assumed	4.434	.035	-1.049	37615	.294	-.004	.004	-.012	.004
	Equal variances not assumed			-1.074	5287.279	**.283**	**-.004**	.004	-.012	.004
V9LowInc	Equal variances assumed	1.805	**.179**	-.665	37615	**.506**	**-.005**	.008	-.020	.010
	Equal variances not assumed			-.667	5226.475	.505	-.005	.008	-.020	.010
sqrt_V10PctBlw50	Equal variances assumed	34.537	.000	-4.359	38815	.000	-.00943	.00216	-.01366	-.00519
	Equal variances not assumed			-4.606	5612.189	**.000**	**-.00943**	.00205	-.01344	-.00541
sqrt_V10PctBlw100	Equal variances assumed	9.558	.002	-6.117	38815	.000	-.01696	.00277	-.02240	-.01153
	Equal variances not assumed			-6.318	5534.150	**.000**	**-.01696**	.00269	-.02223	-.01170
sqrt_V10PctBlw150	Equal variances assumed	8.407	.004	-5.419	38815	.000	-.01621	.00299	-.02208	-.01035
	Equal variances not assumed			-5.520	5488.281	**.000**	**-.01621**	.00294	-.02197	-.01045
arc_V11PctWhite	Equal variances assumed	72.270	.000	14.772	38853	.000	.07213	.00488	.06256	.08170
	Equal variances not assumed			15.563	5605.352	**.000**	**.07213**	.00463	.06304	.08121
sqrt_V11PctNonWhite	Equal variances assumed	54.049	.000	-14.564	38853	.000	-.04590	.00315	-.05208	-.03972
	Equal variances not assumed			-15.186	5569.472	**.000**	**-.04590**	.00302	-.05182	-.03997
sqrt_V11PctBlack	Equal variances assumed	72.589	.000	-7.340	38853	.000	-.01895	.00258	-.02401	-.01389
	Equal variances not assumed			-7.990	5726.243	**.000**	**-.01895**	.00237	-.02360	-.01430
sqrt_V11PctIndigenous	Equal variances assumed	74.961	.000	-4.605	38853	.000	-.00667	.00145	-.00951	-.00383
	Equal variances not assumed			-5.321	5980.193	**.000**	**-.00667**	.00125	-.00912	-.00421
sqrt_V11PctAsian	Equal variances assumed	299.856	.000	-15.222	38853	.000	-.04831	.00317	-.05453	-.04209
	Equal variances not assumed			-17.814	6040.280	**.000**	**-.04831**	.00271	-.05363	-.04300
sqrt_V11PctPacific	Equal variances assumed	175.124	.000	-6.495	38853	.000	-.00658	.00101	-.00856	-.00459
	Equal variances not assumed			-7.974	6290.341	**.000**	**-.00658**	.00083	-.00820	-.00496
sqrt_V12PctRenter	Equal variances assumed	89.803	.000	-9.746	38810	.000	-.03342	.00343	-.04014	-.02670
	Equal variances not assumed			-10.452	5666.433	**.000**	**-.03342**	.00320	-.03969	-.02715
arc_V12PctOwner	Equal variances assumed	104.592	.000	10.126	38810	.000	.05539	.00547	.04467	.06611
	Equal variances not assumed			10.911	5683.924	**.000**	**.05539**	.00508	.04544	.06534

Independent Samples Tests of Social Vulnerability Variables and Reservoir Size for HHP Dams

Group Statistics

	NID_Storage_Cats	N	Mean	Std. Deviation	Std. Error Mean
V1Pct_14_65	Medium Reservoir	14529	.3235903032	.0843720208	.0006999719
	Large Reservoir	16693	.3394808828	.0817137193	.0006324523
V1Pct_14_85	Medium Reservoir	14529	.2030518404	.0730163947	.0006057627
	Large Reservoir	16693	.2123147483	.0748707456	.0005794887
sqrt_V2Pct_NoAuto	Medium Reservoir	14503	.2052	.15887	.00132
	Large Reservoir	16684	.1947	.15009	.00116
arc_V3PctCitizen	Medium Reservoir	14529	.9084	.26553	.00220
	Large Reservoir	16693	.9691	.25846	.00200
sqrt_V3PctForeignBorn	Medium Reservoir	14529	.4560	.17761	.00147
	Large Reservoir	16693	.4156	.17377	.00134
sqrt_V4PctDis	Medium Reservoir	14507	.3587	.10403	.00086
	Large Reservoir	16684	.3795	.09883	.00077
ln1_V4PctDis65	Medium Reservoir	14444	.3037	.14098	.00117
	Large Reservoir	16598	.3134	.13294	.00103
sqrt_V5Pct_No_HS	Medium Reservoir	14521	.3760	.19485	.00162
	Large Reservoir	16692	.3837	.17932	.00139
V5Pct_HS_Deg	Medium Reservoir	14521	.2160837837	.0998444489	.0008285632
	Large Reservoir	16692	.2357161969	.0931205911	.0007207614
sqrt_V5Pct_Abv_HS	Medium Reservoir	14521	.5898	.18092	.00150
	Large Reservoir	16692	.5567	.16795	.00130
sqrt_V6PctUNEMP	Medium Reservoir	14515	.2787	.11096	.00092
	Large Reservoir	16686	.2941	.11596	.00090
sqrt_V7PctHISP	Medium Reservoir	14529	.5425	.23988	.00199
	Large Reservoir	16693	.5264	.21907	.00170
arc_V7PctNotHISP	Medium Reservoir	14529	.7679	.37641	.00312
	Large Reservoir	16693	.7958	.34157	.00264
sqrt_V8PctFHH	Medium Reservoir	14503	.3450	.14114	.00117
	Large Reservoir	16684	.3369	.13847	.00107
sqrt_V8PctMHH	Medium Reservoir	14503	.2125	.12917	.00107
	Large Reservoir	16684	.2115	.13315	.00103
ln_V9MEDHHINC	Medium Reservoir	14017	11.0204	.49518	.00418
	Large Reservoir	16212	10.9605	.47109	.00370
V9ExtrmLow	Medium Reservoir	14017	.01	.099	.001
	Large Reservoir	16212	.01	.098	.001
V9VeryLowI	Medium Reservoir	14017	.07	.257	.002
	Large Reservoir	16212	.06	.245	.002
V9LowInc	Medium Reservoir	14017	.32	.467	.004
	Large Reservoir	16212	.31	.462	.004
sqrt_V10PctBlw50	Medium Reservoir	14507	.2286	.13227	.00110
	Large Reservoir	16684	.2341	.13287	.00103
sqrt_V10PctBlw100	Medium Reservoir	14507	.3632	.16877	.00140
	Large Reservoir	16684	.3742	.16935	.00131
sqrt_V10PctBlw150	Medium Reservoir	14507	.4751	.18549	.00154
	Large Reservoir	16684	.4936	.18223	.00141
arc_V11PctWhite	Medium Reservoir	14529	.7396	.30508	.00253
	Large Reservoir	16693	.7855	.30263	.00234
sqrt_V11PctNonWhite	Medium Reservoir	14529	.5645	.19653	.00163
	Large Reservoir	16693	.5349	.19549	.00151
sqrt_V11PctBlack	Medium Reservoir	14529	.1741	.16358	.00136
	Large Reservoir	16693	.1610	.15200	.00118
sqrt_V11PctIndigenous	Medium Reservoir	14529	.0563	.08542	.00071
	Large Reservoir	16693	.0654	.09772	.00076
sqrt_V11PctAsian	Medium Reservoir	14529	.2707	.19192	.00159
	Large Reservoir	16693	.2563	.20447	.00158
sqrt_V11PctPacific	Medium Reservoir	14529	.0222	.05870	.00049
	Large Reservoir	16693	.0288	.06290	.00049
sqrt_V12PctRenter	Medium Reservoir	14503	.6303	.21817	.00181
	Large Reservoir	16684	.6132	.19998	.00155
arc_V12PctOwner	Medium Reservoir	14503	.6317	.34829	.00289
	Large Reservoir	16684	.6615	.31870	.00247

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
V1Pct_14_65	Equal variances assumed	5.550	.018	-16.882	31220	.000	-.015890580	.0009412848	-.017735535	-.014045624
	Equal variances not assumed			-16.844	30334.903	**.000**	**-.015890580**	.0009433751	-.017739634	-.014041525
V1Pct_14_85	Equal variances assumed	12.595	.000	-11.030	31220	.000	-.009262908	.0008397634	-.010908877	-.007616939
	Equal variances not assumed			-11.050	30820.152	**.000**	**-.009262908**	.0008383052	-.010906020	-.007619796
sqrt_V2Pct_NoAuto	Equal variances assumed	72.665	.000	5.977	31185	.000	.01047	.00175	.00703	.01390
	Equal variances not assumed			5.953	30023.699	**.000**	**.01047**	.00176	.00702	.01391
arc_V3PctCitizen	Equal variances assumed	10.898	.001	-20.445	31220	.000	-.06072	.00297	-.06655	-.05490
	Equal variances not assumed			-20.407	30384.765	**.000**	**-.06072**	.00298	-.06656	-.05489
sqrt_V3PctForeignBorn	Equal variances assumed	6.107	.013	20.267	31220	.000	.04037	.00199	.03647	.04428
	Equal variances not assumed			20.237	30433.559	**.000**	**.04037**	.00200	.03646	.04428
sqrt_V4PctDis	Equal variances assumed	26.637	.000	-18.118	31189	.000	-.02083	.00115	-.02308	-.01858
	Equal variances not assumed			-18.053	30093.004	**.000**	**-.02083**	.00115	-.02309	-.01857
ln1_V4PctDis65	Equal variances assumed	75.563	.000	-6.224	31040	.000	-.00968	.00156	-.01273	-.00663
	Equal variances not assumed			-6.199	29875.726	**.000**	**-.00968**	.00156	-.01275	-.00662
sqrt_V5Pct_No_HS	Equal variances assumed	147.442	.000	-3.613	31211	.000	-.00765	.00212	-.01181	-.00350
	Equal variances not assumed			-3.592	29749.448	**.000**	**-.00765**	.00213	-.01183	-.00348
V5Pct_HS_Deg	Equal variances assumed	101.987	.000	-17.964	31211	.000	-.019632413	.0010928826	-.021774506	-.017490320
	Equal variances not assumed			-17.877	29910.078	**.000**	**-.019632413**	.0010981867	-.021784906	-.017479920
sqrt_V5Pct_Abv_HS	Equal variances assumed	177.768	.000	16.747	31211	.000	.03309	.00198	.02921	.03696
	Equal variances not assumed			16.661	29855.004	**.000**	**.03309**	.00199	.02919	.03698
sqrt_V6PctUNEMP	Equal variances assumed	39.758	.000	-11.915	31199	.000	-.01537	.00129	-.01790	-.01284
	Equal variances not assumed			-11.951	30917.475	**.000**	**-.01537**	.00129	-.01789	-.01285
sqrt_V7PctHISP	Equal variances assumed	279.495	.000	6.218	31220	.000	.01616	.00260	.01106	.02125
	Equal variances not assumed			6.179	29668.840	**.000**	**.01616**	.00261	.01103	.02128
arc_V7PctNotHISP	Equal variances assumed	302.121	.000	-6.856	31220	.000	-.02787	.00406	-.03583	-.01990
	Equal variances not assumed			-6.810	29587.521	**.000**	**-.02787**	.00409	-.03589	-.01985
sqrt_V8PctFHH	Equal variances assumed	10.351	.001	5.116	31185	.000	.00812	.00159	.00501	.01122
	Equal variances not assumed			5.110	30413.601	**.000**	**.00812**	.00159	.00500	.01123
sqrt_V8PctMHH	Equal variances assumed	25.609	.000	.698	31185	.485	.00104	.00149	-.00188	.00396
	Equal variances not assumed			.699	30812.721	**.484**	**.00104**	.00149	-.00188	.00396
ln_V9MEDHHINC	Equal variances assumed	32.599	.000	10.756	30227	.000	.05985	.00556	.04894	.07075
	Equal variances not assumed			10.718	29118.331	**.000**	**.05985**	.00558	.04890	.07079
V9ExtrmLow	Equal variances assumed	.414	**.520**	.322	30227	**.748**	**.000**	.001	-.002	.003
	Equal variances not assumed			.321	29435.378	.748	.000	.001	-.002	.003
V9VeryLowI	Equal variances assumed	22.083	.000	2.350	30227	.019	.007	.003	.001	.012
	Equal variances not assumed			2.342	29153.762	**.019**	**.007**	.003	.001	.012
V9LowInc	Equal variances assumed	18.368	.000	2.148	30227	**.032**	**.012**	.005	.001	.022
	Equal variances not assumed			2.147	29514.193	.032	.012	.005	.001	.022
sqrt_V10PctBlw50	Equal variances assumed	7.863	.005	-3.660	31189	.000	-.00551	.00151	-.00846	-.00256
	Equal variances not assumed			-3.661	30627.864	**.000**	**-.00551**	.00150	-.00846	-.00256
sqrt_V10PctBlw100	Equal variances assumed	3.712	**.054**	-5.713	31189	**.000**	**-.01097**	.00192	-.01473	-.00720
	Equal variances not assumed			-5.715	30618.497	.000	-.01097	.00192	-.01473	-.00721
sqrt_V10PctBlw150	Equal variances assumed	.861	**.354**	-8.834	31189	**.000**	**-.01843**	.00209	-.02252	-.01434
	Equal variances not assumed			-8.823	30433.085	.000	-.01843	.00209	-.02252	-.01433
arc_V11PctWhite	Equal variances assumed	6.925	.009	-13.317	31220	.000	-.04590	.00345	-.05265	-.03914
	Equal variances not assumed			-13.310	30559.582	**.000**	**-.04590**	.00345	-.05266	-.03914
sqrt_V11PctNonWhite	Equal variances assumed	4.317	.038	13.293	31220	.000	.02956	.00222	.02520	.03392
	Equal variances not assumed			13.288	30583.402	**.000**	**.02956**	.00222	.02520	.03392
sqrt_V11PctBlack	Equal variances assumed	13.726	.000	7.338	31220	.000	.01311	.00179	.00961	.01661
	Equal variances not assumed			7.301	29880.471	**.000**	**.01311**	.00180	.00959	.01663
sqrt_V11PctIndigenous	Equal variances assumed	35.221	.000	-8.719	31220	.000	-.00912	.00105	-.01117	-.00707
	Equal variances not assumed			-8.800	31219.445	**.000**	**-.00912**	.00104	-.01115	-.00709
sqrt_V11PctAsian	Equal variances assumed	43.604	.000	6.368	31220	.000	.01436	.00225	.00994	.01878
	Equal variances not assumed			6.396	31042.859	**.000**	**.01436**	.00224	.00996	.01876
sqrt_V11PctPacific	Equal variances assumed	201.756	.000	-9.503	31220	.000	-.00658	.00069	-.00793	-.00522
	Equal variances not assumed			-9.548	31068.838	**.000**	**-.00658**	.00069	-.00792	-.00523
sqrt_V12PctRenter	Equal variances assumed	227.785	.000	7.236	31185	.000	.01714	.00237	.01250	.02178
	Equal variances not assumed			7.193	29665.578	**.000**	**.01714**	.00238	.01247	.02181
arc_V12PctOwner	Equal variances assumed	239.668	.000	-7.864	31185	.000	-.02971	.00378	-.03712	-.02230
	Equal variances not assumed			-7.815	29643.661	**.000**	**-.02971**	.00380	-.03716	-.02226

Group Statistics

	NID_Storage_Cats	N	Mean	Std. Deviation	Std. Error Mean
V1Pct_14_65	Small Reservoir	7654	.3257329449	.0889437837	.0010166498
	Large Reservoir	16693	.3394808828	.0817137193	.0006324523
V1Pct_14_85	Small Reservoir	7654	.2010613892	.0770718234	.0008809503
	Large Reservoir	16693	.2123147483	.0748707456	.0005794887
sqrt_V2Pct_NoAuto	Small Reservoir	7646	.2034	.16153	.00185
	Large Reservoir	16684	.1947	.15009	.00116
arc_V3PctCitizen	Small Reservoir	7654	.9556	.24029	.00275
	Large Reservoir	16693	.9691	.25846	.00200
sqrt_V3PctForeignBorn	Small Reservoir	7654	.4252	.16136	.00184
	Large Reservoir	16693	.4156	.17377	.00134
sqrt_V4PctDis	Small Reservoir	7647	.3565	.10241	.00117
	Large Reservoir	16684	.3795	.09883	.00077
ln1_V4PctDis65	Small Reservoir	7621	.3041	.14167	.00162
	Large Reservoir	16598	.3134	.13294	.00103
sqrt_V5Pct_No_HS	Small Reservoir	7651	.3168	.17349	.00198
	Large Reservoir	16692	.3837	.17932	.00139
V5Pct_HS_Deg	Small Reservoir	7651	.2122608283	.1073535495	.0012273186
	Large Reservoir	16692	.2357161969	.0931205911	.0007207614
sqrt_V5Pct_Abv_HS	Small Reservoir	7651	.6304	.17167	.00196
	Large Reservoir	16692	.5567	.16795	.00130
sqrt_V6PctUNEMP	Small Reservoir	7651	.2749	.11628	.00133
	Large Reservoir	16686	.2941	.11596	.00090
sqrt_V7PctHISP	Small Reservoir	7654	.4690	.20935	.00239
	Large Reservoir	16693	.5264	.21907	.00170
arc_V7PctNotHISP	Small Reservoir	7654	.8853	.32050	.00366
	Large Reservoir	16693	.7958	.34157	.00264
sqrt_V8PctFHH	Small Reservoir	7646	.3345	.13809	.00158
	Large Reservoir	16684	.3369	.13847	.00107
sqrt_V8PctMHH	Small Reservoir	7646	.1963	.13147	.00150
	Large Reservoir	16684	.2115	.13315	.00103
ln_V9MEDHHINC	Small Reservoir	7408	11.0780	.50593	.00588
	Large Reservoir	16212	10.9605	.47109	.00370
V9ExtrmLow	Small Reservoir	7408	.01	.108	.001
	Large Reservoir	16212	.01	.098	.001
V9VeryLowI	Small Reservoir	7408	.07	.251	.003
	Large Reservoir	16212	.06	.245	.002
V9LowInc	Small Reservoir	7408	.27	.444	.005
	Large Reservoir	16212	.31	.462	.004
sqrt_V10PctBlw50	Small Reservoir	7647	.2186	.13783	.00158
	Large Reservoir	16684	.2341	.13287	.00103
sqrt_V10PctBlw100	Small Reservoir	7647	.3437	.17983	.00206
	Large Reservoir	16684	.3742	.16935	.00131
sqrt_V10PctBlw150	Small Reservoir	7647	.4512	.18706	.00214
	Large Reservoir	16684	.4936	.18223	.00141
arc_V11PctWhite	Small Reservoir	7654	.7495	.29596	.00338
	Large Reservoir	16693	.7855	.30263	.00234
sqrt_V11PctNonWhite	Small Reservoir	7654	.5585	.19134	.00219
	Large Reservoir	16693	.5349	.19549	.00151
sqrt_V11PctBlack	Small Reservoir	7654	.2098	.16428	.00188
	Large Reservoir	16693	.1610	.15200	.00118
sqrt_V11PctIndigenous	Small Reservoir	7654	.0511	.07775	.00089
	Large Reservoir	16693	.0654	.09772	.00076
sqrt_V11PctAsian	Small Reservoir	7654	.2932	.18717	.00214
	Large Reservoir	16693	.2563	.20447	.00158
sqrt_V11PctPacific	Small Reservoir	7654	.0315	.06876	.00079
	Large Reservoir	16693	.0288	.06290	.00049
sqrt_V12PctRenter	Small Reservoir	7646	.6171	.22602	.00258
	Large Reservoir	16684	.6132	.19998	.00155
arc_V12PctOwner	Small Reservoir	7646	.6517	.36077	.00413
	Large Reservoir	16684	.6615	.31870	.00247

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
V1Pct_14_65	Equal variances assumed	13.301	.000	-11.849	24345	.000	-.013747938	.0011602926	-.016022182	-.011473694
	Equal variances not assumed			-11.482	13776.637	**.000**	**-.013747938**	.0011973190	-.016094846	-.011401030
V1Pct_14_85	Equal variances assumed	3.725	**.054**	-10.788	24345	**.000**	**-.011253359**	.0010431777	-.013298051	-.009208667
	Equal variances not assumed			-10.672	14466.914	.000	-.011253359	.0010544575	-.013320231	-.009186487
sqrt_V2Pct_NoAuto	Equal variances assumed	69.950	.000	4.114	24328	.000	.00874	.00212	.00458	.01290
	Equal variances not assumed			4.004	13894.690	**.000**	**.00874**	.00218	.00446	.01302
arc_V3PctCitizen	Equal variances assumed	105.101	.000	-3.878	24345	.000	-.01354	.00349	-.02038	-.00670
	Equal variances not assumed			-3.984	15877.979	**.000**	**-.01354**	.00340	-.02020	-.00688
sqrt_V3PctForeignBorn	Equal variances assumed	106.920	.000	4.073	24345	.000	.00956	.00235	.00496	.01416
	Equal variances not assumed			4.186	15894.921	**.000**	**.00956**	.00228	.00508	.01403
sqrt_V4PctDis	Equal variances assumed	9.820	.002	-16.646	24329	.000	-.02298	.00138	-.02569	-.02027
	Equal variances not assumed			-16.427	14367.021	**.000**	**-.02298**	.00140	-.02572	-.02024
ln1_V4PctDis65	Equal variances assumed	30.599	.000	-4.946	24217	.000	-.00929	.00188	-.01297	-.00561
	Equal variances not assumed			-4.831	13977.687	**.000**	**-.00929**	.00192	-.01306	-.00552
sqrt_V5Pct_No_HS	Equal variances assumed	9.609	.002	-27.287	24341	.000	-.06687	.00245	-.07168	-.06207
	Equal variances not assumed			-27.624	15295.293	**.000**	**-.06687**	.00242	-.07162	-.06213
V5Pct_HS_Deg	Equal variances assumed	279.025	.000	-17.368	24341	.000	-.023455369	.0013504826	-.026102397	-.020808341
	Equal variances not assumed			-16.479	13121.273	**.000**	**-.023455369**	.0014233088	-.026245260	-.020665477
sqrt_V5Pct_Abv_HS	Equal variances assumed	17.979	.000	31.553	24341	.000	.07368	.00234	.06910	.07825
	Equal variances not assumed			31.297	14551.116	.000	.07368	.00235	.06906	.07829
sqrt_V6PctUNEMP	Equal variances assumed	2.853	**.091**	-11.967	24335	**.000**	**-.01918**	.00160	-.02232	-.01604
	Equal variances not assumed			-11.955	14806.706	.000	-.01918	.00160	-.02232	-.01603
sqrt_V7PctHISP	Equal variances assumed	26.643	.000	-19.252	24345	.000	-.05742	.00298	-.06327	-.05158
	Equal variances not assumed			-19.579	15478.124	**.000**	**-.05742**	.00293	-.06317	-.05167
arc_V7PctNotHISP	Equal variances assumed	49.435	.000	19.352	24345	.000	.08952	.00463	.08045	.09858
	Equal variances not assumed			19.814	15742.636	**.000**	**.08952**	.00452	.08066	.09837
sqrt_V8PctFHH	Equal variances assumed	.091	**.763**	-1.246	24328	**.213**	**-.00238**	.00191	-.00613	.00136
	Equal variances not assumed			-1.248	14867.415	.212	-.00238	.00191	-.00612	.00136
sqrt_V8PctMHH	Equal variances assumed	1.952	**.162**	-8.271	24328	**.000**	**-.01515**	.00183	-.01874	-.01156
	Equal variances not assumed			-8.310	15002.827	.000	-.01515	.00182	-.01872	-.01158
ln_V9MEDHHINC	Equal variances assumed	35.302	.000	17.366	23618	.000	.11746	.00676	.10420	.13072
	Equal variances not assumed			16.911	13472.597	**.000**	**.11746**	.00695	.10384	.13107
V9ExtrmLow	Equal variances assumed	8.980	.003	1.499	23618	.134	.002	.001	-.001	.005
	Equal variances not assumed			1.445	13160.994	**.148**	**.002**	.001	-.001	.005
V9VeryLowI	Equal variances assumed	3.761	**.052**	.971	23618	.332	.003	.003	-.003	.010
	Equal variances not assumed			.962	14050.033	**.336**	**.003**	.003	-.003	.010
V9LowInc	Equal variances assumed	159.086	.000	-6.091	23618	.000	-.039	.006	-.052	-.026
	Equal variances not assumed			-6.182	14884.634	**.000**	**-.039**	.006	-.051	-.027
sqrt_V10PctBlw50	Equal variances assumed	4.582	.032	-8.367	24329	.000	-.01553	.00186	-.01917	-.01190
	Equal variances not assumed			-8.254	14354.115	**.000**	**-.01553**	.00188	-.01922	-.01185
sqrt_V10PctBlw100	Equal variances assumed	26.549	.000	-12.773	24329	.000	-.03047	.00239	-.03514	-.02579
	Equal variances not assumed			-12.492	14060.406	.000	-.03047	.00244	-.03525	-.02569
sqrt_V10PctBlw150	Equal variances assumed	2.275	**.131**	-16.708	24329	**.000**	**-.04240**	.00254	-.04737	-.03742
	Equal variances not assumed			-16.546	14488.151	.000	-.04240	.00256	-.04742	-.03738
arc_V11PctWhite	Equal variances assumed	3.165	**.075**	-8.667	24345	**.000**	**-.03596**	.00415	-.04409	-.02783
	Equal variances not assumed			-8.739	15152.975	.000	-.03596	.00411	-.04403	-.02789
sqrt_V11PctNonWhite	Equal variances assumed	3.115	**.078**	8.803	24345	**.000**	**.02360**	.00268	.01834	.02885
	Equal variances not assumed			8.873	15141.103	.000	.02360	.00266	.01838	.02881
sqrt_V11PctBlack	Equal variances assumed	33.204	.000	22.697	24345	.000	.04887	.00215	.04465	.05309
	Equal variances not assumed			22.052	13860.872	**.000**	**.04887**	.00222	.04452	.05321
sqrt_V11PctIndigenous	Equal variances assumed	152.278	.000	-11.308	24345	.000	-.01435	.00127	-.01684	-.01186
	Equal variances not assumed			-12.295	18342.819	**.000**	**-.01435**	.00117	-.01664	-.01206
sqrt_V11PctAsian	Equal variances assumed	82.628	.000	13.417	24345	.000	.03689	.00275	.03150	.04228
	Equal variances not assumed			13.863	16108.370	**.000**	**.03689**	.00266	.03168	.04211
sqrt_V11PctPacific	Equal variances assumed	42.304	.000	3.026	24345	.002	.00271	.00089	.00095	.00446
	Equal variances not assumed			2.927	13726.714	**.003**	**.00271**	.00092	.00089	.00452
sqrt_V12PctRenter	Equal variances assumed	268.746	.000	1.371	24328	.170	.00395	.00288	-.00170	.00959
	Equal variances not assumed			1.310	13328.927	**.190**	**.00395**	.00301	-.00196	.00985
arc_V12PctOwner	Equal variances assumed	270.694	.000	-2.132	24328	.033	-.00979	.00459	-.01879	-.00079
	Equal variances not assumed			-2.037	13310.661	**.042**	**-.00979**	.00481	-.01921	-.00037

Independent Samples Tests of Social Vulnerability Variables and Inspection Compliance for HHP Dams

Group Statistics

	Inspect_Test_Cats	N	Mean	Std. Deviation	Std. Error Mean
V1Pct_14_65	PASS	20395	.3374631488	.0817966162	.0005727611
	FAIL	18481	.3235212886	.0868185673	.0006386308
V1Pct_14_85	PASS	20395	.2075654387	.0713627526	.0004997004
	FAIL	18481	.2056131720	.0783865584	.0005766056
sqrt_V2Pct_NoAuto	PASS	20371	.1813	.14322	.00100
	FAIL	18462	.2213	.16605	.00122
arc_V3PctCitizen	PASS	20395	.9592	.27647	.00194
	FAIL	18481	.9267	.23748	.00175
sqrt_V3PctForeignBorn	PASS	20395	.4218	.18550	.00130
	FAIL	18481	.4445	.15913	.00117
sqrt_V4PctDis	PASS	20373	.3692	.10340	.00072
	FAIL	18465	.3650	.10053	.00074
ln1_V4PctDis65	PASS	20247	.3000	.13007	.00091
	FAIL	18416	.3166	.14534	.00107
sqrt_V5Pct_No_HS	PASS	20390	.3744	.18018	.00126
	FAIL	18474	.3603	.19179	.00141
V5Pct_HS_Deg	PASS	20390	.2270786520	.0950248398	.0006654701
	FAIL	18474	.2201039984	.1033523836	.0007603964
sqrt_V5Pct_Abv_HS	PASS	20390	.5746	.16799	.00118
	FAIL	18474	.5935	.18350	.00135
sqrt_V6PctUNEMP	PASS	20379	.2816	.10976	.00077
	FAIL	18473	.2878	.11941	.00088
sqrt_V7PctHISP	PASS	20395	.5286	.23359	.00164
	FAIL	18481	.5128	.21886	.00161
arc_V7PctNotHISP	PASS	20395	.7905	.36499	.00256
	FAIL	18481	.8168	.34021	.00250
sqrt_V8PctFHH	PASS	20371	.3316	.13466	.00094
	FAIL	18462	.3482	.14408	.00106
sqrt_V8PctMHH	PASS	20371	.2090	.12957	.00091
	FAIL	18462	.2087	.13358	.00098
ln_V9MEDHHINC	PASS	19661	11.0370	.47124	.00336
	FAIL	17976	10.9720	.50586	.00377
V9ExtrmLow	PASS	19661	.00	.066	.000
	FAIL	17976	.02	.127	.001
V9VeryLowI	PASS	19661	.05	.212	.002
	FAIL	17976	.09	.286	.002
V9LowInc	PASS	19661	.28	.450	.003
	FAIL	17976	.33	.471	.004
sqrt_V10PctBlw50	PASS	20373	.2218	.12314	.00086
	FAIL	18465	.2369	.14415	.00106
sqrt_V10PctBlw100	PASS	20373	.3535	.15852	.00111
	FAIL	18465	.3757	.18430	.00136
sqrt_V10PctBlw150	PASS	20373	.4680	.17777	.00125
	FAIL	18465	.4898	.19218	.00141
arc_V11PctWhite	PASS	20395	.8007	.30086	.00211
	FAIL	18481	.7178	.29938	.00220
sqrt_V11PctNonWhite	PASS	20395	.5251	.19463	.00136
	FAIL	18481	.5787	.19270	.00142
sqrt_V11PctBlack	PASS	20395	.1297	.13266	.00093
	FAIL	18481	.2260	.17167	.00126
sqrt_V11PctIndigenous	PASS	20395	.0688	.09940	.00070
	FAIL	18481	.0486	.07627	.00056
sqrt_V11PctAsian	PASS	20395	.2543	.20496	.00144
	FAIL	18481	.2851	.18645	.00137
sqrt_V11PctPacific	PASS	20395	.0209	.05263	.00037
	FAIL	18481	.0335	.07162	.00053
sqrt_V12PctRenter	PASS	20371	.5890	.20714	.00145
	FAIL	18462	.6549	.21260	.00156
arc_V12PctOwner	PASS	20371	.6989	.32815	.00230
	FAIL	18462	.5927	.34150	.00251

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
V1Pct_14_65	Equal variances assumed	15.765	.000	16.300	38874	.000	.0139418602	.0008553388	.0122653752	.0156183452
	Equal variances not assumed			16.252	37928.852	**.000**	**.0139418602**	.0008578488	.0122604543	.0156232661
V1Pct_14_85	Equal variances assumed	142.510	.000	2.570	38874	.010	.0019522667	.0007594954	.0004636371	.0034408963
	Equal variances not assumed			2.559	37496.778	**.011**	**.0019522667**	.0007630036	.0004567592	.0034477741
sqrt_V2Pct_NoAuto	Equal variances assumed	422.883	.000	-25.457	38831	.000	-.03996	.00157	-.04304	-.03689
	Equal variances not assumed			-25.274	36648.124	**.000**	**-.03996**	.00158	-.04306	-.03686
arc_V3PctCitizen	Equal variances assumed	641.211	.000	12.347	38874	.000	.03243	.00263	.02729	.03758
	Equal variances not assumed			12.439	38764.177	**.000**	**.03243**	.00261	.02732	.03755
sqrt_V3PctForeignBorn	Equal variances assumed	664.776	.000	-12.924	38874	.000	-.02277	.00176	-.02622	-.01931
	Equal variances not assumed			-13.021	38758.813	**.000**	**-.02277**	.00175	-.02619	-.01934
sqrt_V4PctDis	Equal variances assumed	15.881	.000	4.120	38836	.000	.00427	.00104	.00224	.00630
	Equal variances not assumed			4.126	38645.273	**.000**	**.00427**	.00104	.00224	.00630
ln1_V4PctDis65	Equal variances assumed	145.855	.000	-11.866	38661	.000	-.01662	.00140	-.01937	-.01388
	Equal variances not assumed			-11.804	37106.807	**.000**	**-.01662**	.00141	-.01938	-.01386
sqrt_V5Pct_No_HS	Equal variances assumed	140.818	.000	7.470	38862	.000	.01410	.00189	.01040	.01780
	Equal variances not assumed			7.447	37882.734	**.000**	**.01410**	.00189	.01039	.01781
V5Pct_HS_Deg	Equal variances assumed	196.374	.000	6.931	38862	.000	.0069746536	.0010063051	.0050022710	.0089470362
	Equal variances not assumed			6.902	37614.874	**.000**	**.0069746536**	.0010104717	.0049941023	.0089552048
sqrt_V5Pct_Abv_HS	Equal variances assumed	382.848	.000	-10.621	38862	.000	-.01894	.00178	-.02243	-.01544
	Equal variances not assumed			-10.575	37558.454	**.000**	**-.01894**	.00179	-.02245	-.01543
sqrt_V6PctUNEMP	Equal variances assumed	87.283	.000	-5.356	38850	.000	-.00623	.00116	-.00851	-.00395
	Equal variances not assumed			-5.334	37605.926	**.000**	**-.00623**	.00117	-.00852	-.00394
sqrt_V7PctHISP	Equal variances assumed	214.463	.000	6.878	38874	.000	.01584	.00230	.01132	.02035
	Equal variances not assumed			6.900	38830.723	**.000**	**.01584**	.00230	.01134	.02033
arc_V7PctNotHISP	Equal variances assumed	234.315	.000	-7.346	38874	.000	-.02637	.00359	-.03340	-.01933
	Equal variances not assumed			-7.372	38843.012	**.000**	**-.02637**	.00358	-.03338	-.01936
sqrt_V8PctFHH	Equal variances assumed	115.328	.000	-11.703	38831	.000	-.01656	.00141	-.01933	-.01378
	Equal variances not assumed			-11.664	37794.311	**.000**	**-.01656**	.00142	-.01934	-.01377
sqrt_V8PctMHH	Equal variances assumed	30.162	.000	.232	38831	.817	.00031	.00134	-.00231	.00293
	Equal variances not assumed			.231	38196.737	**.817**	**.00031**	.00134	-.00231	.00293
ln_V9MEDHHINC	Equal variances assumed	71.659	.000	12.903	37635	.000	.06499	.00504	.05512	.07486
	Equal variances not assumed			12.862	36694.458	**.000**	**.06499**	.00505	.05509	.07489
V9ExtrmLow	Equal variances assumed	559.802	.000	-11.750	37635	.000	-.012	.001	-.014	-.010
	Equal variances not assumed			-11.451	26413.601	**.000**	**-.012**	.001	-.014	-.010
V9VeryLowI	Equal variances assumed	1119.220	.000	-16.541	37635	.000	-.043	.003	-.048	-.038
	Equal variances not assumed			-16.327	32968.840	**.000**	**-.043**	.003	-.048	-.038
V9LowInc	Equal variances assumed	463.291	.000	-10.856	37635	.000	-.052	.005	-.061	-.042
	Equal variances not assumed			-10.833	36949.706	**.000**	**-.052**	.005	-.061	-.042
sqrt_V10PctBlw50	Equal variances assumed	429.398	.000	-11.185	38836	.000	-.01518	.00136	-.01784	-.01252
	Equal variances not assumed			-11.100	36495.524	**.000**	**-.01518**	.00137	-.01786	-.01250
sqrt_V10PctBlw100	Equal variances assumed	546.348	.000	-12.765	38836	.000	-.02221	.00174	-.02562	-.01880
	Equal variances not assumed			-12.672	36608.913	**.000**	**-.02221**	.00175	-.02565	-.01878
sqrt_V10PctBlw150	Equal variances assumed	177.201	.000	-11.619	38836	.000	-.02181	.00188	-.02549	-.01813
	Equal variances not assumed			-11.574	37672.398	**.000**	**-.02181**	.00188	-.02550	-.01812
arc_V11PctWhite	Equal variances assumed	.711	**.399**	27.199	38874	**.000**	**.08291**	.00305	.07694	.08889
	Equal variances not assumed			27.205	38535.889	.000	.08291	.00305	.07694	.08888
sqrt_V11PctNonWhite	Equal variances assumed	.117	**.732**	-27.241	38874	**.000**	**-.05359**	.00197	-.05745	-.04974
	Equal variances not assumed			-27.255	38570.772	.000	-.05359	.00197	-.05745	-.04974
sqrt_V11PctBlack	Equal variances assumed	1315.337	.000	-62.237	38874	.000	-.09636	.00155	-.09940	-.09333
	Equal variances not assumed			-61.469	34686.607	**.000**	**-.09636**	.00157	-.09943	-.09329
sqrt_V11PctIndigenous	Equal variances assumed	680.011	.000	22.276	38874	.000	.02017	.00091	.01840	.02194
	Equal variances not assumed			22.562	37864.950	**.000**	**.02017**	.00089	.01842	.02192
sqrt_V11PctAsian	Equal variances assumed	128.433	.000	-15.433	38874	.000	-.03078	.00199	-.03469	-.02687
	Equal variances not assumed			-15.505	38873.403	**.000**	**-.03078**	.00199	-.03467	-.02689
sqrt_V11PctPacific	Equal variances assumed	1304.806	.000	-19.811	38874	.000	-.01255	.00063	-.01379	-.01131
	Equal variances not assumed			-19.522	33682.880	**.000**	**-.01255**	.00064	-.01381	-.01129
sqrt_V12PctRenter	Equal variances assumed	8.255	.004	-30.905	38831	.000	-.06587	.00213	-.07005	-.06169
	Equal variances not assumed			-30.865	38239.330	**.000**	**-.06587**	.00213	-.07005	-.06169
arc_V12PctOwner	Equal variances assumed	31.486	.000	31.237	38831	.000	.10620	.00340	.09953	.11286
	Equal variances not assumed			31.176	38103.588	**.000**	**.10620**	.00341	.09952	.11287

Appendix E: Inundation Boundary Maps by Dam Name and High Hazard Potential

Dam Name (NID 2016)	HHP Dam (CalOES 2016)	HHP Dam (NID 2002)	Non-HHP Dam
1) 10 Mg Walteria	X		
2) 10th and Western	X		
3) 18 Mg Walteria	X		
4) Adobe Creek	X		
5) Agnew Lake	X		
6) Agua Tibia			X
7) Alessandro	X		
8) Alisal Creek	X		
9) Almaden	X		
10) Almaden Valley	X		
11) Almond	X		
12) Alta Loma Basin #1	X		
13) Anderson			X
14) Antelope Kern	X		
15) Antelope Plumas			X
16) Anthony House			X
17) Antioch Res	X		
18) Argyle No 2	X		
19) Austrian	X		
20) Azalea	X		
21) Balch Afterbay	X		
22) Balch Diversion	X		
23) Balsam Meadow Forebay Main	X		
24) Barrett	X		
25) Bayley Reservoir			X
26) Bear Dam		X	
27) Bear Gulch	X		
28) Bear Valley		X	
29) Beardsley	X		
30) Bell Canyon	X		
31) Berrenda Mesa	X		
32) Bethany Forebay	X		
33) Bidwell Bar Canyon Saddle			X
34) Bidwell Lake	X		
35) Big Canyon	X		
36) Big Creek	X		
37) Big Creek Dam No. 4			X

38) Big Creek Dam No. 5	X		
39) Big Creek Dam No. 6			X
40) Big Creek Dam No. 7	X		
41) Big Dalton	X		
42) Big Dry Creek		X	
43) Big Pine Creek	X		
44) Big Sage	X		
45) Big Santa Anita	X		
46) Big Tujunga No. 1	X		
47) Bishop Creek Intake No. 2	X		
48) Black Butte Dam		X	
49) Black Mountain Water Tank	X		
50) Black Rock Creek			X
51) Blackburn	X		
52) Blakely			X
53) Blossom Valley Reservoir	X		
54) Boca		X	
55) Bouquet Canyon	X		
56) Bowman Main	X		
57) Box Canyon	X		
58) Boxsprings	X		
59) Boyd No. 1	X		
60) Boyd No. 2	X		
61) Bradbury		X	
62) Brand Park	X		
63) Brea Dam		X	
64) Bridgeport		X	
65) Briones	X		
66) Brooktrails 3 North	X		
67) Buchanan Dam		X	
68) Bucks Lake			X
69) Butt Valley	X		
70) C L Tilden Park	X		
71) Calavera	X		
72) Calaveras	X		
73) Calero	X		
74) Camanche Main	X		
75) Cameron Park	X		
76) Camille, Lake			X
77) Camp Far West	X		
78) Caples Lake Main		X	
79) Carbon Canyon Dam		X	
80) Caribou Lake	X		
81) Casitas		X	

82) Castaic	X		
83) Cedar Lake	X		
84) Cedar Springs	X		
85) Central	X		
86) Century	X		
87) Chabot	X		
88) Chabot, Lake	X		
89) Cherry Flat	X		
90) Chet Harritt	X		
91) Chevy Chase 1290	X		
92) Chili Bar	X		
93) Chollas	X		
94) Chorro Creek	X		
95) Clear Lake		X	
96) Clifton Court Forebay		X	
97) Clover Valley			X
98) Cogswell	X		
99) Coit			X
100) Columbine	X		
101) Combie	X		
102) Conn Creek	X		
103) Contra Loma		X	
104) Copco No 1	X		
105) Copper Basin	X		
106) Courtright	X		
107) Coyote	X		
108) Coyote Creek	X		
109) Coyote Percolation	X		
110) Coyote Valley Dam		X	
111) Crafton Hills	X		
112) Crane Valley	X		
113) Cresta			X
114) Crocker		X	
115) Crocker Diversion			X
116) Cucamonga Creek Debris Basin	X		
117) Cull Creek	X		
118) Cuyamaca	X		
119) Cynthia, Lake			X
120) Danville	X		
121) De Sabla Forebay			X
122) Declez Retention	X		
123) Decoto Reservoir	X		
124) Deer Creek	X		
125) Deer Creek Diversion	X		

126) Del Valle	X		
127) Delta Pond	X		
128) Devils Gate	X		
129) Diamond Valley Lake	X		
130) Diamond Valley Lake Forebay	X		
131) Diederich Res	X		
132) Diemer No. 8	X		
133) Diemer Reservoir	X		
134) Dixon	X		
135) Don Pedro Main	X		
136) Donnells	X		
137) Donner Lake	X		
138) Dos Pueblos	X		
139) Drum Forebay		X	
140) Dry Canyon	X		
141) Dry Creek	X		
142) Dunsmuir Reservoir	X		
143) Dutch Flat Afterbay			X
144) Dutch Flat Forebay			X
145) Eagle Rock	X		
146) East Glorietta	X		
147) East Park		X	
148) Eastlake	X		
149) Eaton Wash Debris Basin	X		
150) Echo Lake	X		
151) Ed R Levin	X		
152) El Capitan	X		
153) El Toro Reservoir	X		
154) Eleanor, Lake	X		
155) Elmer J Chesbro	X		
156) Elysian	X		
157) Emerald Lake 1 Lower	X		
158) Emerson	X		
159) Encino	X		
160) Ewing			X
161) Exchequer Main		X	
162) Fairmont			X
163) Fancher Creek	X		
164) Farmington Dam			X
165) Felt Lake	X		
166) Fern Lake	X		
167) Ferro Debris Basin			X
168) Fleming Hill No. 2	X		
169) Florence Lake	X		

170) Folsom		X	
171) Folsom - Mormon Island Auxiliary Dam			X
172) Folsom Dike 4		X	
173) Folsom Dike 5		X	
174) Folsom Dike 6		X	
175) Folsom Dike 7		X	
176) Folsom Dike 8		X	
177) Folsom Right Wing		X	
178) Foothill Regulating Park	X		
179) Forbestown Diversion			X
180) Forest Lake	X		
181) Foster	X		
182) Fountaingrove	X		
183) Francis, Lake			X
184) French Lake		X	
185) Frenchman	X		
186) Friant		X	
187) Fullerton Dam		X	
188) Garvey Reservoir	X		
189) Gastaldi			X
190) Gem Lake	X		
191) Gene Wash	X		
192) Gibraltar	X		
193) Giffen Reservoir	X		
194) Glen Anne		X	
195) Grant Company 2			X
196) Grant Lake	X		
197) Green Verdugo	X		
198) Gregory, Lake	X		
199) Greystone Reservoir	X		
200) Grizzly Forebay	X		
201) Grizzly Valley	X		
202) Groveland Wastewater Reclamation #2			X
203) Guadalupe	X		
204) Haiwee	X		
205) Halsey Forebay No. 2	X		
206) Hansen Dam		X	
207) Harbor View	X		
208) Harold Reservoir	X		
209) Harrison Street	X		
210) Harry L. Englebright Dam			X
211) Heenan Lake			X
212) Henne	X		
213) Henry J Mills Reservoir	X		

214) Henshaw	X		
215) Herman, Lake	X		
216) Hernandez	X		
217) Hidden Dam		X	
218) Highland Creek	X		
219) Hillside	X		
220) Hinkle	X		
221) Hodges, Lake	X		
222) Hume Lake			X
223) Ice House Main	X		
224) Independence			X
225) Indian Ole	X		
226) Indian Valley	X		
227) Iron Canyon	X		
228) Iron Gate	X		
229) Isabella Dam		X	
230) J C Jacobsen	X		
231) Jackson Creek	X		
232) Jackson Meadows	X		
233) Jacobs Creek			X
234) James H Turner	X		
235) James J. Lenihan	X		
236) Jeff Davis	X		
237) Juncal	X		
238) Jurupa Basin	X		
239) Kelly Cabin Can			X
240) Keswick		X	
241) Kidd Lake Main	X		
242) Kimball Creek	X		
243) Kunkle			X
244) La Grange			X
245) Lafayette	X		
246) Laguna Regulating Basin			X
247) Lagunita Santa Clara	X		
248) Lagunita Sonoma	X		
249) Lake Almanor	X		
250) Lake Alta			X
251) Lake Arrowhead			X
252) Lake Arthur			X
253) Lake Co San Dist	X		
254) Lake Curry	X		
255) Lake Frey	X		
256) Lake Hemet	X		
257) Lake Loveland	X		

258) Lake Madigan	X		
259) Lake Ranch		X	
260) Lake Sherwood	X		
261) Lake Theodore			X
262) Lang Creek Detention Basin	X		
263) Las Llajas	X		
264) Laurel Creek	X		
265) Lauro		X	
266) Lee Lake			X
267) Leland	X		
268) Lewiston		X	
269) Little Dalton Debris Basin	X		
270) Little Mountain	X		
271) Little Panoche Detention			X
272) Littlerock	X		
273) Live Oak	X		
274) Live Oak Reservoir	X		
275) Log Cabin	X		
276) Loma Rica Airport	X		
277) Long Lake			X
278) Long Valley	X		
279) Loon Lake Main	X		
280) Lopez	X		
281) Los Angeles Reservoir			X
282) Los Banos Creek Detention		X	
283) Los Carneros, Lake	X		
284) Los Padres	X		
285) Los Vaqueros	X		
286) Lower Crystal Springs	X		
287) Lower Franklin	X		
288) Lower Howell			X
289) Lower Peak Lake Main			X
290) Lower San Fernando	X		
291) Lower Stehly	X		
292) Lower Twin Lake	X		
293) Lundy Lake	X		
294) Lytton			X
295) Mabey Canyon	X		
296) Macumber	X		
297) Madeline			X
298) Maerkle	X		
299) Magalia	X		
300) Magnolia	X		
301) Maloney	X		

302) Mammoth Pool	X		
303) Mammoth Reservoir	X		
304) Marie, Lake	X		
305) Mariposa Dam		X	
306) Mark Edson	X		
307) Marsh Creek	X		
308) Martinez		X	
309) Martis Creek Dam		X	
310) Mary Street	X		
311) Mary, Lake			X
312) Matanzas Creek	X		
313) Mathews	X		
314) Matilija	X		
315) Mccloud	X		
316) Mcswain	X		
317) Meadow Lane			X
318) Merced Falls		X	
319) Middlefield Res	X		
320) Milliken	X		
321) Miner'S Ranch	X		
322) Miramar	X		
323) Moccasin Lower	X		
324) Mockingbird Canyon	X		
325) Modesto Res	X		
326) Mojave Dam		X	
327) Monticello		X	
328) Moraga	X		
329) Morena	X		
330) Morning Star			X
331) Morris Los Angeles	X		
332) Morris Mendocino	X		
333) Morris S. Jones	X		
334) Mount Stoneman			X
335) Mulholland	X		
336) Murphys Wastewater			X
337) Murray	X		
338) Murry			X
339) Nacimiento	X		
340) Nash	X		
341) Nevada City Raw Water Reservoir			X
342) New Bullards Bar	X		
343) New Hogan Dam		X	
344) New Melones		X	
345) New Upper San Leandro	X		

346) Newell	X		
347) Nimbus		X	
348) North	X		
349) North Battle Creek	X		
350) Notre Dame	X		
351) Novato Creek	X		
352) Olson	X		
353) O'Neill Forebay		X	
354) Orange County Reservoir	X		
355) Orinda, Lake	X		
356) Oroville	X		
357) Owens Dam		X	
358) Pacific Grove		X	
359) Pacoima	X		
360) Palisades Reservoir	X		
361) Palo Verde	X		
362) Palos Verdes Res	X		
363) Paradise	X		
364) Pardee	X		
365) Pardee South Spillway			X
366) Patterson	X		
367) Pennsylvania Creek	X		
368) Perris	X		
369) Peters	X		
370) Peters Canyon	X		
371) Philbrook Main			X
372) Phoenix	X		
373) Phoenix Lake	X		
374) Piedmont	X		
375) Pigeon Pass	X		
376) Pilarcitos	X		
377) Pine Creek	X		
378) Pine Flat Dam		X	
379) Pit No. 1 Forebay	X		
380) Pit No. 3 Diversion	X		
381) Pit No. 4 Diversion	X		
382) Pit No. 5 Diversion	X		
383) Pit No. 5 Open Conduit	X		
384) Pit No. 6 Diversion	X		
385) Pit No. 7 Diversion	X		
386) Pleasant Valley	X		
387) Poe			X
388) Pond No 2	X		
389) Ponderosa			X

390) Portola	X		
391) Poway	X		
392) Prado Dam		X	
393) Prenda	X		
394) Priest	X		
395) Prosser Creek		X	
396) Puddingstone	X		
397) Puddingstone Diversion	X		
398) Putts Lake			X
399) Pyramid	X		
400) Quail Lake	X		
401) Quartz			X
402) R. W. Matthews	X		
403) Railroad Canyon	X		
404) Ralphine, Lake	X		
405) Ramona	X		
406) Rancho Del Ciervo	X		
407) Rancho Seco	X		
408) Rattlesnake Canyon	X		
409) Reba	X		
410) Rector Creek	X		
411) Red Mountain Reservoir	X		
412) Redbank	X		
413) Redhawk Lake			X
414) Reservoir No 1		X	
415) Reservoir No 4	X		
416) Reservoir No 5	X		
417) Rhinedollar	X		
418) Rickey			X
419) Righetti	X		
420) Rinconada Reservoir	X		
421) Riviera Reservoir	X		
422) Robert A Skinner	X		
423) Rock Creek	X		
424) Rollins	X		
425) Ross No 1	X		
426) Ross No 2	X		
427) Round Mountain	X		
428) Runkle	X		
429) Rush Meadows	X		
430) Sabrina	X		
431) Saddlebag Lake	X		
432) Salinas Dam		X	
433) Salinger			X

434) Salt Springs	X		
435) San Andreas	X		
436) San Antonio Los Angeles		X	
437) San Antonio Monterey	X		
438) San Clemente		X	
439) San Dieguito	X		
440) San Dimas	X		
441) San Felipe Ranch			X
442) San Gabriel	X		
443) San Joaquin Reservoir	X		
444) San Lorenzo Creek	X		
445) San Marcos San Diego	X		
446) San Marcos San Luis Obispo	X		
447) San Pablo	X		
448) San Pablo Clearwell	X		
449) San Sevaine Basin #5	X		
450) San Vicente	X		
451) Sand Canyon	X		
452) Sand Creek	X		
453) Santa Anita Debris Basin			X
454) Santa Fe Dam	X		
455) Santa Felicia	X		
456) Santa Monica Debris Basin	X		
457) Santa Ynez Canyon	X		
458) Santiago Creek	X		
459) Savage	X		
460) Sawpit	X		
461) Sawpit Debris Basin	X		
462) Scott	X		
463) Scotts Flat	X		
464) Scout Lake	X		
465) Searsville	X		
466) Seeger	X		
467) Sempervirens			X
468) Seneca			X
469) Sepulveda Dam		X	
470) Sequoia Lake	X		
471) Seven Oaks	X		
472) Shasta		X	
473) Shasta River	X		
474) Shaver Lake	X		
475) Shiloh Ranch			X
476) Sierra Madre	X		
477) Silver Lake	X		

478) Sinaloa Lake	X		
479) Skinner Clearwell	X		
480) Slab Creek		X	
481) Sly Park	X		
482) Small Canyon	X		
483) Sobrante Clearwell	X		
484) Soulajule	X		
485) Spenser Lake		X	
486) Spring Valley	X		
487) St. Helena Lower	X		
488) Stampede		X	
489) Stanford Heights	X		
490) Stanley A Mahr Reservoir	X		
491) Stevens Creek	X		
492) Stewart Canyon Debris Basin	X		
493) Stockton Creek	X		
494) Stone Canyon	X		
495) Stony Gorge		X	
496) Success Dam		X	
497) Sulphur Creek	X		
498) Summit	X		
499) Summit Reservoir	X		
500) Sunset North Basin	X		
501) Sunset South Basin	X		
502) Sutherland	X		
503) Sutro Reservoir	X		
504) Suttenfield	X		
505) Swanzy Lake	X		
506) Sweetwater Main	X		
507) Sycamore	X		
508) Syphon Canyon	X		
509) Tahchevah	X		
510) Temescal, Lake	X		
511) Terminal	X		
512) Terminus Dam		X	
513) Thermalito Afterbay	X		
514) Thermalito Diversion	X		
515) Thermalito Forebay	X		
516) Thompson			X
517) Thompson Creek	X		
518) Tinemaha	X		
519) Tioga Lake Main	X		
520) Trampas Canyon	X		
521) Trinity		X	

522) Tulloch	X		
523) Tuolumne Log Pond			X
524) Turner		X	
525) Twitchell		X	
526) Union Main			X
527) Union Valley	X		
528) University Mound North Basin	X		
529) University Mound South Basin	X		
530) Upper Franklin Dam		X	
531) Upper Howell			X
532) Upper Oso	X		
533) Upper Otay			X
534) Upper Peak Lake			X
535) Upper Stehly	X		
536) Uvas	X		
537) Vail	X		
538) Vasona Percolating	X		
539) Vermilion	X		
540) Villa Park	X		
541) Virginia Ranch	X		
542) Wallace			X
543) Walnut Canyon	X		
544) Ward Creek	X		
545) Warm Springs Dam		X	
546) Wastewater Storage			X
547) West Point Regulating			X
548) West Valley	X		
549) Westlake Reservoir	X		
550) Weymouth Memorial Reservoir	X		
551) Whale Rock	X		
552) Whiskeytown		X	
553) White Pines			X
554) Whittier Narrows Dam		X	
555) Whittier Res No 4			X
556) Wide Canyon	X		
557) Williams			X
558) Wishon Main	X		
559) Wohlford Lake	X		
560) Wood Ranch	X		
561) Woodcrest	X		
562) Wrigley Reservoir	X		
563) Wyandotte, Lake	X		
564) Yosemite, Lake	X		

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