Impacts on Santa Cruz County, California's Landscape and Community from Major Flood Events

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ABSTRACT

As natural disasters continue to increase in frequency and intensity due to climate change, extreme hydrologic events have heavily impacted many communities. In December 2022 and January 2023, storms swept into the United States West Coast, bringing heavy precipitation, widespread flooding, and dangerous landslides. This study investigates how the California landscape, specifically Santa Cruz County, reacted to the December 2022 and January 2023 rainstorms. Most flood hazard maps depict only coastal storm surge flooding and fluvial (riverine) flooding, and not pluvial (rainfall) flooding, which is an issue with mapping flooding in urban areas. By mapping observed flood data, I identified areas of widespread flooding. I analyzed the flood maps in relation to land cover classifications, physical and geographic factors, and socioeconomic factors, finding common characteristics that suggest higher flood occurrence. I found that more flooding occurred in land types containing soils with less vegetation and more degradation, thus causing higher runoff. Within the physical and geographic factor analysis, agricultural areas flooded more (8.55% in January 2023) due to their proximity to the river floodplain. Within built areas, more flooding occurred in areas with higher percentages of impervious surfaces. Current literature about past flood events, along with media coverage of the flood event, suggested that flooding disproportionately affected those from disadvantaged populations. Overall, this study supports mitigation strategies for flood risk management by identifying area types (i.e. agricultural cropland, urban areas) to monitor closely during flood events, thereby reducing loss of life and property.

KEYWORDS

flood modeling, GIS, pluvial flooding, fluvial flooding, Pajaro River

INTRODUCTION

As climate change continues to increase the frequency and intensity of natural disasters, many communities have been negatively impacted by extreme hydrologic events, such as megastorms and massive flooding (Huang and Swain 2022). New research has examined the process of extreme event attribution, which identifies connections and causal relationships between climate change and extreme weather events (Stott et al. 2016, Otto et al. 2018). Because precipitation volatility and sea level rise is projected to increase in coming years due to climate change, effective research is essential to the health and safety of these coastal communities, who are expected to bear the brunt of effects from hydrologic climate change (Kermanshah and Derrible 2016). Specifically, California is a notable flood zone of concern, where nearly 68% of the population lives in coastal areas (NOAA 2024). Though California's Mediterranean climate has characteristic dry summers and wet winters, year-to-year weather can switch from extreme drought to extremely wet years (Swain et al. 2018). Despite California's persistent drought status, the state is already starting to face increased precipitation and flooding during extreme weather events — such as the storms that recently engulfed the West Coast in December 2022 and January 2023 (Gimeno et al. 2014). Across California, 11.47 inches of recorded rainfall was the average – equating to over 32 trillion gallons of water of rainfall in that time period (Lee 2023). Analyses about flooding locations during extreme hydrologic events are essential to understanding the contributing factors of flooding, and thus how we can mitigate flood risk in the future.

Many studies have analyzed historical flood data to examine the impacts on the California landscape, but have neglected data from more recent flood events. One popular technique is through digital simulations based on historical data and climate change models, such as RCP4.5, 6.0, and 8.5 (Kirchmeier-Young and Zhang 2020). These climate change models have different levels of radiative forcing, which quantifies the effect of aerosols in the atmosphere on radiative flux. Higher levels of radiative forcing equates to an increase in global temperature (Carslaw 2022). Data can be collected from a variety of methods, such as utilizing ensembles of different climate models to predict precipitation levels and flooding impacts (Kirchmeier-Young and Zhang 2020), creating different scenarios using historical data and climate change data to compare storm risk levels (Huang and Swain 2022), and simulating precipitation under different levels of radiative forcing (Swain et al. 2018). However, simulations may not incorporate all real-life factors. In contrast, flood hazard maps are also useful in quantifying flood risk, but do not show the complete picture. Most flood hazard maps, many of which are released by the Federal Emergency Management Agency (FEMA), depict only coastal storm surge flooding and fluvial flooding, which is riverine flooding that occurs due to the overflow of rivers and streams. Most hazard maps do not depict the risk from pluvial flooding, which is flooding that occurs from the ponding of rainfall (Tonn and Czajkowski 2022). This problem is especially exacerbated in urbanized areas, where there is inefficient stormwater drainage and a higher percentage of impervious surfaces that increase runoff (Mobini et al. 2021). Despite existing studies that hypothesize the effects and extent of flooding in the near future, there is an urgent lack of research joining remote sensing and land cover vulnerability analysis using recent flood data. By studying the effect of rainfall effects on the entire landscape, we can collect data to improve future simulated prediction models and hazard maps.

For efficiency in spatial and data analysis, this study will focus on an area that contains both coastal habitats and urbanized areas that represent California's diverse landscape for greater application of the results. Santa Cruz County experienced intense flooding during the December 2022 and January 2023 storms. From December 26th 2022 to January 17, 2023, a large majority of Santa Cruz County recorded more than 15 inches of rainfall, shown in Figure 1 – and some parts of the mountains recorded up to 36 inches (Santa Cruz County Office of Response, Recovery, and Resilience 2023).

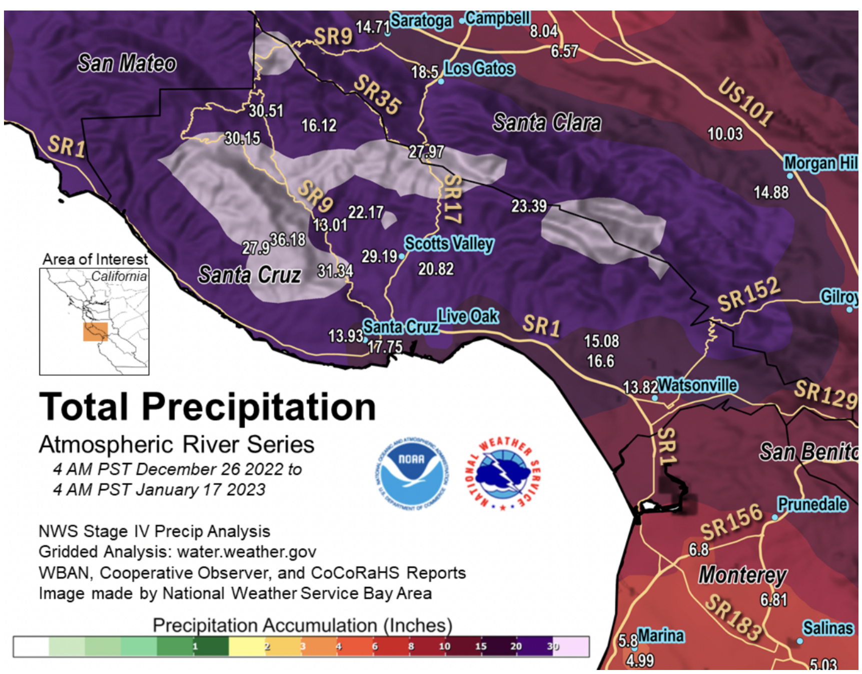


Figure 1. Total recorded precipitation from the storm event in Santa Cruz County (NWS). Most of the county recorded more than 15 inches of rainfall, and up to 36 inches in the mountains.

Santa Cruz County is prone to flooding due to a high number of rivers and creeks with flashy flow regimes paired with frequent coastal storms. The main rivers of the county that have the most interaction with populated areas include the Pajaro River and the San Lorenzo River (Santa Cruz County Planning Department 2017). Pajaro River, specifically, has a system of levees that hold back the river during times of flooding, which was first constructed in 1949. Over the years, the levees have diminished in effectivity and strength, culminating in the breaching of the levees during the 1995 and 1998 storms, and again in 2017 (PRWFPA 2023). The breaching of the levees would cause a devastating effect on the nearby city of Watsonville, Santa Cruz County, and the unincorporated town of Pajaro, Monterey County. During the December 2022 and January 2023 floods, many of the roads were inundated with floodwater, and much of the community had to be evacuated (Hattis 2023). Any future floods of higher intensity would most likely be detrimental to the communities of Santa Cruz County and beyond, which makes this area a priority for study and research.

In this study, I asked how the December 2022 and January 2023 California floods have affected the landscapes and communities in Santa Cruz County. The objectives of this study are to analyze 1) flood occurrence with land cover classification, 2) flood occurrence with physical and geographic factors (natural, agricultural, urban), and 3) flood occurrence with socioeconomic factors. I hypothesized that the results of my analysis would show large-scale flooding in urban areas with high percentages of impervious surfaces, agricultural areas with overworked soil, and natural areas with less vegetation. I predicted that areas with lower census-derived income values will reflect higher percentages of flooding due to ineffective infrastructure. I analyzed the flooding via Sentinel-1 satellite imagery, and utilized the National Land Cover Dataset for land classifications. I obtained socioeconomic data from census websites and open source data. From combining the datasets and flood maps, I analyzed the relationships between physical and geographical factors with flood occurrence, and socioeconomic factors with flood occurrence.

METHODS

Study site

Santa Cruz County is located on the northern tip of Monterey Bay and is home to over 276,000 residents (County of Santa Cruz 2023). The county has 29 miles of coastline, and is composed of several major watersheds that impact land use and natural environmental processes (County of Santa Cruz 2023). The two main watersheds that impact the county's urban areas the most are the San Lorenzo River and the Pajaro River, respectively 138 and 1,300 square miles (200 square miles of the Pajaro River Basin being in Santa Cruz County). The San Lorenzo River watershed is primarily forested, with some pockets of urban development. The Pajaro River watershed is composed of cropland, timberland, rangeland, urban development, and agricultural residential areas (Santa Cruz County Environmental Health 2023). Of the incorporated cities of the county, Santa Cruz has a population of 59,946; Watsonville a population of 51,199; Scotts Valley a population of 11,580; and Capitola a population of 9,918 (County of Santa Cruz 2023). Due to frequent coastal storms, and the high number of rivers and creeks in these watersheds (Figure 2), many areas within the county are prone to flooding.

The Pajaro River, which borders the southern county line, has a system of levees that have constantly faced overtopping during extreme rain events, due to ineffective standards during the time of their construction in 1949 (Warner 2001). Flooding occurs in Watsonville, north of the river and in Santa Cruz County, and Pajaro, south of the river and in Monterey County. During the December 2022 and January 2023 storms, much of the communities in the area had to be evacuated (Hattis 2023).

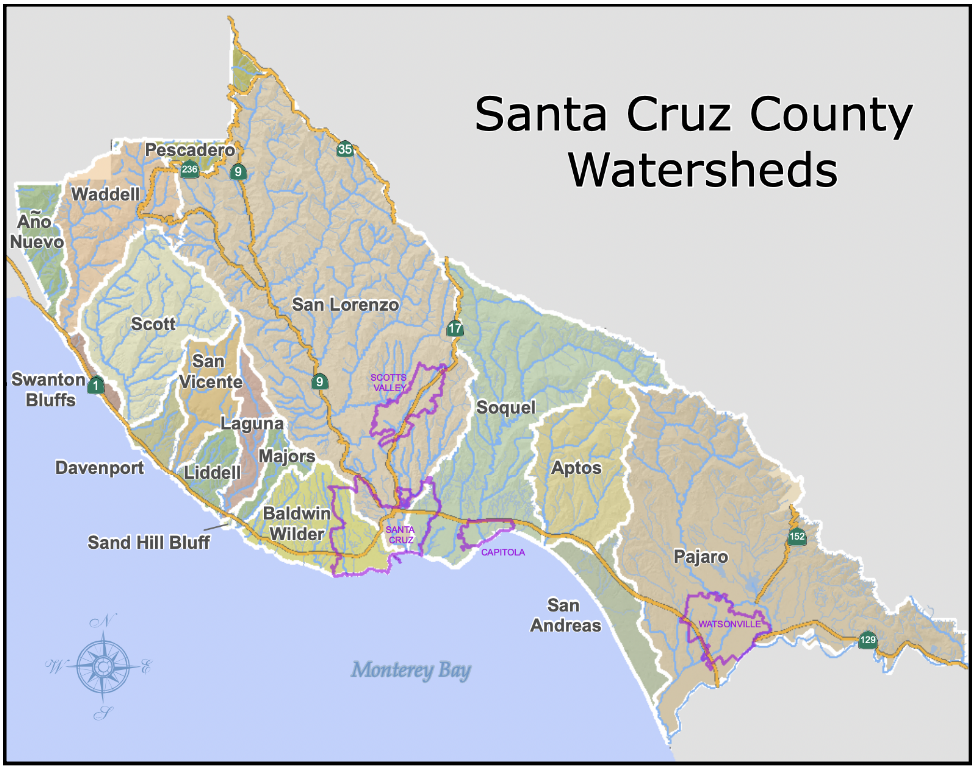


Figure 2. Map of the Santa Cruz County watersheds (Santa Cruz County Environmental Health 2023).

In terms of socioeconomic status of the region, according to the 2022 census, 86.5% of the population identify as White, 34.5% identify as Hispanic or Latino, and 5.4% identify as Asian. Though the median household income from 2017-2021 was $96,093, 10.6% of the population is under the poverty line (U.S. Census Bureau 2022). The geographic distribution of wealth varies from place to place in the county, visualized in Figure 3.

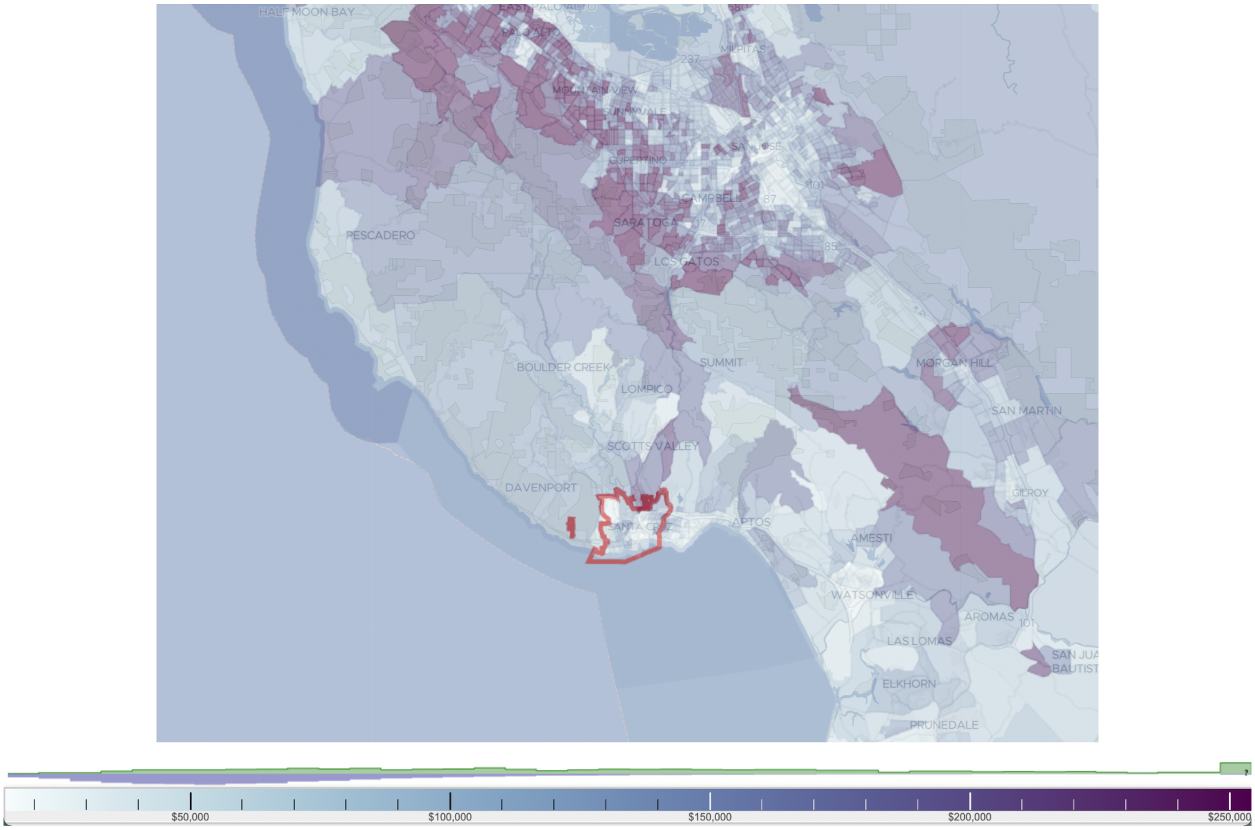


Figure 3. Income map derived from the U.S. Census. Darker purple areas indicate areas with higher median household income.

Landcover classification

To determine the categories that would be the most appropriate for my land classification analysis, I looked at existing land classifications that existed in literature and in past government projects, such as the NLCD 2021 California Land Cover Subset (Dewitz 2023).

For a general analysis for the entirety of Santa Cruz County, I used the 30m National Land Cover Database 2021. The category of “Open Water” was excluded from calculations. The following classifications fall under the “natural” category: deciduous forest, evergreen forest, mixed forest, shrub/scrub, herbaceous, woody wetlands, emergent herbaceous wetlands, and barren land. Hay/pasture and cultivated crops fall under the “agricultural” category. The “built” environment category contains the following classifications: developed, open space; developed, low intensity; developed, medium intensity; and developed, high intensity (see Appendix for classification descriptions) (California Department of Fish and Wildlife 2023).

Identifying flooded areas

To identify the flooded areas during the December 2022 and January 2023 rainstorms, I utilized 10 meter Sentinel-1 satellite imagery (Copernicus Sentinel Data 2023). Sentinel-1 uses C-band Synthetic Aperture Radar (SAR) imaging, which allows it to capture imagery regardless of the weather or cloud cover, an essential feature during storms (Copernicus Sentinel Information 2023). From the Sentinel-1 imagery, I can obtain backscattering values observed from the satellite's passive microwave sensors. SAR-based flood mapping utilizes a thresholding on the backscatter values that indicates flooded areas as areas with high backscatter values (Moharrami et al. 2021). I applied the Otsu thresholding method to the images extracted for November 2022, December 2022, January 2023, and February 2023. I conducted this analysis in Google Earth Engine (GEE) using modified code from Moharrami et al. 2021. The output was an image segmented into flooded and non-flooded areas, which I then brought into ArcGIS to resample to 30m resolution to match the NLCD. Using the prior land cover classifications, I performed geospatial analysis by extracting the data from the flooded area shapefile, and calculated the statistics that indicated which categories had the highest amounts of flooding. I calculated percentages of how many pixels in each land classification category was flooded, and additional percentages on how much of the total flooded area was that particular land classification type.

Analysis of physical and geographic factors with flooding

To identify if there was a correlation between physical and geographic factors with flooding, I performed further statistical analysis of the natural, agricultural, and built categories, using the categories from the land cover classification step. Based on those larger categories, I calculated the percentage of how much of each category was flooded (Figure 4).

Percentages calculated:
Percent flooding in built = flooded and built pixels/ total built pixels
Percent flooding in agricultural = flooded and agricultural pixels/ total agricultural pixels
Percent flooding in natural = flooded and natural pixels/ total natural pixels

Figure 4. Formulas for percent flooding occurrence in physical factor analysis.

Analysis of social and economic factors with flooding

To observe the impact of social and economic factors with flooding, I conducted an analysis on which types of socioeconomic groups were more affected by large-scale flooding. From government census data, I extracted the income information for Santa Cruz County and brought it into ArcGIS Pro (U.S. Census Bureau 2021). I performed geospatial analysis by overlaying the data from the flooded area shapefile onto the census data, and calculated how many flooded pixels were in each income bracket class type. Using census block group income data divided into brackets of "below poverty line", "low income", "middle income", and "high income" (Figure 6, Table 1), I compared the percentages of the flooded pixel areas sorted into each category. After modifying the census block group shapefiles into rasters, I calculated the percentage of flooded areas of each category out of the entire area of each category. and visualized those percentages to analyze growth (Figure 5).

Percentages calculated:
Percent flooding in lower income = flooded and low income pixels/ total low income pixels
Percent flooding in lower-middle income = flooded and lower-middle income pixels/ total lower-middle income pixels
Percent flooding in middle income = flooded and middle income pixels/ total middle income pixels
Percent flooding in upper-middle income = flooded and upper-middle income pixels/ total upper-middle income pixels
Percent flooding in upper income = flooded and upper income pixels/ total upper income pixels

Figure 5. Formulas for percent flooding occurrence in socioeconomic analysis.

Table 1. Household income dispersion in 2022. Household income dispersion from 1967 to 2022 (2022 Census Bureau Income Report).

Year	Measures of income dispersion												
	Household income at selected percentiles										Household income ratios at selected percentiles		
	10th percentile limit	20th percentile limit	30th percentile limit	40th percentile limit	50th (median)	60th percentile limit	70th percentile limit	80th percentile limit	90th percentile limit	95th percentile limit	90th/10th	90th/50th	50th/10th
2022	17,100	30,000	43,930	58,020	74,580	94,000	118,700	153,000	216,000	295,000	12.63	2.90	4.36
2021	16,890	30,200	43,700	59,310	76,330	96,770	122,100	160,800	228,600	308,700	13.53	2.99	4.52
2020[1] . . .	17,650	30,740	44,980	59,280	76,660	96,420	122,300	160,100	227,700	310,000	12.90	2.97	4.34
2019	18,250	31,990	46,020	60,940	78,250	98,510	125,000	162,300	229,100	307,500	12.55	2.93	4.29
2018	16,910	29,590	42,770	57,790	73,030	91,940	115,800	150,300	213,000	287,500	12.60	2.92	4.32
2017[2] . . .	16,870	29,270	41,340	55,680	72,090	90,980	115,600	149,300	214,300	287,800	12.71	2.97	4.27

Income Brackets in 2022
Lower class: less than or equal to $30,000
Lower-middle class: $30,001 – $58,020
Middle class: $58,021 – $94,000
Upper-middle class: $94,001 – $153,000
Upper class: greater than $153,000

Figure 6. Income bracket according to the 2022 Census Bureau Income Report.

RESULTS

Landcover and income bracket classification

From the NLCD 2021, I found a total of 14 categories present in Santa Cruz County (Figure 7). Within Santa Cruz County, the categories of Evergreen Forest (34.58%), Herbaceous (23.39%), and Mixed Forest (12.13%) had the highest pixel counts (Figure 8, Table 2). 77.34% of pixels in Santa Cruz County were marked as “Natural”, 4.46% were marked as “Agricultural”, and 18.20% were marked as “Built” (Figure 9, Table 3). The spatial majority of census block groups were marked as “Middle” class, “Upper-Middle” class, or “Upper” class (Figure 10).

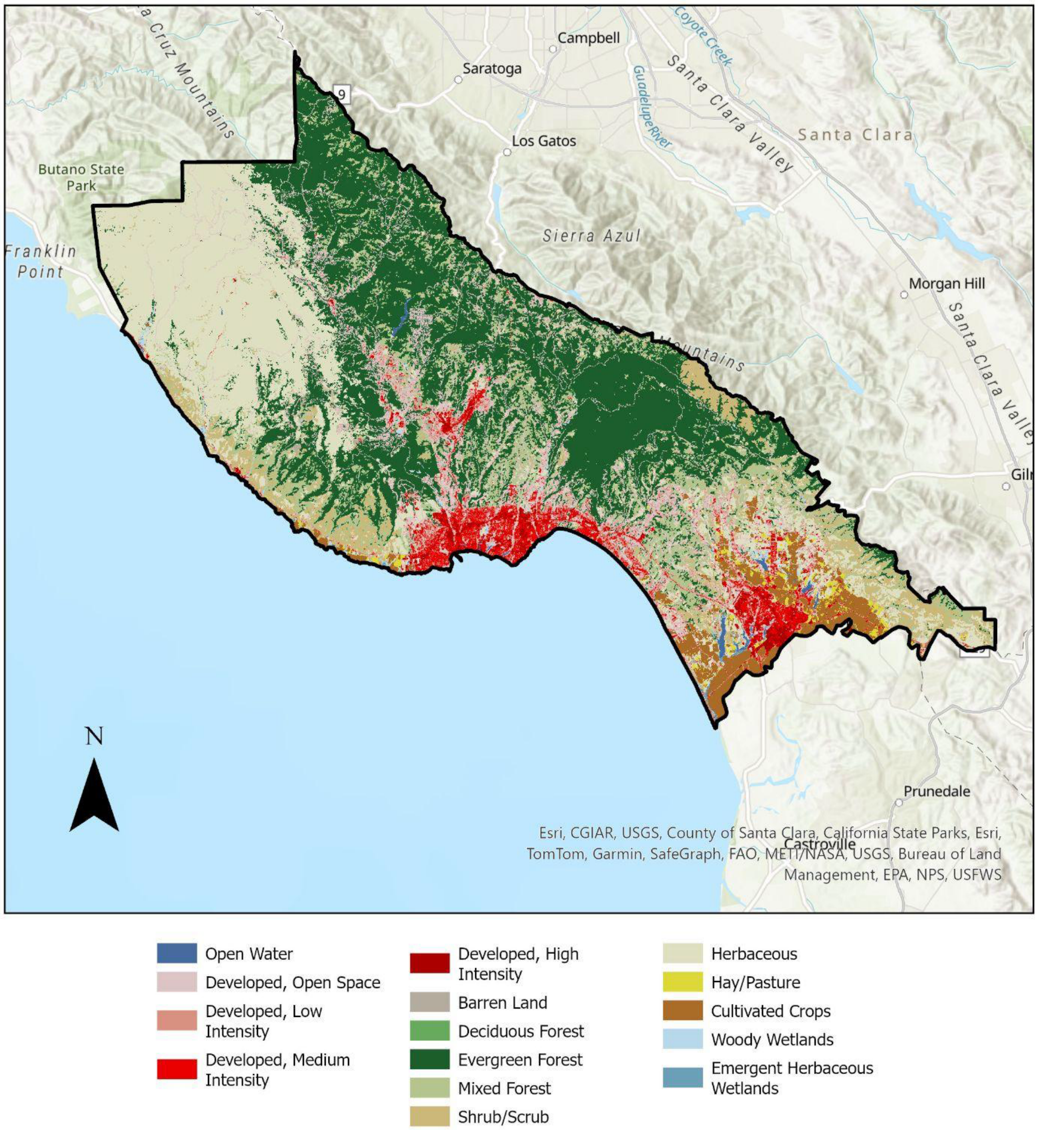


Figure 7. NLCD of Santa Cruz County. Land cover type within Santa Cruz County according to NLCD.

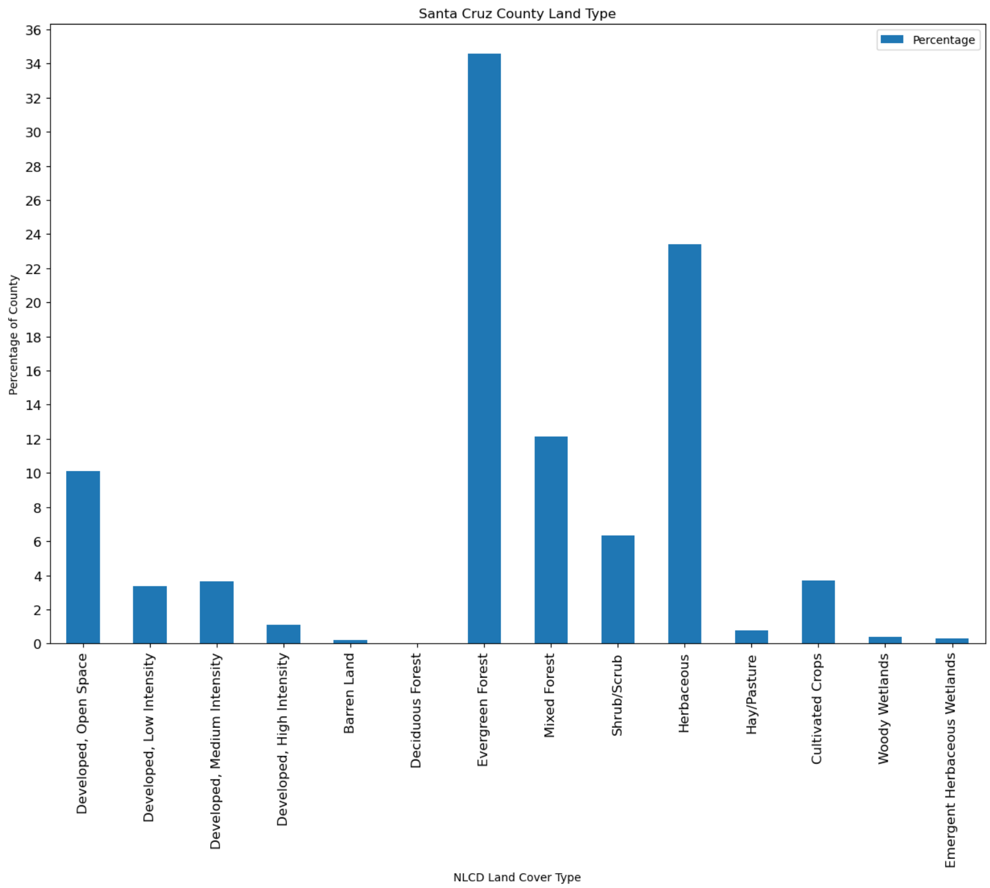


Figure 8. Percent land cover type within Santa Cruz County.

Table 2. Percent land cover type within Santa Cruz County.

NLCD_Land	Percentage
Developed, Open Space	10.120894
Developed, Low Intensity	3.350326
Developed, Medium Intensity	3.646932
Developed, High Intensity	1.080435
Barren Land	0.214417
Deciduous Forest	0.023405
Evergreen Forest	34.581658
Mixed Forest	12.143721
Shrub/Scrub	6.325832
Herbaceous	23.392504
Hay/Pasture	0.766784
Cultivated Crops	3.695878
Woody Wetlands	0.376361
Emergent Herbaceous Wetlands	0.280854

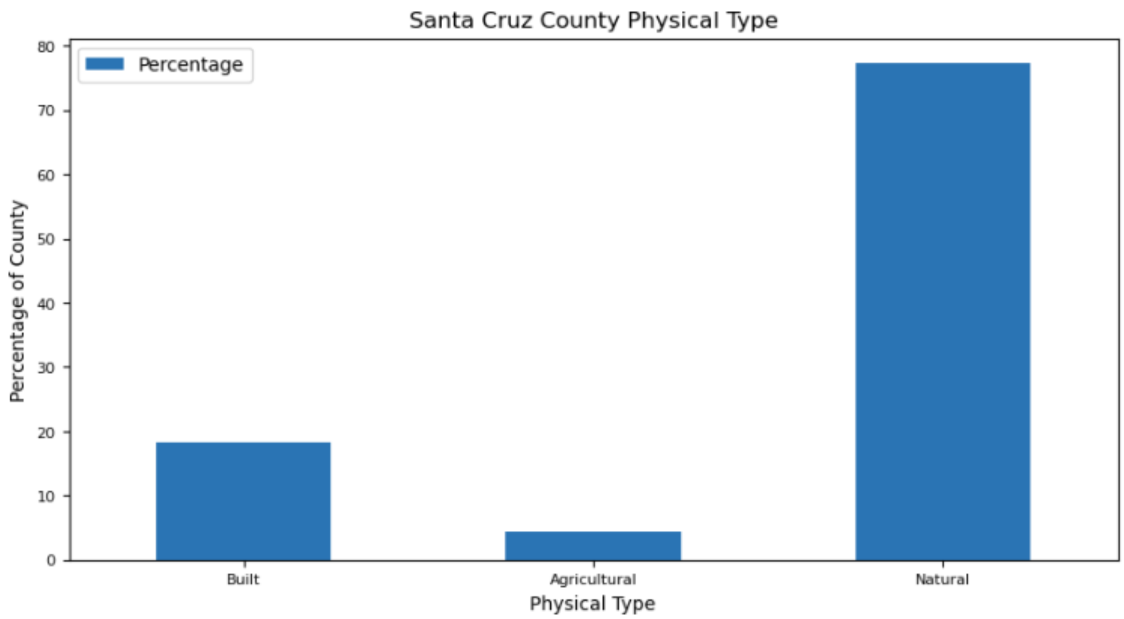


Figure 9. Percent physical factor type within Santa Cruz County.

Table 3. Percent physical factor type within Santa Cruz County.

Physical Type	Percentage
Built	18.198587
Agricultural	4.462662
Natural	77.338751

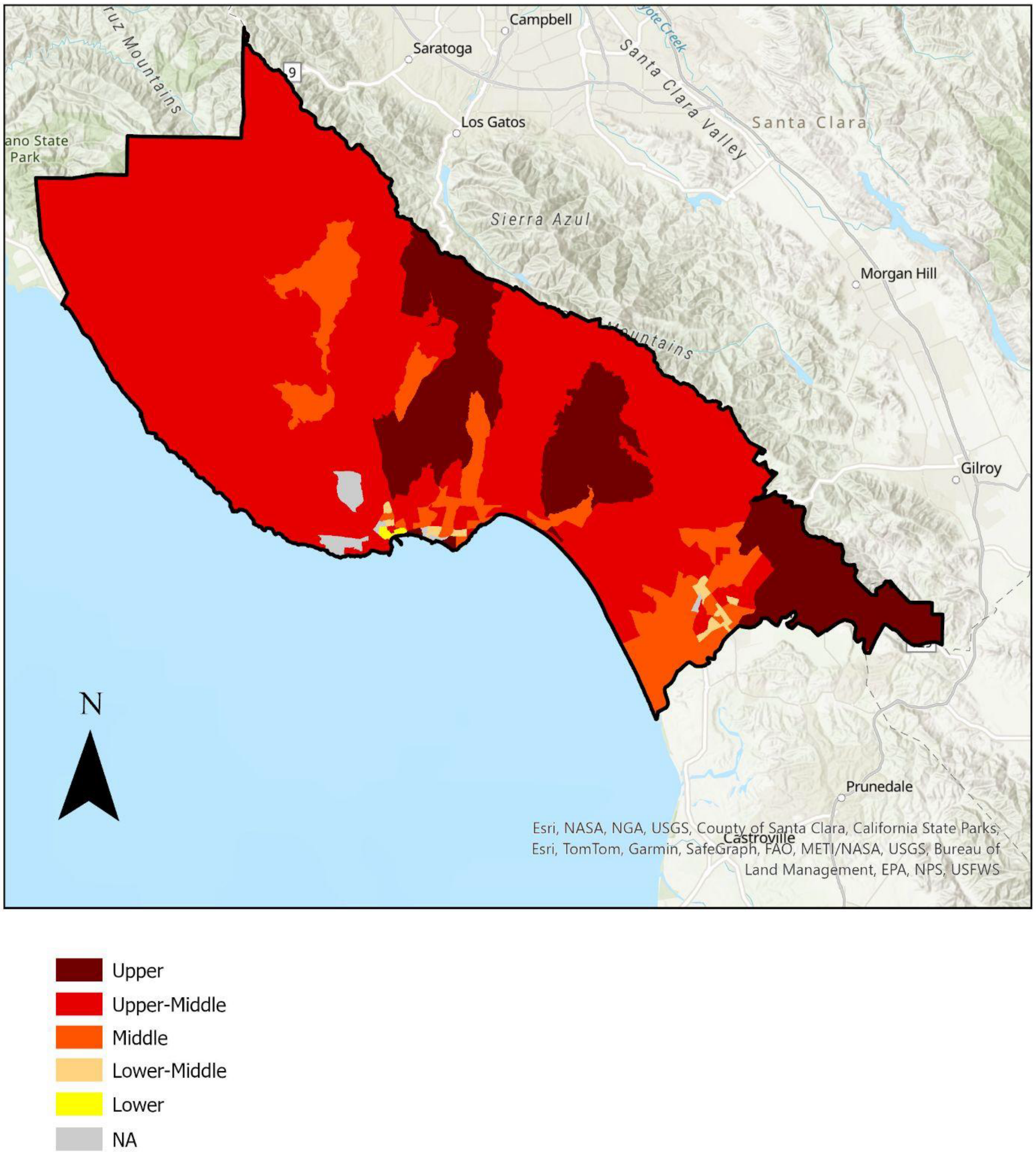


Figure 10. Income brackets of Santa Cruz County. Income brackets sorted according to median household income.

Identifying flooded areas

I found that most of the flooding occurred in months December 2022, January 2023, and February 2023 (Figure 11). Based on pixel count, the flooded areas within the delineated Santa Cruz boundary are 1.57% in November 2022, 4.28% in December 2022, 4.30% in January 2023, 3.94% in February 2023, and 2.79% in March 2023 (Figure 12, Table 4). These flood area calculations do not include bodies of water that are present throughout the entire year.

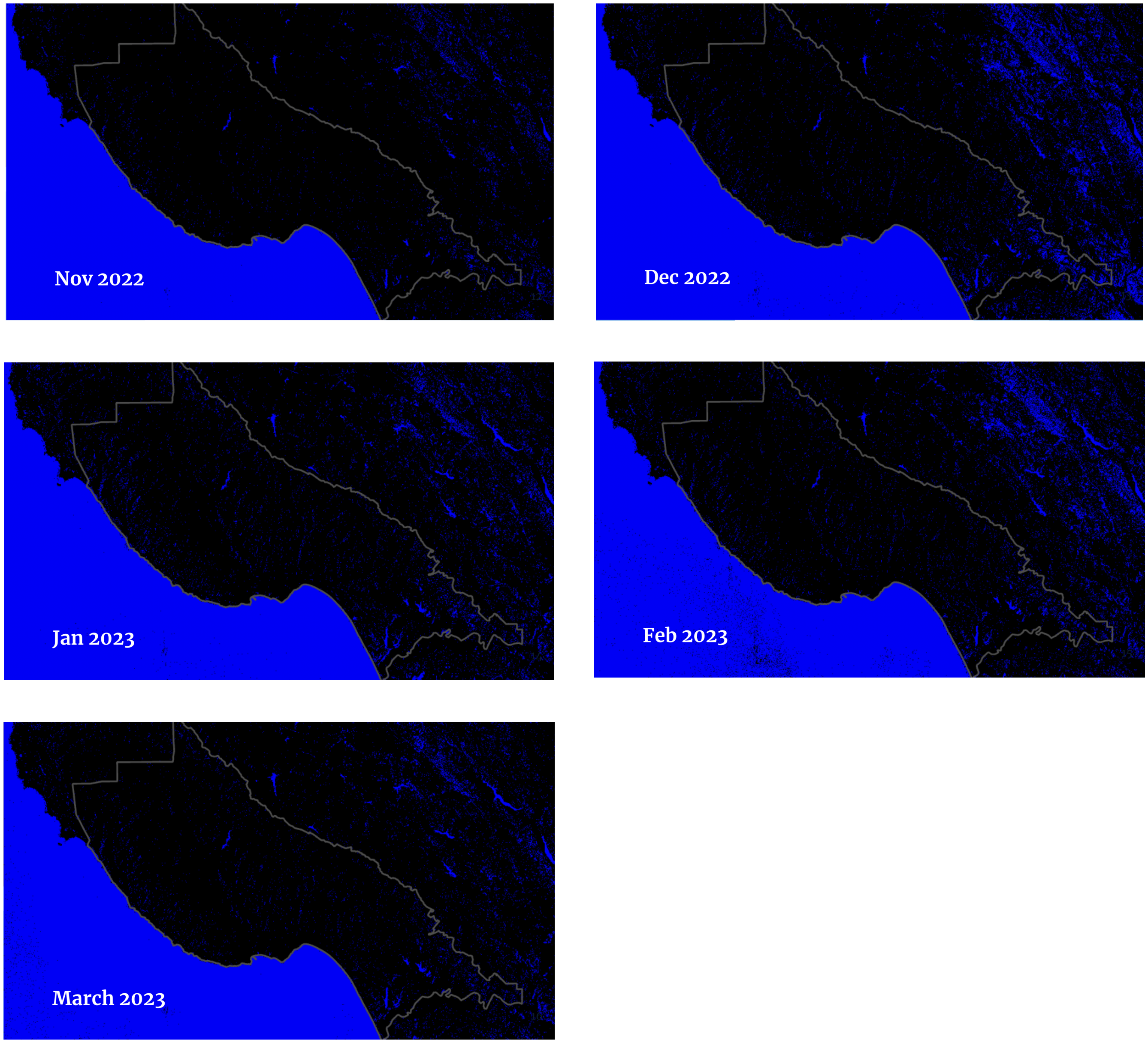


Figure 11. Areas inundated with water marked in bright blue. Image depicts both bodies of water (oceans, lakes, rivers) along with areas inundated with flooding.

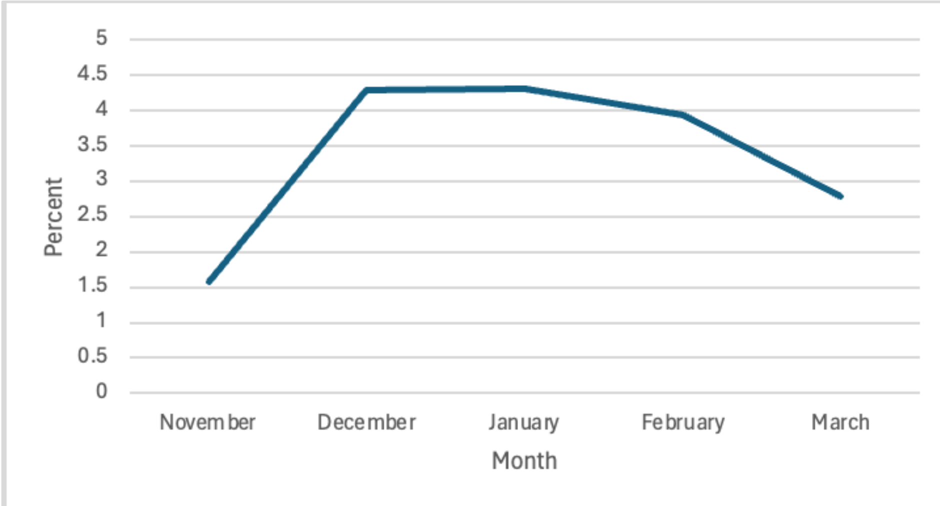


Figure 12. Percent of flooded area in Santa Cruz County. Graph of total percent flooding over November 2022-March 2023.

Table 4. Percentages of flooded area in Santa Cruz County. Total percent flooding over November 2022-March 2023.

Month	% of flooded area
November	1.57
December	4.28
January	4.3
February	3.94
March	2.79

From the flood mapping visualizations extracted for each month for Santa Cruz County, I calculated the percentages within NLCD classification types that were marked as flooded for each of the months of interest. Most notably, emergent herbaceous wetlands, barren land, and shrub/scrub had the highest percentages of flooded area in November 2022, December 2022, and February 2023; emergent herbaceous wetlands, barren land, and cultivated crops had the highest percentages of flooded area in January 2023 and March 2023 (Table 5, Figure 13).

Table 5. Percent flooding in the land classifications over November 2022-March 2023.

	Land Class	Nov 2022	Dec 2022	Jan 2023	Feb 2023	Mar 2023
0	Developed, Open Space	1.109605452	3.288065359	3.267444372	3.15255602	2.221665783
1	Developed, Low Intensity	1.030805511	3.525503167	2.941132848	2.862524658	1.874731175
2	Developed, Medium Intensity	1.404785263	3.692500545	3.568508829	3.313712666	2.212775234
3	Developed, High Intensity	1.816676632	4.387619004	4.185255025	3.596559812	2.520351377
4	Shrub/Scrub	3.595359104	9.388623992	7.021829808	7.16558133	4.525423596
5	Mixed Forest	1.012341233	3.041115621	3.084899175	3.049299463	2.3540821
6	Evergreen Forest	0.85698028	2.689774288	3.269428622	3.087801682	2.426242794
7	Herbaceous	2.406544339	5.556358044	5.137246738	4.490417582	2.653592716
8	Emergent Herbaceous Wetlands	16.84359519	29.10474168	34.02335456	29.81245577	27.1054494
9	Barren Land	13.16338355	21.13557358	24.47276941	23.05909618	18.67902665
10	Woody Wetlands	2.495378928	4.75310272	4.92474254	4.594665963	4.502244521
11	Deciduous Forest	1.486199575	3.609341826	2.547770701	2.123142251	1.27388535
12	Cultivated Crops	1.44130578	7.53862081	9.649488417	6.768221359	5.824381193
13	Hay/Pasture	0.991510596	4.257663146	3.233750243	3.006934094	1.944138423

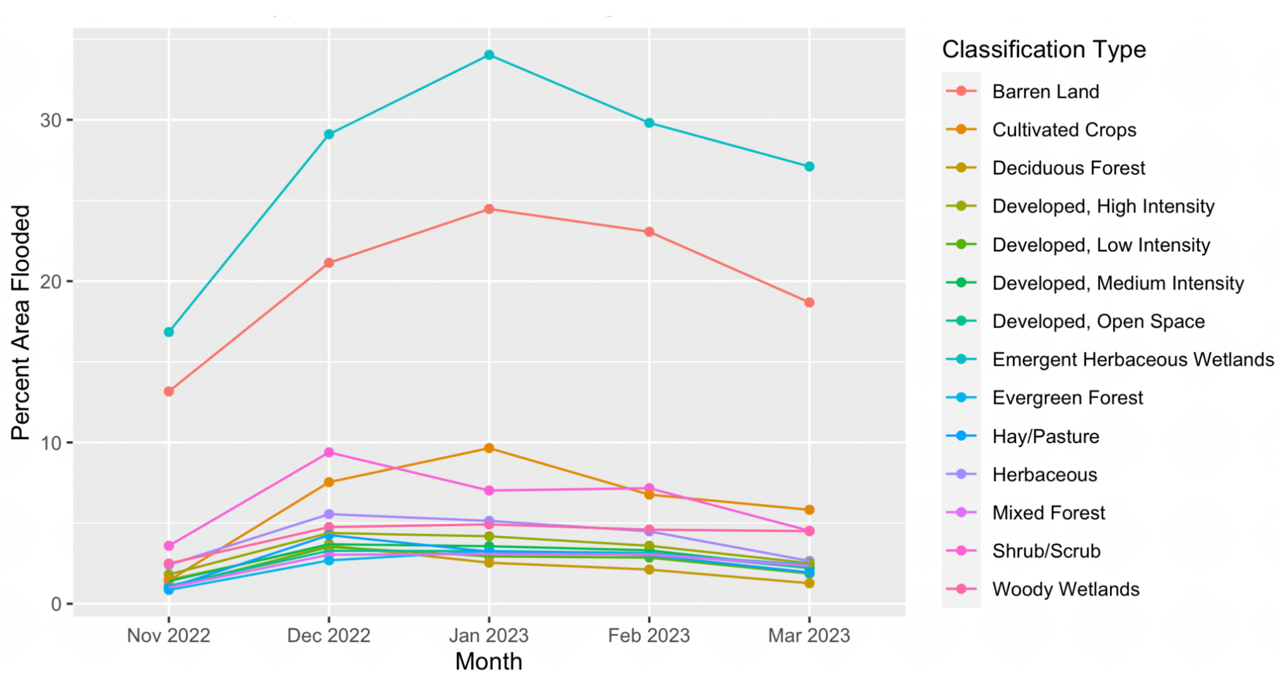


Figure 13. Graph of percent flooding within land classification types over November 2022-March 2023. The classifications with the highest flooding were Emergent Herbaceous Wetlands (teal), Barren Land (red), Scrub/Shrub (pink), and Cultivated Crops (orange).

Analysis of physical and geographic factors with flooding

In a further analysis, I compared the 30m NLCD land classification classes sorted into "natural", "agricultural", and "built" categories, with the flood maps from November 2022 to March 2023. I found that the "agricultural" category was consistently higher in percent flooding than "built" and "natural" categories for all months after November 2022. "Natural" also stayed consistently higher in percent flooding than the "built" category. While "built" (3.48%) and "natural" (4.32%) reached their peak in December, "agricultural" reached its peak in January (8.55%) (Table 6, Figure 14).

Table 6. Percent flooding in relation to physical factor type over November 2022-March 2023.

	Physical Type	Nov 2022	Dec 2022	Jan 2023	Feb 2023	Mar 2023
0	Built	1.196229733	3.478104163	3.322192915	3.157817133	2.173746839
1	Agricultural	1.364021023	6.974879743	8.547122751	6.121949047	5.157669695
2	Natural	1.674388601	4.317301137	4.290636852	3.99900025	2.799814185

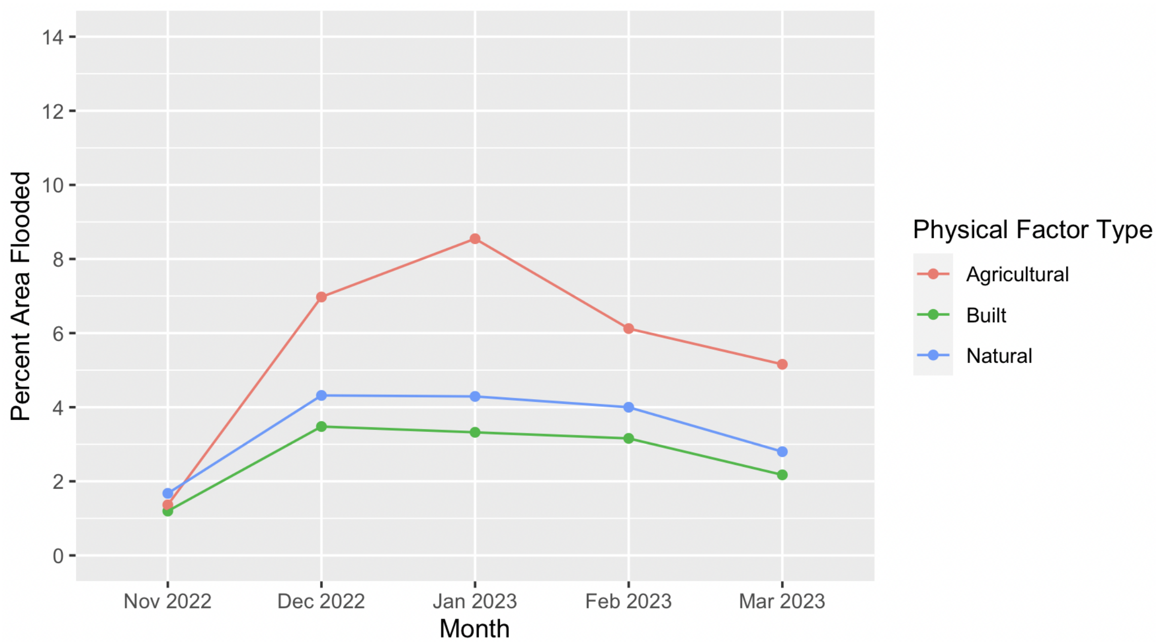


Figure 14. Graph of percent flooding within physical factor types over November 2022-March 2023.

When analyzing the "built" category split into its land classifications, "Developed, High Intensity" was consistently higher in percent flooding than other categories with lower development levels for all months. The pattern continued in "Developed, Medium Intensity", but became weak in "Developed, Low Intensity" and "Developed, Open Space" (Figure 15, Table 7).

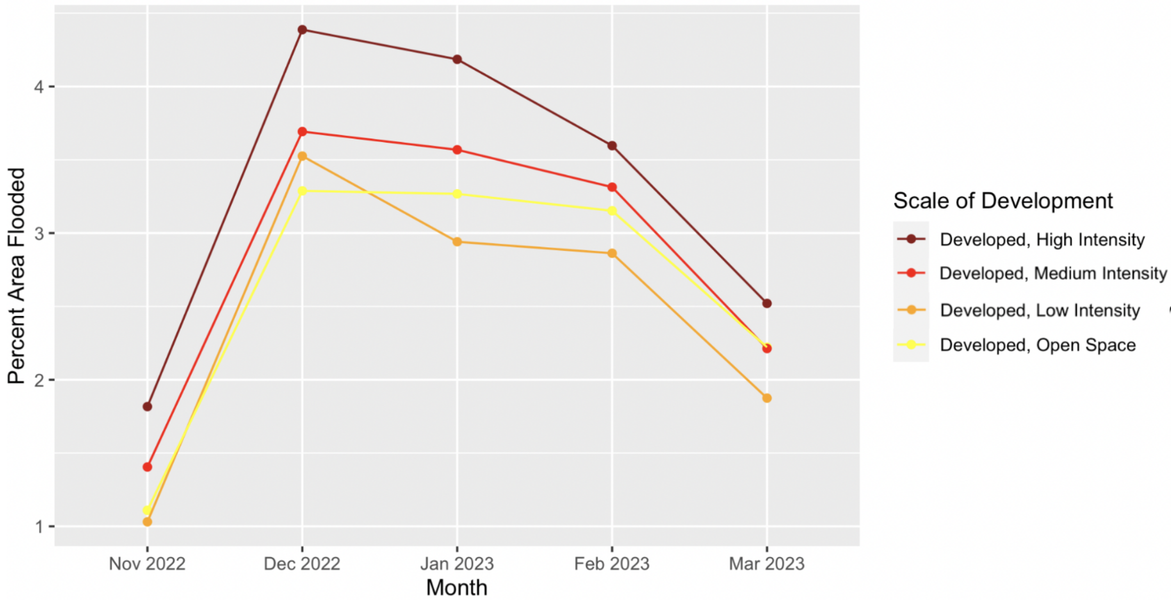


Figure 15. Graph of percent flooding within the extent of development type over November 2022-March 2023.

Table 7. Percent flooding in relation to development extent over November 2022-March 2023.

	Development Extent	Nov 2022	Dec 2022	Jan 2023	Feb 2023	Mar 2023
0	Developed, Open Space	1.109605452	3.288065359	3.267444372	3.15255602	2.221665783
1	Developed, Low Intensity	1.030805511	3.525503167	2.941132848	2.862524658	1.874731175
2	Developed, Medium Intensity	1.404785263	3.692500545	3.568508829	3.313712666	2.212775234
3	Developed, High Intensity	1.816676632	4.387619004	4.185255025	3.596559812	2.520351377

Analysis of social and economic factors with flooding:

From the same analysis using census block group income data, my results were inconclusive, as there was no clear trend in the relationship between income brackets and percent area flooded (Figure 16, Table 8).

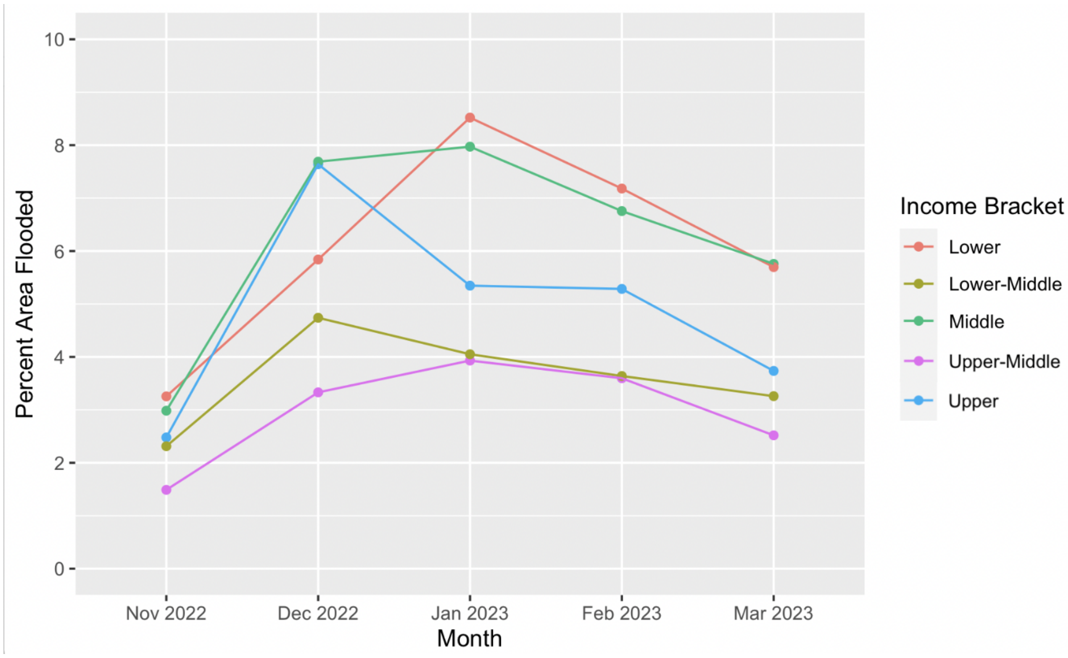


Figure 16. Graph of percent flooding within socioeconomic factor type over November 2022-March 2023.

Table 8. Percent flooding in relation to socioeconomic factor type over November 2022-March 2023.

	Income Bracket	Nov 2022	Dec 2022	Jan 2023	Feb 2023	Mar 2023
1	Upper	2.479286203	7.639821445	5.346309202	5.284473012	3.735648962
0	Upper-Middle	1.489024019	3.330746829	3.931369843	3.597682567	2.518884771
2	Middle	2.984010748	7.687968575	7.971549593	6.755176764	5.757771556
3	Lower-Middle	2.313148967	4.739385216	4.050580857	3.639354374	3.258969878
4	Lower	3.255146003	5.840114888	8.52082336	7.180469124	5.696505505

DISCUSSION

Modeling of recent extreme flood data is essential to understanding the study's flood patterns and areas of risk. Through analyzing the previous 2022-2023 flood season's data, I found that December 2022, January 2023, and February 2023 had the highest overall percentages of flooding, with percentages of 4.28%, 4.30%, and 3.94% respectively. When comparing the flooded areas to their land cover classifications, I observed that the months with the most flooding, December 2022 and February 2023, had the same classifications that had the highest amount of flooding: Emergent Herbaceous Wetlands, Barren Land, and Shrub/Scrub, ranked from most flooding to third most. Whereas in January 2023 and March 2023, Shrub/Scrub was replaced by the classification of Cultivated Crops. The land cover analysis suggested that more flooding occurred in land types containing soils with less vegetation and more degradation, thus causing higher runoff. Within the physical categorical analysis, agricultural areas flooded at higher percentages due to their proximity to the river floodplain. Within built areas, more flooding occurred in areas with higher percentages of impervious surfaces. Despite inconclusive findings when analyzing socioeconomic factors and flood occurrence, current literature about past flood events along with media coverage of the December 2022 and January 2023 events suggested that flooding disproportionately affected those from disadvantaged populations. Overall, results from this study can support mitigation strategies for flood risk management by identifying areas types to monitor closely during flood events, thereby reducing loss of life and property.

Flooding in relation to land cover type and physical and geographic factors

The analysis of flooding in conjunction with land cover suggests that there is a relationship between flood occurrence and the physical factors of the landscape, especially in extreme cases (e.g. months of December 2022-February 2023). Based on just the NLCD classifications, "natural" land cover types (e.g. emergent herbaceous wetlands, barren land, and shrub/scrub) dominate the flood categories. In the months of January 2023 and March 2023, the category of "shrub/scrub" was replaced by "cultivated crops" as the third most dominant flooded classification. These classifications are prone to flooding primarily due to their ecosystem dynamics and soil types.

Flooded NLCD classification types

Emergent herbaceous wetlands. I found 34.02% of emergent herbaceous wetlands in Santa Cruz County were classified as flooded in January 2023, with that trend continuing in the other months – suggesting a pattern in areas designated "emergent herbaceous wetlands." Emergent herbaceous wetlands are characterized by areas where the vegetation is predominantly perennial herbaceous plants that are adapted to survive periodically in semi-aquatic environments (Dewitz 2023). Though these habitats can occur in isolated systems, they are commonly associated with other bodies of water, such as rivers, lakes, and estuaries (EPA 2016). This means that emergent herbaceous wetlands are essential ecosystems for flood management and shoreline protection, since the rich habitat traps water and distributes it slowly throughout the floodplain (Muñoz et al. 2019). As emergent herbaceous wetlands are always in a state of flux according to season and hydrologic conditions, extreme precipitation events tend to have a larger effect on the flooded status of these areas.

Barren land and scrub/shrub. I found 24.47% of barren lands and 9.65% of scrub/shrub in Santa Cruz County were classified as flooded in January 2023, with similar percentages in the other months. These two classifications are characterized by their large soil/bare earth exposure, which indicates an effect on flooding occurrence. From the NLCD classification definitions, barren land is characterized by areas of earthen material, such as rock, sand, or clay) with less than 15% of total cover for vegetation. Some examples of barren land include bedrock, desert pavement, and volcanic material (Dewitz 2023). Similarly, scrub/shrub is characterized by areas dominated by shrubs and less established/stunted vegetation (e.g. young trees). Areas in this category have vegetation less than 5 meters tall with shrub canopy greater than 20% of the total vegetation (Dewitz 2023). The presence of some type of vegetation can intercept rainwater, which can increase the possibility of infiltration, as raindrop impact is reduced (Morgan & Rickson 2003). Unlike forests, which infiltrate rainfall more efficiently due to root and leaf density, soil porosity, and litterfall (Archer et al. 2013), barren land and scrub/shrub classifications have increased surface runoff in comparison due to lower percentages of vegetation compared to the size of the region's area (Rahman et al. 2021) indicating that the flood analysis shows similar results compared to other study areas with similar land cover classifications.

Analysis of flooded physical categorical types

My study's finding of a relationship between the landscape's physical factors and flooding occurrence is largely supported by existing literature, especially in the case of examining land cover change with increasing flood effects from climate change. Land cover greatly affects how precipitation flows over and infiltrates into the land surface (Sugianto et al. 2022). Despite my calculation of Santa Cruz County being classified as over 77% natural areas, the conversion of natural areas to agricultural and built areas still continues to pose a threat to flood mitigation and community hazards. In months with more extreme precipitation, the effects of land cover on flood events are exacerbated. As I have discussed the more dominant "natural" classifications in the previous section (*Flooded NLCD Classification Types*), I will focus more on "agricultural" and "built" areas in this section.

Agricultural areas. The results suggest that flooding occurred in significantly larger quantities in areas marked as agricultural. "Agricultural Areas" includes the classifications of Cultivated Crops and Pasture/Hay from the NLCD – this includes a variety of land cover including annual crops, perennial woody crops, actively tilled land, seed/hay crops, and areas dedicated to livestock grazing (Dewitz 2023). Shown in Figure 7, most of the agricultural areas are clustered around Watsonville and the floodplains of the Pajaro River, located in the southern area of the county. Floodplains are commonly used for agricultural development due to the nutrient-rich soil of the region. However, this has caused a need for more flood protection, such as levees, in these developed areas (Wheater and Evans 2009). In the agricultural areas in Watsonville, flooding is a common occurrence from the overtopping of levees of the Pajaro River, as well as overflows from Pajaro River's tributaries (Corralitos and Salsipuedes Creeks) (USACE 2024). Aside from issues from floodplain development, agricultural areas also face infiltration issues due to soil degradation. When there is intensification in agriculture or grazing activity, soil structure can degrade – reducing soil infiltration ability and causing increased overland flow runoff (Basche and DeLonge 2019, Wheater and Evans 2009). As my study yielded results that consistently ranked agricultural areas to have the highest percentages of flooding, I found that existing literature supports my findings.

Built areas. The results suggest that flooding occurred in significantly less quantities in areas marked as built, contradicting the expected findings. However, when examining the breakdown of flooded pixels in the different intensity of development, I observe a different conclusion. This study's "built" category includes four classifications of the NLCD: "Developed, Open Space," "Developed, Low Intensity," "Developed, Medium Intensity," "Developed, High Intensity." These classifications range in the percentage of impervious surfaces compared to the total cover. "Developed, Open Space" has impervious surfaces as less than 20% of total cover; "Developed, Low Intensity" as 20%-49%, "Developed, Medium Intensity" as 50%-79%, "Developed, High

Intensity" as 80%-100%. From the observed data, the percentage of flooded pixels in those categories increases as the intensity of development and the percentage of impervious surfaces increases, as shown in Figure 15. However, in months with less flooding, this difference is less pronounced, and "Developed, Low Intensity" and "Developed, Open Space" switch rankings occasionally.

As porous soil surfaces are replaced with impervious surfaces, natural infiltration is reduced and overland flow is increased. Thus, areas with higher percentages of impervious surfaces are likely to face extreme storm runoff and inundation (Rahman et al. 2021). Storm-water drainage systems can further increase flood peak flows, as water is collected from built areas and transported to the nearest discharge point (Guan et al. 2016, Wheater and Evans 2009). Floodwaters can also overwhelm the stormwater system and inundate surrounding areas (Committee on Urban Flooding in the United States 2019). The effect of urbanization on runoff may explain the relationship between flooding and development intensity.

Flooding in relation to socioeconomic factors

Despite calculating flood occurrence in conjunction with income brackets derived from census data, I found inconclusive results (Figure 16). Because the census block groups are delineated based on containing 600 to 3,000 people, in the areas with lower population density, the census block groups are much larger spatially. When analyzing the NLCD and Income Bracket map together, many of these areas with larger census block groups contain areas with natural classifications.

Although the spatial analysis results were ambiguous, much of the media coverage that was released during the time of the flooding, as well as current literature, support that the flooding effects disproportionately affect marginalized populations. Flooding affects a large number of people and their property, but at varying degrees of intensity. Lower income populations, the elderly, renters, non-native English speakers, and those with disabilities were found to be the most vulnerable in times of flooding (Committee on Urban Flooding in the United States 2019). Widespread evacuations were issued across the county – for areas like Santa Cruz, due to high tides and powerful breaking waves (ABC7 News 2023), and for areas like Watsonville, due to threat of rainfall and riverine flooding (Hattis 2023). When the storms rolled through the county, the evacuations had a greater impact on Watsonville's majority Hispanic and Latino population (82.6%) (U.S. Census Bureau 2022). Watsonville's population is largely composed of agricultural workers, all of whom were extremely affected by the flooding on their livelihoods, job security, and property (Guild & Hannula 2023).

These types of racial/ethnic socioeconomic injustices in the face of natural disasters are not an isolated incident. In other instances in history, extreme weather events largely affect disadvantaged populations that are less equipped to deal with the fallout. Poorer neighborhoods and communities are also likely to have less money invested in public infrastructure for natural hazard mitigation (Hallegatte et al. 2020). This conclusion is evident in other environmental disasters, such as 2017's Hurricane Harvey in Houston, Texas. In spatial analyses following Hurricane Harvey, researchers found that the flood extent significantly increased in areas with higher percentages of Black, Hispanic, and other socioeconomically disadvantaged residents (Chakraborty et al. 2019). Furthermore, following the major AR events in December 2022 and January 2023, the unincorporated agricultural town of Pajaro, located across Pajaro River and under Monterey County's jurisdiction, flooded heavily in response to another AR event in March 2023. A combination of heavy storms and lack of levee maintenance caused the levee to breach, which was the town's primary flood infrastructure (Kathan 2023). Compared to Watsonville's Hispanic and Latino population of 82.6%, Pajaro stands at 95% (U.S. Census Bureau 2022). While Santa Cruz County Flood Control and Water Conservation District has invested $16.9 million on flood control within the past few years, the Monterey County Water Resources Agency invested nearly a fifth of that, $3.4 million (Woolfolk 2023). Due to the county's investments in flood infrastructure work, Watsonville avoided the same fate as Pajaro's south levee breach, emphasizing how community economic status and demographics plays a major role in natural disaster mitigation planning.

Synthesis

The landscape and communities within Santa Cruz County react similarly to flood occurrence as predicted in flood literature and current research. According to land classification and physical categorization analyses, my study confirmed that more flooding occurred in land types with less vegetation, degraded soil, and with higher percentages of impervious built surfaces

(Basche and DeLonge 2019, Wheater and Evans 2009, Rahman et al. 2021). While this study found the physical factor category of "agricultural" to have higher percent flooding, this may not be reflected in other areas that do not have cropland placed in floodplains or bodies of water. This may be a unique characteristic of the Santa Cruz County area. Despite the inconclusive results of the socioeconomic analysis, most of the media coverage published at the time support the hypothesis of flooding disproportionately affecting disadvantaged communities (ABC7 News 2023, Hattis 2023, Committee on Urban Flooding in the United States 2019). Excluding the "agricultural" results, I conclude that these findings are applicable to much of California's landscape and communities, for past and future extreme storm events.

Limitations

The findings presented in this paper are subject to several limitations. First, I had originally created the flood maps at a resolution of 10m from Sentinel-1 data. To match the 30m NLCD, I had to resample the flood maps to the resolution of the NLCD, which caused a loss of data from the original flood maps. Second, the flood maps created only show the occurrence, and do not show the depth, duration, or intensity of the flooding, which is essential to gauging the risk levels of flood mapped areas. Lastly, the socioeconomic census data analysis had many limitations that led to the inconclusive results – as census block group sizes are so variable according to population density, a dataset of this type would not be effective in a spatially-dependent analysis.

Future directions

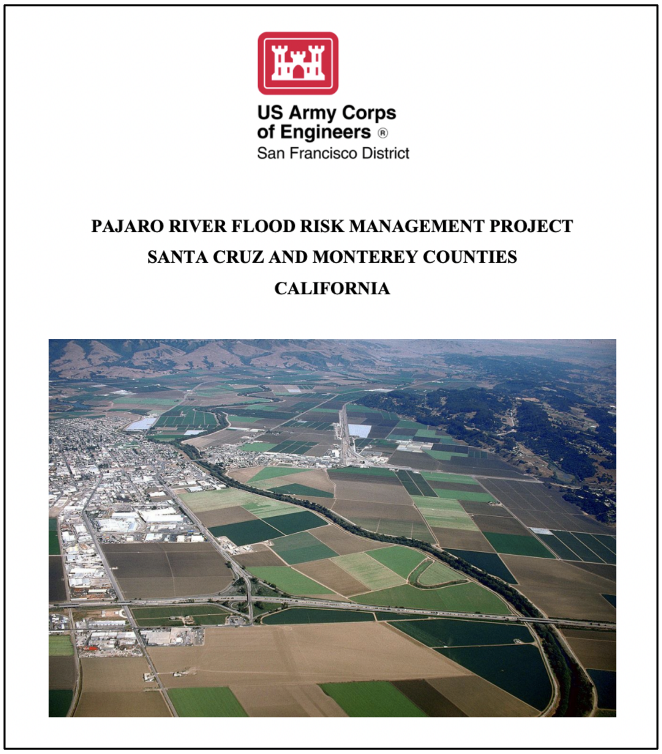
I recommend that any future analyses conduct a socioeconomic factor analysis in relation to flooding occurrence with a more spatially detailed dataset pertaining to income, property value, or demographics. The land classification step should be conducted with a supervised land classification on 10m satellite imagery, along with an accuracy assessment beside the 30m NLCD. The resulting results from the land cover analysis would be much more accurate and precise. For the flood maps, validation should be conducted using river discharge data (Notti et al. 2018), citizen science (Assumpção et al. 2018), and observed data (Molinari et al. 2019). Lastly, statistical significance tests between the variables of the physical categorical factor analysis and the socioeconomic factor analysis with flooding occurrence should be conducted, to determine the exact level of correlation from each variable pair.

Beyond the scope of this study, I have considered a few fascinating research questions that address research gaps in literature. First would be an analysis of flood occurrence before and after the implementation of a flood infrastructure project, to gauge effectiveness of the project. Another research topic would be to analyze the change of land cover over time alongside flooding events at different time periods, as human activity continues to rapidly change the built and natural landscape. Lastly, a flood analysis under different levels of radiative forcing to simulate climate change, similar to Swain et al. 2018, would introduce a new factor into this type of flood analysis.

Broader implications

Since anthropogenic climate change has been attributed to more extreme weather events (Otto et al. 2018), California's whiplash effect from extreme drought to extreme precipitation on a year-to-year basis is expected to intensify (Swain et al. 2018), requiring interdisciplinary solutions from flood management organizations. Local, state, and federal governments can utilize the results of this study to prioritize mitigation strategies to maximize impact. By identifying certain types of areas that are prone to flooding, state and federal agencies can monitor these regions more closely and be able to mitigate flood issues early on to reduce progressive effects down the line. Organizations may also use these results to inform decisions on designing new flood infrastructure and maintaining old systems. For instance, the US Army Corps of Engineers is implementing the Pajaro River Flood Risk Management Project (PRFRMP) in 2024, which seeks to update old flood infrastructure like levees, while also enacting nature based solutions (Figure 17). One nature based solution of the PRFRMP is to restore floodplains to reduce flood risk for the surrounding community. These floodplains would slow down fast-flowing floods and lower peak flows (Serra-Llobet et al. 2022). This would involve restoring riparian habitat around the river, which in Watsonville, is predominantly agricultural cropland. These types of nature based solutions are long term solutions to flooding, especially since climate change is expected to exacerbate high precipitation events (Clarke et al. 2022). Identifying contributing flooding factors is essential to the success of costly flood risk reduction strategies. These projects, which are difficult to implement and fund, must often produce quick and visible results for the community.

There is little-to-no margin for error in these types of management solutions. Therefore, more research on this topic is needed to ensure the health and safety of communities across California as we step into this new era of equitable flood management.



US Army Corps
of Engineers ®
San Francisco District

PAJARO RIVER FLOOD RISK MANAGEMENT PROJECT
SANTA CRUZ AND MONTEREY COUNTIES
CALIFORNIA

Figure 17. The Pajaro River Flood Risk Management Project.

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APPENDIX A

Table A1. The National Land Cover Database Class Legend and Description (Dewitz 2023).

Class\ Value	Classification Description
Water	
11	**Open Water-** areas of open water, generally with less than 25% cover of vegetation or soil.
12	**Perennial Ice/Snow-** areas characterized by a perennial cover of ice and/or snow, generally greater than 25% of total cover.
Developed	
21	**Developed, Open Space-** areas with a mixture of some constructed materials, but mostly vegetation in the form of lawn grasses. Impervious surfaces account for less than 20% of total cover. These areas most commonly include large-lot single-family housing units, parks, golf courses, and vegetation planted in developed settings for recreation, erosion control, or aesthetic purposes.
22	**Developed, Low Intensity-** areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 20% to 49% percent of total cover. These areas most commonly include single-family housing units.
23	**Developed, Medium Intensity** -areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 50% to 79% of the total cover. These areas most commonly include single-family housing units.
24	**Developed High Intensity**-highly developed areas where people reside or work in high numbers. Examples include apartment complexes, row houses and commercial/industrial. Impervious surfaces account for 80% to 100% of the total cover.
Barren	
31	**Barren Land (Rock/Sand/Clay)** - areas of bedrock, desert pavement, scarps, talus, slides, volcanic material, glacial debris, sand dunes, strip mines, gravel pits and other accumulations of earthen material. Generally, vegetation accounts for less than 15% of total cover.
Forest	
41	**Deciduous Forest-** areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. More than 75% of the tree species shed foliage simultaneously in response to seasonal change.
42	**Evergreen Forest-** areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. More than 75% of the tree species maintain their leaves all year. Canopy is never without green foliage.

43	**Mixed Forest**- areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. Neither deciduous nor evergreen species are greater than 75% of total tree cover.
Shrubland	
51	**Dwarf Scrub**- Alaska only areas dominated by shrubs less than 20 centimeters tall with shrub canopy typically greater than 20% of total vegetation. This type is often co-associated with grasses, sedges, herbs, and non-vascular vegetation.
52	**Shrub/Scrub**- areas dominated by shrubs; less than 5 meters tall with shrub canopy typically greater than 20% of total vegetation. This class includes true shrubs, young trees in an early successional stage or trees stunted from environmental conditions.
Herbaceous	
71	**Grassland/Herbaceous**- areas dominated by gramanoid or herbaceous vegetation, generally greater than 80% of total vegetation. These areas are not subject to intensive management such as tilling, but can be utilized for grazing.
72	**Sedge/Herbaceous**- Alaska only areas dominated by sedges and forbs, generally greater than 80% of total vegetation. This type can occur with significant other grasses or other grass like plants, and includes sedge tundra, and sedge tussock tundra.
73	**Lichens**- Alaska only areas dominated by fruticose or foliose lichens generally greater than 80% of total vegetation.
74	**Moss**- Alaska only areas dominated by mosses, generally greater than 80% of total vegetation.
Planted/Cultivated	
81	**Pasture/Hay**-areas of grasses, legumes, or grass-legume mixtures planted for livestock grazing or the production of seed or hay crops, typically on a perennial cycle. Pasture/hay vegetation accounts for greater than 20% of total vegetation.
82	**Cultivated Crops** -areas used for the production of annual crops, such as corn, soybeans, vegetables, tobacco, and cotton, and also perennial woody crops such as orchards and vineyards. Crop vegetation accounts for greater than 20% of total vegetation. This class also includes all land being actively tilled.
Wetlands	
90	**Woody Wetlands**- areas where forest or shrubland vegetation accounts for greater than 20% of vegetative cover and the soil or substrate is periodically saturated with or covered with water.

95	**Emergent Herbaceous Wetlands**- Areas where perennial herbaceous vegetation accounts for greater than 80% of vegetative cover and the soil or substrate is periodically saturated with or covered with water.