Adapting to Rising Tides:
Vulnerability to Sea Level Rise in Select Communities in the San Francisco Bay Region

Prepared by Matthew Heberger and Eli Moore of the Pacific Institute, Oakland, California

For

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1 Introduction

The San Francisco Bay Conservation and Development Commission (BCDC) is working with Bay Area communities to better understand and plan for sea level rise. The Adapting to Rising Tides (ART) project is a partnership with the National Oceanic and Atmospheric Administration Coastal Services Center (NOAA CSC). The Adapting to Rising Tides project is a collaborative effort evaluating how the Bay Area can become more resilient to climate change, in particular sea level rise and storm events. The primary goal of the ART project is to increase the Bay Area's preparedness and resilience to sea level rise and storm events while protecting critical ecosystem and community services. The ART project is a pilot project that will ultimately provide guidance on how best to approach two broad questions:

- How will sea level rise and other climate change impacts affect the future of Bay Area communities, ecosystems, infrastructure, and economy?
- What strategies should we pursue, both locally and regionally, to address these challenges and reduce and manage these risks?

As a part of this project, the Pacific Institute is helping to more closely examine socio-economic vulnerabilities of sea level rise impacts in the ART project area which includes the shoreline communities in Alameda County from Emeryville in the north to Union City in the south. The study area encompasses a portion of Alameda County shoreline from the City of Emeryville to the City of Union City, extending inland approximately a half a mile beyond the area projected to be exposed to storm event flooding with 55 inches of sea level rise.

The Bay Area comprises nine counties that have, according to the 2010 US Census, a population of 7.15 million, or about 1/5 of the state's population. These counties share a connection to nearly 1,000 miles of the San Francisco Bay shoreline. In recent years, the threat of sea level rise has been shown to be real, with potential impacts on residents, the economy, and infrastructure of the Bay Area. Adaptation to climate change and sea level rise are complicated by the fact that 101 cities share responsibility for land use along the San Francisco Bay shoreline (Travis 2009). Because of the size and complexity of the region, the Adapting to Rising Tides project team has chosen to focus on a smaller study area. It is our hope not only that the results of this study will shed light on key issues, but also that the methods illustrated here will be of use to analysts and planners in other areas. The ART study area, shown in Figure 1, is made up of six shoreline cities: Emeryville, Oakland, Alameda, San Leandro, Hayward and Union City, and the unincorporated community of San Lorenzo.

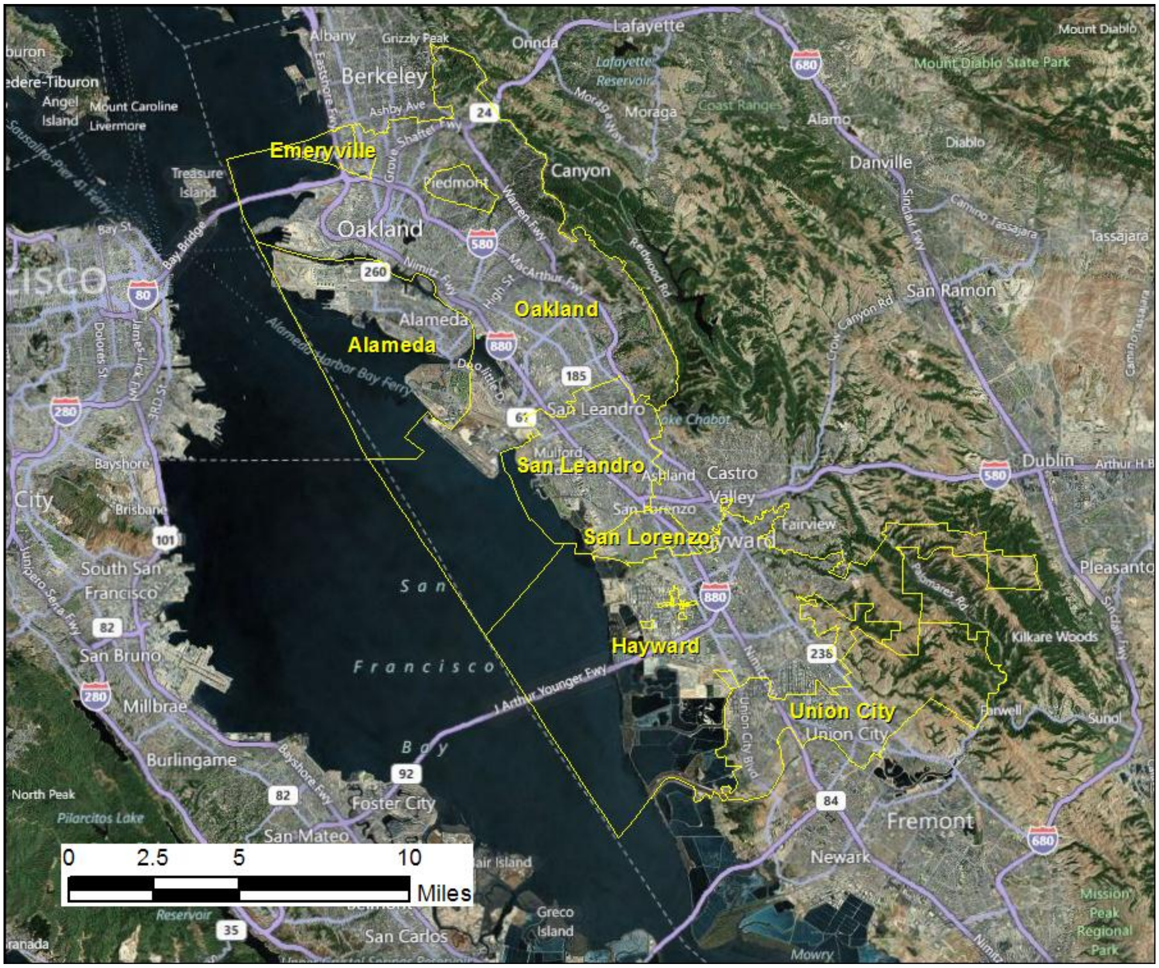

Figure 1 Cities in the ART study area

Previous studies have shown that nearly a quarter million Bay Area residents may be exposed to flooding by the end of the century under a plausible scenario of sea level rise (Heberger 2009; Knowles 2009). Furthermore, there is evidence that the population that could be exposed to flooding is diverse and includes communities with heightened vulnerabilities. Within this group, a significant fraction are low-income, minorities, immigrants who do not speak English well, and those that lack access to transportation.

A priority for the ART project is to develop and test an adaptation planning approach that explicitly identifies equity issues in vulnerability and risk assessments, and integrates consideration of equity into selection of adaptation strategies. Equity issues can underlie the way some communities are disproportionately burdened by the effects of storm events and flooding, which are projected to become more frequent with climate change. While many traditionally disenfranchised communities struggle to get by, flooding associated with climate change will create added challenges, as well as opportunities to build resiliency. Communities that may specifically be vulnerable to natural hazards should also be considered, such as households with no car, less mobile and institutionalized populations. As a cross-cutting issue, equity should be considered across jurisdictions and thematic areas, including public health, emergency response and preparedness, secondary impacts to communities, disaster recovery and adaptation/resilience.

The purpose of the analysis presented in this report is to support the ART project adaptation planning process. Below, we describe a number of analyses that were conducted to assess:

1. Social vulnerability of the populations exposed to SLR in the ART project area
2. Employment and workplace vulnerability
3. Value of the property exposed to SLR in the ART project area
4. Exposure of community assets and liabilities

Following this introduction, Section 2 describes the data and methods used in the Geographic Information System (GIS) analyses and processing of the sea-level rise scenario layers. In Section 3, we estimate the population exposed to inundation risk under each of the sea-level rise scenarios, and analyze the social vulnerability and demographics of the population exposed. The Social Vulnerability Index, or SOVI, developed by Susan Cutter at the University of South Carolina, combines 32 different factors to create a single index of social vulnerability. It includes factors that the literature suggests contribute to a community's ability to prepare for, respond to, and recover from hazards (Cutter et al. 2003). The SoVI index quantifies social vulnerability using available data, mostly from the US Census, including income, race, unemployment, and others. In this study, we use the SoVI index to help understand the social vulnerability of residents in the ART study area and among those exposed to flood risks.

In Section 4, we analyze the workplace vulnerability, tabulating the number of employees that may be exposed to future flooding. In Section 5, we analyze the value of property exposed to inundation risks. We perform the property analysis twice using two different public-domain datasets and compare the results for each method.

In Section 6, we identify which community assets or liabilities may be exposed to future flooding. Assets include critical facilities for emergency response such as police and fire stations, and facilities that deliver social services such as homeless shelters and food banks. Liabilities include areas where toxic materials are stored and have the possibility of being mobilized during a flood.

1.1 A Note about Data and Methods

In this report, we report on each of the four analyses in a separate chapter. Each chapter includes a detailed description of the data, methods, limitations and results. We have attempted to give sufficient detail so that others will be able to repeat this analysis, or perform similar analyses in other cities or regions. We assume the analyst will have experience with GIS, spreadsheets, and databases, and with the use of raster datasets, ESRI's Spatial Analyst, and working with US Census data. We do not attempt to provide a step-by-step tutorial that includes every action required in the analysis; we assume that most analysts undertaking a similar analysis would not benefit from this level of detail. Please contact the authors of this study at the Pacific Institute with any questions or clarification.

1.2 Definitions

Here we define several terms that we use in this report, drawn from Adapting to Rising Tides publications and other sources.

Hazard - The threat of an event that will have a negative effect on people or the environment.

Disaster - The effect of a hazard, that leads to financial, environmental or human losses. To illustrate the difference between a hazard and a disaster, an earthquake is a natural hazard. An earthquake that occurs in an unpopulated area and does not result in damages is not considered a disaster.

Vulnerability - The susceptibility of people, property, and resources to negative impacts from climate change. Vulnerability is a function of the level of exposure to climate change impacts, and the sensitivity and adaptive capacity of the communities and resources that are affected.

Risk - The threat posed by a negative impact or hazard event. The level or degree of risk is the product of the likelihood of an impact occurring and the magnitude of societal, economic, environmental and governance consequences should that impact occur.

Climate Change Adaptation – "Adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities" (IPCC 2007).

1.3 Social Vulnerability Overview

Exposure to a flood event can result in a range of harmful physical, economic, and social and psychological effects on the affected population. Studies have also shown that socio-economic conditions of the affected population shape or influence these effects and cause them to be disproportionately severe for certain social groups. Planners, communities, and decision-makers can make use of this research by incorporating an analysis of social vulnerabilities into climate adaptation and other preparedness efforts. Here we summarize a selection of the literature on this topic as background for the analyses in this report.

Those with low incomes are particularly vulnerable to disasters in a number of ways, and for a variety of reasons. They are often under-insured, and more likely to have a home that is damaged in a disaster due to lower quality construction (Fothergill and Peek 2004; Bolin and Bolton 1986; Blanchard-Boehm 1997). During emergency response, studies have found that the poor are one of the groups most likely to not have their needs met (Fothergill and Peek 2004). Further, those with low incomes are more likely to suffer emotional stress and other psychological impacts after a disaster (Fothergill and Peek 2004 citing Bolin and Bolton 1986 and Bolin 1993). Additionally, they may not have the resources, such as car ownership and access to public transit, to evacuate when a disaster hits (Bolin and Bolton 1986; Blanchard-Boehm 1997 cited in Heberger et al. 2009; Brodie et al. 2006).

Besides poverty, age and other socio-economic factors are commonly associated with increased vulnerability to a disaster. Multiple studies have found people of color and ethnic minorities to be particularly vulnerable to disasters (Hajat et al. 2003; Blanchard-Boehm 1997; Perry and Mushkatel 1986; Phillips and Ephraim 1992). Women (who are disproportionately poor), the elderly (who often live on fixed incomes), and children are also vulnerable groups (Hajat et al. 2003). Those who are disabled or have a disabled family member are also more vulnerable, as disabilities can make evacuation more difficult (Hajat et al. 2003; Brodie et al. 2006). Social and geographic isolation are also factors in how people are impacted by a disaster. Wang and Yasui (2008) note that "many recent disaster response crises illustrate how language barriers, isolation from public agencies, and fear of interacting with public agencies combine to increase the vulnerability of many residents."

Finally, institutionalized populations, such as those in hospitals, nursing homes and prisons are reliant on the preparedness and response of the facility, and many post-disaster analyses have found flaws in the disaster preparedness and evacuation planning of institutions (Moser and Ekstrom 2010; Caruson and MacManus 2008).

2 Sea Level Rise and Flood Exposure

For this study, we conducted four separate but related analyses. Here we describe the analytical methods for generating the data on the flood exposure area, and the software and overarching methods that apply to the subsequent four analyses.

2.1 Software

2.1.1 GIS

The bulk of our analysis was performed using Geographic Information Systems (GIS) software. We used ArcGIS Desktop versions 9 and 10. This is commercial software sold by ESRI, a company in Redlands, California. It is among the most widely-used GIS packages. There are free and open-source alternatives that are available, such as qGIS, GRASS, and others. We do not have experience with these packages, however, and cannot say whether they are suitable for performing the range of analyses described below. Any GIS software requires some specialized skill and training to use effectively.

In addition to the basic software, ArcGIS Desktop, the Spatial Analyst extension is required for performing analyses on the raster (grid) flood layers.

We offer the following advice for performing similar analyses. Before committing to performing an operation on a large dataset, experiment with a small dataset. Do not assume that because the operation finished without error that the results are what you wanted. Examine your results periodically by opening the new data layer in a map; examine it by using the identify tool, select tool, opening the attribute table, etc. According to ESRI trainers (Honeycutt et al. 2010), "overlaying large datasets is CPU and RAM intensive." They offer the following advice for performing overlay operations:

- Schedule large overlays accordingly (i.e., lunch, after hours)
- Shut down all other applications
- Use computers with lots of memory

For operations that must be repeated several times (for example, for multiple inundation layers), ArcGIS has built in tools to partially automate some of these procedures. In ArcGIS 9, commands can be run via the Command Line, or in ArcGIS 10, commands can be run via the Python window. We found that it was simple to copy a command from the Results window, change the name of the target input and output files in a text editor, and paste the new command into the Python window. This was generally faster than it would have been to create a custom model in Model Builder or to write a custom Python script to loop over the six files. However, if we were dealing with fifty files rather than six, a custom script would have likely saved time.

2.1.2 Database and Data Analysis

We used Microsoft Access to store several large datasets. The main advantage to using Access is that it can be accessed from both ArcGIS and Microsoft Excel. For example, ArcGIS 9 and 10 can create and edit geographic features in a format that ESRI calls a "personal geodatabase" or PGDB. A personal geodatabase file is a Microsoft Access 2003 database (.mdb) file.

We found these files to have advantages over the newer "file geodatabase" format, because they can be opened directly with MS Access. This means that you can create your own queries in Access to summarize or update the data, which is often faster and easier than using ArcGIS commands. Most importantly, tables can also be accessed from Microsoft Excel via the "Import Data" or "Connect to Data Source" feature. This is useful for summarizing large datasets using Excel's Pivot Table feature.

2.2 Data

In this section, we describe the datasets that were common to several of the analyses. The GIS data layers that we used to estimate the extent of inundation hazard zone within the project area are listed in Table 1 and described below.

Table 1 Data sources for defining flood risk areas

Data layer	Source
Parcels	Alameda County Assessor's Office
Census Block Boundaries	US Census Bureau
Census Block Group Boundaries	US Census Bureau
Census Tract Boundaries	US Census Bureau
Inundation Depth rasters	AECOM
MHHW + 16"	
MHHW + 55"	
100-year Stillwater + 16"	
100-year Stillwater + 55"	
100-year + wind + waves + 16"	
100-year + wind + waves + 55"	

2.2.1 Areas Possibly Exposed to Future Inundation

In order to conduct an exposure assessment, we required a geographic data layer that represents the area possibly exposed to future flooding under a given scenario of sea level rise. These datalayers were developed from 2011-2012 by AECOM, and engineering consulting firm, under contract with BCDC. A more detailed description of the data and methods for creating these datalayers is available in the consultant report (AECOM 2012). The analysis covered three floodwater elevations:

- Mean Higher High Water (MHHW): A standard measure of high tide that occurs on average once a day. NOAA defined MHHW as "the average of the higher high water height of each tidal day observed over the National Tidal Datum Epoch" (NOAA 2000). Higher high water is "the highest of the high waters (or single high water) of any specified tidal day due to the declinational effects of the Moon and Sun."

- 100-year Stillwater: The water level with a 1% chance of occurring in any given year. Stillwater refers to a measurement taken inside a stilling well, which excludes "short period surface waves while freely admitting the tide, other long period waves, and sea level variations." Thus, this measure does not include the effect of wind and waves.

- 100-year Stillwater with Wind and Waves: This is the 1% annual-chance water level including tides, storm surge, and wind and waves. Wind-generated waves can greatly increase the water levels during a storm, causing overtopping of shoreline protection and extensive, however short duration, flooding.

AECOM produced each of these datalayers for both a 16-inch (0.4 m) and 55-inch (1.4 m) sea level rise. These sea level rise scenarios were originally adopted by California's Climate Change Center for climate analysis and planning for the state's Biennial Climate Change Assessment (Heberger 2009). We worked with data files that combined the two SLR scenarios with the three flood elevations, for a total of six files:

- MHHW + 16"
- MHHW + 55"
- 100-year Stillwater + 16"
- 100-year Stillwater + 55"
- 100-year Stillwater + wind + waves + 16"
- 100-year Stillwater + wind + waves+ 55"

For this study, we did not analyze exposure to inundation under current, present-day conditions. However, previous studies (Heberger et al. 2009; Knowles 2009) and current FEMA floodplain maps indicate that the existing flood risk is high in some parts of the Bay Area. As has been often argued, our society is not well adapted to current climate; much less so to future climate. For future studies, it would be worthwhile to analyze present-day hazards as well. This allows us to analyze how much of the future flood risk represents an increase over present-day levels.

2.2.2 Coordinate Systems

We performed a series of analyses in GIS that fall in the category of "overlay analysis." This allowed us to answer the question, "Which features in the study area are exposed to floodwaters under each scenario?" In order to perform such analyses, the input datasets must share a common coordinate system.

Prior to running the analyses, we re-projected all of the GIS datalayers into a common coordinate system. At the suggestion of BCDC staff, we chose a standard projection for Northern California: "NAD 1983 California Teale Albers." The coordinate system is defined by the following parameters:

Projected Coordinate System:	NAD_1983_California_Teale_Albers
Projection:	Albers
False_Easting:	0
False_Northing:	-4,000,000
Central_Meridian:	-120
Standard_Parallel_1:	34
Standard_Parallel_2:	40.5
Latitude_Of_Origin:	0
Linear Unit:	Meter
Geographic Coordinate System:	GCS_North_American_1983
Datum:	D_North_American_1983
Prime Meridian:	Greenwich
Angular Unit:	Degree

2.2.3 Pre-Processing Steps

We should state right off that the analysis required some trial and error. Because of the large size of the inundation data files (each flood raster is about 1 GB in size), not all of the ArcGIS tools worked as expected. We found ourselves patiently waiting over an hour for a process to continue only to be confronted with an error message saying "Out of memory." The procedures described in this document work reliably but require a number of steps to complete.

We had to first transform the flood layers into a simpler format which occupies less space on disk and can be used with our computers' available memory. We experimented with creating vector polygon files from the inundation layers. We had success with using the vector-based analysis tools for this type of analysis in the past. However, we were not able to use ArcGIS tools to process these vector layers. We believe that this is due to the large number of vertices contained by some of the polygon features.

We found that the inundation rasters contained more information than was strictly necessary to perform the analysis. The flood depth was stored as a double-precision floating point number, which translates to 15–17 significant decimal digits precision. This level of precision is not warranted by the input data or the analysis methods, neither of which carry this level of precisions, so simplifying the data will not greatly affect our results. Note that we did not "downsample" the raster; we maintained the 2 foot grid cell size throughout the analysis. Rather, we converted the data value contained in each grid cell from a floating point number to a Boolean (true/false) value. The grid cells of the new layers contained a value of either 1 (inundated) or 0 (not inundated). Converting the raster datasets from double-precision to Boolean, as shown in Figure 2, made the files 99.3% smaller (Table 2), and allowed us to run ArcGIS geoprocessing tools on a desktop computer.

Table 2 Raster formats for inundation hazard zones

Raster Format	Example Value	Size on Disk
Double-precision floating point number	2.23498123876541321	1 GB
Integer	2	10 MB
Boolean	1	7 MB

Converting the inundation layers to Boolean also facilitated our analysis of the question, “Is a particular feature inside or outside of the inundation zone?” or “What percentage of an area is inundated?” Using these layers, we cannot answer the question, “What is the depth of inundation for a structure?” Other researchers have shown that it is difficult to assess flooding depth for structures via a desktop study. Generally, digital terrain data does not give sufficient information, and accurate site surveys are needed to determine the elevation of a particular structure (see for example Heinz Center 2000).

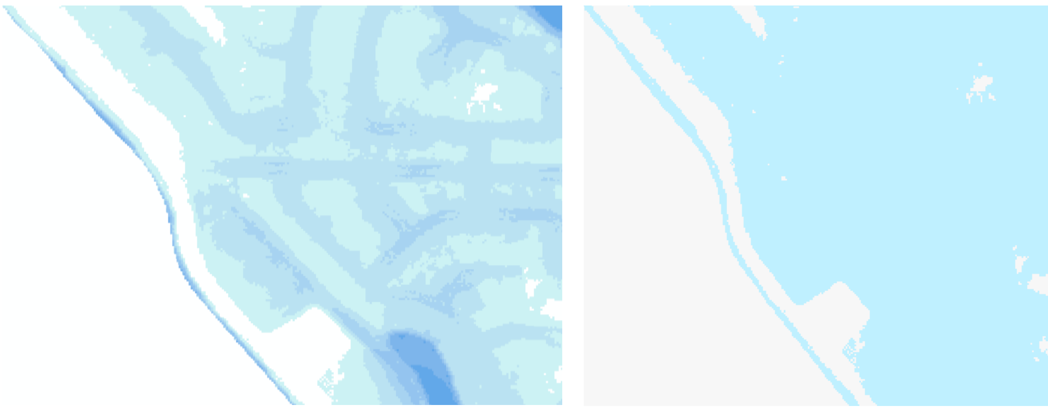

Figure 2 Comparison of flood depth layer (left) with binary flood layer (right).

Care was taken to use a consistent naming scheme throughout the project to avoid confusion. Files and database fields representing the various inundation layers were named as shown in Table 3.

Table 3 Naming convention for files and database fields associated with the six inundation scenarios

Inundation Scenario	Flood Percentage Naming Convention	Boolean (True/False) Flood Naming Convention
MHHW + 16”	fld_mhhw16	b_mhhw16
MHHW + 55”	fld_mhhw55	b_mhhw55
100-year Stillwater + 16”	fld_sw16	b_sw16
100-year Stillwater + 55”	fld_sw55	b_sw55
100-year + wind + waves + 16”	fld_ww16	b_ww16
100-year + wind + waves + 55”	fld_sw55	b_sw55

3 Population, Demographics, and Social Vulnerability

This section estimates the population exposed to inundation under each sea-level rise scenario, and the demographics and social vulnerability of the affected population. The analysis provides answers to the following questions:

- How many people are exposed to flooding under each inundation scenario?
- What are the demographics of this population?

- Which areas exposed have populations with social characteristics that increase their vulnerability to potential harm?
- In the most vulnerable areas, what are the specific vulnerabilities that contribute the greatest amount to the population's social vulnerability?

For adaptation measures to protect all populations from sea-level rise, the vulnerabilities of the population potentially exposed must be considered and integrated into planning decisions. The impact of sea-level rise on exposed populations will be more or less severe depending on various socio-economic conditions. The diverse and complex relationships shaping social vulnerability cannot be predicted with complete certainty, but studies have identified specific factors and methods for quantifying the relative social vulnerability within populations. Foremost among these is the Social Vulnerability Index (SoVI), which we use to estimate the overall relative social vulnerability of local communities within the study area.

SoVI is a methodology increasingly used in planning to account for the socio-economic conditions that influence population vulnerability to a range of hazards, including hurricanes, flood events, and others. SoVI compiles datasets from the US Census and creates a 'score' for each block group indicating the local population's degree of social vulnerability. The National Oceanic and Atmospheric Administration (NOAA) has published complete datasets of SoVI analysis results for all block groups in coastal US states. The following methodology utilizes the NOAA data and additional US Census data.

3.1 Data

We used two sources of data for population, households, and demographics, both obtained online from public sources. To estimate the total population exposed, we used US Census data on households and total population at the census block level. For social vulnerability and population demographics, we used a composite indicator of Social Vulnerability published by NOAA that aggregates 31 variables and is compiled at the Census Block Group level (NOAA CSC 2011). Table 4 lists all population data used.

A household is defined by the Census Bureau as "all the persons who occupy a housing unit. A housing unit is a house, an apartment, a mobile home, a group of rooms, or a single room." In the study area, there is an average of 2.6 people per household. The Census Bureau classifies people not living in households are classified as living in *group quarters*. We consider some populations in group quarters as especially vulnerable, for example those in prisons or nursing homes, while others may not have especially heightened vulnerability, such as college students living in dormitories. We analyze exposure of those in group quarters in more detail in Section 6, Community Assets and Liabilities Exposed to Flood Risk.

Table 4 Datasets and their sources for population characteristics contributing to social vulnerability

Boundary Files	
Census Block Boundaries	US Census Bureau, 2009
Census Block Group Boundaries	US Census Bureau, 2009
Census Block Tables	
Total population	US Census, 2000
Households	US Census, 2000
Census Block Group Tables	
Social Vulnerability Index (SoVI) Score	NOAA/USC, 2011
Percent African American	NOAA/USC (2000 Census)
Percent Native American	NOAA/USC (2000 Census)
Percent Asian and Hawaiian Islander	NOAA/USC (2000 Census)
Percent Hispanic	NOAA/USC (2000 Census)
Percent of population under 5 years of age	NOAA/USC (2000 Census)
Percent of population age 65 and over	NOAA/USC (2000 Census)
Median age	NOAA/USC (2000 Census)
Percent female population	NOAA/USC (2000 Census)
Average number of people per household	NOAA/USC (2000 Census)
Percent renter occupied units	NOAA/USC (2000 Census)
Percent female headed households, no spouse present	NOAA/USC (2000 Census)
Nursing home residents per capita	NOAA/USC (2000 Census)
Percent civilian unemployment	NOAA/USC (2000 Census)
Per capita Income (2000 dollars)	NOAA/USC (2000 Census)
Percentage of households earning 100,000 or more	NOAA/USC (2000 Census)
Percent living below the poverty level	NOAA/USC (2000 Census)
Mean House Value	NOAA/USC (2000 Census)
Mean contract rent for renter occupied housing units	NOAA/USC (2000 Census)
Number persons per 100,000 population employed as healthcare practitioners and technical occupations	NOAA/USC (2000 Census)
Percent rural farm population	NOAA/USC (2000 Census)
Percent of housing units that are mobile homes	NOAA/USC (2000 Census)
Percent of population 25 years or older with no high school diploma	NOAA/USC (2000 Census)
Percent of population participating in the labor force	NOAA/USC (2000 Census)
Percent females participating in the labor force	NOAA/USC (2000 Census)
Percent employment in farming, fishing, and forestry occupations	NOAA/USC (2000 Census)
Percent employed in transportation, communications, and other public utilities	NOAA/USC (2000 Census)
Percent Employed in service industry	NOAA/USC (2000 Census)
Percent of population collecting social security benefits	NOAA/USC (2000 Census)

Percent Foreign Born Citizens Immigrating between 1990 and 2000	NOAA/USC (2000 Census)
Percent urban population	NOAA/USC (2000 Census)
Housing Density	NOAA/USC (2000 Census)
Linguistically isolated households	US Census, 2000
Households with no vehicle	US Census, 2000
People of color (non-white, non-Hispanic)	US Census, 2000
Households in poverty (earning less than 200% of the national poverty level)	US Census, 2000
Renter-occupied households	US Census, 2000
Population living in "group quarters"	US Census, 2000

The Census Bureau has published population data from the 2010 Census. However these data are aggregated according to new geographic boundaries that are different from, and not compatible with, data from the 2000 Census. Because of the changing Census boundaries between 2000 and 2010, we chose to use total population data from the 2000 Census. The boundaries of Census blocks were updated with the 2010 Census, adjusting the geographic area covered by some blocks and creating nearly 3 million new Census blocks in the country (US Census Bureau 2011). This prevents the reliable integration of 2000 and 2010 datasets for Census blocks and block groups. Therefore, our analysis does not include data from the 2010 Census.

For the break-down of different social groups, demographic data from the 2000 Census rather than the American Community Survey was used. Data on local demographics is available from the 2005–2009 American Community Survey (ACS), but due to the sampling methods of the ACS, this data is often suppressed or has high margins of error at the block group level. Using demographic data from higher levels, such as Census tracts, is unreliable due to the heterogeneous population and large geographic areas within tracts. For these reasons, we recommend using demographic data from the 2000 Census until a more recent dataset with high reliability at the block group level has been released.

3.2 Methods

Methods for estimating population exposed and social vulnerability involve four steps:

1. Calculate percentage of area inundated for all blocks in study area
2. Estimate population exposed to inundation for all bocks, and sum block population exposed up to the block group level
3. Append demographic data and sort block group population exposed into categories of social vulnerability
4. Estimate demographics of population exposed, and identify key vulnerabilities of population with high overall social vulnerability

Estimating population exposed at the *block* level rather than at the level of the *block group* is an important aspect of this methodology. Steps 1 and 2 are described in section 3.2.1 below and utilize *block* level data. Steps 3 and 4 are described in section 3.2.2 below and utilize *block group* level data.

3.2.1 Population Exposed to Flooding

We clipped Census block boundaries (US Census 2009) to remove water bodies from Block Group areas. This step was necessary because many census blocks have boundaries extending far out into the Bay, and with this geometry it is not possible to calculate the area of formerly dry land that would be inundated by a flood layer. The 2009 Census block boundary files include only the blocks from the 2000 Census, but the boundaries have been updated to more accurately reflect the roads, waterways, and other reference points for block boundaries.[1] For each Census block in the study area, we calculated the percent area inundated using the methods described in Appendix D.

The result of the procedure described in Appendix D is a table with the percent area inundated for each Census block in the study area. Multiplying the percent area inundated by the total block population generates a figure for population exposed to inundation. Next the figures for block population exposed are summed to the block group level using the attribute column noting the block group identification number for each block. The same is done for the block households exposed. We did this step by exporting the attribute table to Excel and using the Excel Pivot Table tool to sum block population and households exposed to the block group level.

3.2.2 Social Vulnerability of Population Exposed

The SoVI score for all block groups in Coastal US states have been calculated and published by the National Oceanic and Atmospheric Administration (NOAA) in partnership with the University of South Carolina. The SoVI dataset from NOAA for California uses Census 2000 data for analyzing 31 variables to calculate index scores at the Census block group level (NOAA 2011). Shapefiles with SoVI scores for block groups within a coastal state can be downloaded from the NOAA Data Access Viewer link at http://www.csc.noaa.gov/digitalcoast/data/SoVI/. The methodology used to calculate SoVI scores was first published and has been refined by Susan Cutter and the Hazards and Vulnerability Research Institute at the University of South Carolina (Cutter 2003, Cutter et al 2009). For a list of all variables included in the SoVI scoring methodology used in the NOAA dataset, see Table 5.

Table 5 Variables included in the composite Social Vulnerability Index

Variable	Label in Data Files	Relation to vulnerability
Percent African American	QBLACK	Positive
Percent Native American	QINDIAN	Positive
Percent Asian and Hawaiian Islander	QASIAN	Negative
Percent Hispanic	QSPANISH	Positive
Percent of population under 5 years of age	QKIDS	Positive
Percent of population age 65 and over	QPOP65O	Positive
Median age	MEDAGE	Negative
Percent female population	QFEMALE	Positive
Average number of people per household	PPUNIT	Positive
Percent renter occupied units	QRENTER	Positive

[1] TIGER/Line Shapefiles and TIGER/Line Files. Retrieved from http://www.census.gov/geo/www/tiger/shp.html

Variable	Label in Data Files	Relation to vulnerability
Percent female headed households, no spouse present	QFHH	Positive
Nursing home residents per capita	NRRESPC	Positive
Percent civilian unemployment	QCVLUN	Positive
Per capita Income (2000 dollars)	PERCAP	Negative
Percentage of households earning 100,000 or more	QRICH	Negative
Percent living below the poverty level	QPOVTY	Positive
Mean house value	MEAN_HSEVA	Negative
Mean contract rent for renter occupied housing units	MC_RENT	Positive
Number persons per 100,000 population employed as healthcare practitioners and technical occupations	PHYSICN	Negative
Percent rural farm population	QRFRM	Positive
Percent of housing units that are mobile homes	QMOHO	Positive
Percent of population 25 years or older with no high school diploma	QED12LES	Positive
Percent of population participating in the labor force	QCVLBR	Negative
Percent females participating in the labor force	QFEMLBR	Positive
Percent employment in farming, fishing, and forestry occupations	QAGRI	Positive
Percent employed in transportation, communications, and other public utilities	QTRAN	Positive
Percent Employed in service industry	QSERV	Positive
Percent of population collecting social security benefits	QSSBEN	Positive
Percent Foreign Born Citizens Immigrating between 1990 and 2000	QMIGRA	Positive
Percent urban population	QURBAN	Positive
Housing Density	HODENSTY	Negative

The detailed methodology for calculating SoVI scores is re-printed in Appendix A as a reference. This is a useful reference, but most analysts will not need to learn the details, as SoVI scores have already been calculated for all block groups in California by NOAA's Coastal Services Center (CSC). For more information on SoVI methods, see the online document, "HVRI Frequently Asked Questions" (HVRI 2011). In brief, calculating SoVI scores involves following the seven steps below.

1. Collect the data for each variable and normalize all variables as either percentages, per capita values, or density functions
2. Verify accuracy of the dataset using descriptive statistics
3. Standardize the input variables using z-score standardization
4. Perform a principal components analysis (PCA) to reduce the tendency for a variable to load highly on more than one factor.
5. Adjust the cardinality (positive or negative) of the variables so that the signs of the subsequent defining variables are appropriately describing the tendency of the phenomena to increase or decrease vulnerability
6. Place the components in an additive model and sum to generate the overall SoVI score for the place

7. Map SoVI scores using an objective classification (i.e. quantiles or standard deviations) with 3 or 5 divergent classes so illustrate area of high, medium, and low social vulnerability.

We joined the Census block group data table (containing data on population and number of households) with the table containing SoVI scores and the flood percent table described in the previous section. The join is based on the Census block group FIPS code, which is a 12-digit unique identifier (see Figure 12 on page 73 for more information on FIPS codes). This allowed us to calculate the population and households exposed to flooding in each block group under each of the six scenarios. There are a number of ways to perform a table join. We used the VLOOKUP function in Excel with the block group FIPS codes as the join field joins the two tables. Once the tables are joined, the block groups can be sorted according to their SoVI score. We also used SQL queries within MS Access to double-check the results of our calculations.

With the population exposed and the SoVI scores in one table, the block groups were broken into three groups according to their SoVI scores. Based on the SoVI scores for all block groups in Alameda County, three categories were created with scores below the 33rd percentile considered "Low Vulnerability," those between the 33rd and 66th percentile considered "Medium," and the higher third comprising "High Vulnerability." Basing categories on all block groups in the county allows the analysis to compare the vulnerability of flood-exposed areas to all areas in the county. Breaks at the 33 and 66th percentile SoVI score in Alameda County are shown in Table 6.

Table 6 Breaks for ranking social vulnerability into bins

Social Vulnerability	SoVI Scores
Low	–8.181 to –0.0384
Medium	–0.0385 to +2.450
High	+2.451 to +12.364

In Table 7, we report the population in blocks by social vulnerability rank and by city. Nearly half (48%) of the population in the 7 study-area cities lives in Census block groups with a high social vulnerability rank. Note that there are a small number of block groups in the study area for which a SOVI score has not been calculated. These areas are largely commercial or industrial, and have a small population, thus there was probably not enough information to compile the SOVI score for these block groups.

Table 7 Population in Block Groups, by Social Vulnerability Rank and by City

	Low	Medium	High	Missing	Total
Alameda	18,006	32,972	21,281	-	72,259
Emeryville	3,867	759	2,256	-	6,882
Hayward	16,907	91,257	31,866	-	140,030
Oakland	58,615	67,946	272,918	5	399,484
San Leandro	4,240	42,826	32,386	-	79,452
San Lorenzo		18,602	3,296	-	21,898
Union City	10,913	38,747	17,209	-	66,869
Total	112,548	293,109	381,212	5	786,874
	14%	37%	48%	0%	100%

To estimate the absolute numbers of people in socially vulnerable groups, data from the NOAA SoVI dataset on social variables can be used, or new tables of Census block group data can be integrated. If the social variable of interest is in the SoVI dataset, the percentage with a chosen variable of vulnerability (e.g. percentage of population under age five) is multiplied by the population exposed to flooding in a sea-level rise scenario. If the social vulnerability variable is not in the SoVI dataset, a new table can be downloaded from the census for block groups in the study area, and joined to the existing table using the block group FIPS codes.

Additional datasets of socially vulnerable populations outside of SoVI were compiled to analyze the absolute numbers of several populations known to have increased vulnerability to environmental hazards. These include:

- Households with limited English (no member over age 14 identifies as speaking English ‘well’)
- Households with no vehicle
- People of color (non-white, non-Hispanic)
- Households in poverty (earning less than 200% of the national poverty level)
- Renter-occupied households
- Population living in “group quarters”, including institutions like correctional facilities, nursing homes, and mental hospitals, college dormitories, military barracks, group homes, missions, and shelters.

3.3 Limitations

Our estimates of the number of people affected were based on current population figures, as reported in the US Census. Our analysis did not use population projections because these projections are not available below the county level. The actual rate and distribution of population growth, and social and economic change will play a key role in shaping vulnerability in the future. As reported in Table 8, the region experienced modest population growth over the past decade. Every city added to its population except Oakland, which experienced a slight decline. The greatest percent growth occurred in Emeryville, where population grew by 46% over 10 years.

Table 8 Cities in the Adapting to Rising Tides study area and their population in 2000 and 2010

City	2000 Population	2010 Population	10-year Change	Percent Change
Alameda	72,259	73,812	+ 1,553	2%
Emeryville	6,882	10,080	+ 3,198	46%
Hayward	140,030	144,186	+ 4,156	3%
Oakland	399,484	390,724	– 8,760	–2%
San Leandro	79,452	84,950	+ 5,498	7%
San Lorenzo	21,898	23,452	+ 1,554	7%
Union City	66,869	69,516	+ 2,647	4%
Total	**786,874**	**796,270**	**+ 9,846**	**1%**

Certain populations with heightened vulnerability are not well represented in Census datasets. Homeless individuals and families are a particularly vulnerable segment of the population due to their lack of shelter, lack of resources and the difficulty in connecting with services and public agencies. However, local data on the location and size of this population is limited, as it is often changing and the Census only counts homeless people at shelters and pre-selected locations. Alameda County conducts a more comprehensive count of the homeless population every two years, and in 2011 documented 4,178 homeless individuals in the county (Focus Strategies 2011). The data is not broken down by geographic area within the county, preventing a quantitative analysis of those that may be exposed to flooding with projected sea-level rise.

Our analysis summarized social vulnerability at the census block group level, obscuring any variation within block groups. The Census Bureau periodically redraws boundaries so that the population within each tract is relatively homogenous and ranges between 600 and 3,000 residents. However, population changes happen more frequently than adjustments to boundaries, allowing for potentially significant demographic variation within tracts and size differences between tracts. Particularly in coastal areas, there is a chance that the part of a block group adjacent to the shoreline is less populated than areas further inland.

The science of measuring social vulnerability is rapidly developing and the SoVI methodology is still being refined. The variables included in the SoVI index were changed by its creators to reflect new understanding in 2010.[2]

Certain variables in SoVI explain a greater degree of the differences in scores between geographic areas. When the Hazards and Vulnerability Research Institute looked at which variables in the SoVI analysis contributed the greatest amount to the overall score nationally, they found that nine components explained 76% of the variance in the data. These nine components were: socioeconomic status, elderly and children, rural agriculture, housing density, black female-headed households, gender, service

[2] Hazards and Vulnerability Research Institute (2012). Changes and Improvements in the SoVI Formulation. Retrieved March 10th, 2012, from http://webra.cas.sc.edu/hvri/products/sovi_details.aspx

industry employment, unemployed Native Americans, and infrastructure employment.[3] This does not imply, however, that these components are the most important determinant the SoVI score at a local or county level.

3.4 Findings

3.4.1 Land Area Exposed to Flooding

The following set of tables show the area in each study-area city that is vulnerable to inundation, by scenario. These tables are shown for reference; we did not attempt to classify the land cover type that is inundated. Table 9 shows the area exposed to inundation in each city, in square miles. Table 10 shows the percentage of the total land area in each city that is exposed to inundation, by scenario.

Table 9 Land area in square miles exposed to inundation risk for the 6 ART scenarios, by city

	MHHW		100-year Stillwater		100-year + Wind and Waves		Total Land Area in City
	+ 16”	+ 55”	+ 16”	+ 55”	+ 16”	+ 55”	(for reference)
Alameda	0.72	3.48	2.50	6.32	6.37	8.28	10.61
Emeryville	0.02	0.03	0.03	0.20	0.20	0.43	1.23
Hayward	5.60	14.11	13.45	16.23	16.24	17.88	44.56
Oakland	1.46	6.04	4.39	9.80	9.77	12.82	55.85
San Leandro	0.51	1.44	1.14	2.88	2.76	3.79	13.25
San Lorenzo	0.07	0.26	0.21	0.69	0.65	0.99	2.79
Union City	0.55	2.63	1.45	3.80	3.83	5.04	19.47
Total	8.94	27.99	23.15	39.91	39.82	49.22	147.76

Table 10 Percentage of each city's land area exposed to flood risk, by scenario and by city

	MHHW		100-year Stillwater		100-year + Wind and Waves	
	+ 16”	+ 55”	+ 16”	+ 55”	+ 16”	+ 55”
Alameda	7%	33%	24%	60%	60%	78%
Emeryville	2%	3%	2%	16%	16%	35%
Hayward	13%	32%	30%	36%	36%	40%
Oakland	3%	11%	8%	18%	17%	23%
San Leandro	4%	11%	9%	22%	21%	29%
San Lorenzo	2%	9%	8%	25%	23%	36%
Union City	3%	13%	7%	20%	20%	26%
Total	6%	19%	16%	27%	27%	33%

[3] Hazards and Vulnerability Research Institute (2012). “Social Vulnerability Index for the United States - 32 Variables”. Retrieved March 19th, 2012, from http://webra.cas.sc.edu/hvri/products/SoVI_32.aspx.

3.4.2 Population Exposed to Flooding

Depending on the scenario, there are between approximately 2,000 and 123,000 residents currently living in the areas that would be exposed to flooding (Table 11). Under the most extreme scenario, a 55-inch rise in sea levels and a 100-year storm event plus wind and wave scenario, 43,300 households are exposed to inundation. Table 12 shows the percentage of each city's population exposed to inundation risk for each of the six scenarios. Table 13 shows the number of households exposed to flood risk. In each of the tables, results are rounded to whole numbers. However, the reader should keep in mind the approximate nature of the analysis methods do not reflect this level of precision.

Table 11 Population exposed to inundation risk for the 6 ART scenarios, by city

	MHHW		100-year Stillwater		100-year + Wind and Waves		City Population
	+ 16"	+ 55"	+ 16"	+ 55"	+ 16"	+ 55"	(for reference)
Alameda	1,103	14,227	8,619	30,009	30,376	41,461	72,259
Emeryville	29	96	56	725	718	1,909	6,882
Hayward	82	187	167	5,011	4,999	10,620	140,030
Oakland	16	1,370	233	6,107	5,965	14,831	399,484
San Leandro	356	4,246	3,220	10,070	9,447	15,466	79,452
San Lorenzo	13	200	177	2,888	2,628	5,337	21,898
Union City	353	17,940	4,849	25,253	25,501	34,163	66,869
Total	1,952	38,266	17,321	80,063	79,634	123,787	786,874

Table 12 Percentage of each city's population exposed to flood risk, by scenario and by city

	MHHW		100-year Stillwater		100-year + Wind and Waves	
	+ 16"	+ 55"	+ 16"	+ 55"	+ 16"	+ 55"
Alameda	1.5%	19.7%	11.9%	41.5%	42.0%	57.4%
Emeryville	0.4%	1.4%	0.8%	10.5%	10.4%	27.7%
Hayward	0.1%	0.1%	0.1%	3.6%	3.6%	7.6%
Oakland	0.0%	0.3%	0.1%	1.5%	1.5%	3.7%
San Leandro	0.4%	5.3%	4.1%	12.7%	11.9%	19.5%
San Lorenzo	0.1%	0.9%	0.8%	13.2%	12.0%	24.4%
Union City	0.5%	26.8%	7.3%	37.8%	38.1%	51.1%
Total	0.2%	4.9%	2.2%	10.2%	10.1%	15.7%

Table 13 Households exposed to flood risk, by scenario and by city

	MHHW		100-year Stillwater		100-year + Wind and Waves		Total Households (for reference)
	+ 16”	+ 55”	+ 16”	+ 55”	+ 16”	+ 55”	
Alameda	397	5,883	3,557	12,297	12,440	16,830	30,226
Emeryville	21	70	41	512	507	1,329	3,975
Hayward	25	62	54	1,910	1,906	3,568	44,804
Oakland	6	490	120	1,945	1,905	5,394	150,790
San Leandro	112	1,690	1,317	3,702	3,487	5,538	30,642
San Lorenzo	5	70	62	984	896	1,840	7,500
Union City	95	4,533	1,248	6,499	6,566	8,856	18,642
Total	**661**	**12,798**	**6,399**	**27,849**	**27,707**	**43,355**	**286,579**

3.4.3 Social Vulnerability of Population Exposed

Combining the diverse social factors that influence the likelihood of harm during a flood event into a composite score allows for an estimate of the overall level of vulnerability in a local area and a comparison among areas. In this analysis, the block groups in Alameda County are sorted into thirds according to their SoVI score. The population in block groups that are in the top third most socially vulnerable in the county is labeled “high”, with “medium” and “low” representing the middle and bottom third.

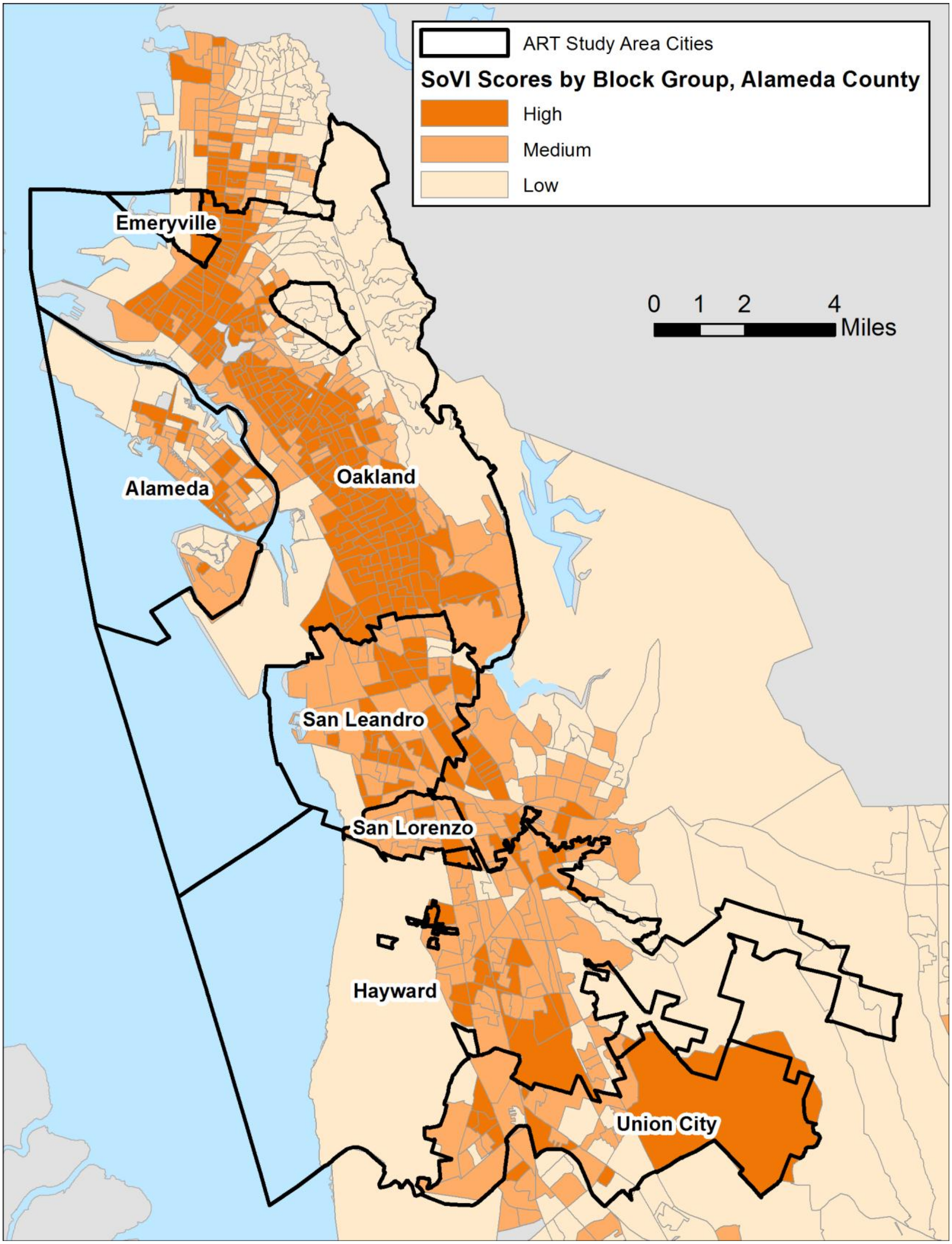

Figure 3 Social Vulnerability Index Score by Block Group in the ART Study Area (Census 2000)

Mapping the social vulnerability scoring clearly displays the distinct social geography of the study area, with more highly vulnerable populations concentrated in the low-land areas (Figure 3). The areas adjacent to the shoreline are somewhat of an exception to this pattern, with a more mixed geography of vulnerability. These areas also have a higher proportion of industrial and commercial areas, which may also contribute to the lower social vulnerability scores.

Table 14 reports exposure to flood risk by level of social vulnerability. Thirty six percent or 44,000 of the people at risk of inundation under the most severe scenario fall within the category of high social vulnerability. An additional 60,000 or 48% are considered in the middle range of social vulnerability. Sorting the population vulnerability into the seven cities in the study area (Table 15) allows us to identify where the more vulnerable population is located. The greatest population percentages with high social vulnerability in flood risk areas occur in Oakland and Hayward. In Alameda and Union City the high vulnerability population does not comprise as high a percentage of the total population at risk, but still comprise significant numbers in absolute terms (11,000 and 9,200 respectively).

Table 14 Population at risk of inundation by level of social vulnerability

	MHHW		100-year Stillwater		100-year + Wind and Waves		Total Population
	+ 16”	+ 55”	+ 16”	+ 55”	+ 16”	+ 55”	(for reference)
High	78	12,100	5,625	27,554	27,309	44,111	381,212
Medium	1,472	19,803	8,104	39,730	39,516	59,871	293,109
Low	402	6,364	3,591	12,780	12,808	19,803	112,548
missing	0	0	0	0	0	0	5
Total	**1,952**	**38,266**	**17,320**	**80,065**	**79,633**	**123,786**	**786,874**
Percentage of population at risk							
High	4%	32%	32%	34%	34%	36%	48%
Medium	75%	52%	47%	50%	50%	48%	37%
Low	21%	17%	21%	16%	16%	16%	14%
Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

Table 15 Social Vulnerability Ranking of Population by City

		MHHW		100-year Stillwater		100-year + Wind and Waves		Population
		+ 16"	+ 55"	+ 16"	+ 55"	+ 16"	+ 55"	(for reference)
Alameda								
	Low	107	3,777	2,648	8,404	8,483	12,470	18,006
	Medium	985	6,866	4,241	13,429	13,619	17,785	32,972
	High	11	3,584	1,730	8,176	8,273	11,206	21,281
	Total	**1,103**	**14,227**	**8,619**	**30,009**	**30,376**	**41,461**	**72,259**
Emeryville								
	Low	29	96	56	725	718	1,909	3,867
	Medium	0	0	0	0	0	0	759
	High	0	0	0	0	0	0	2,256
	Total	**29**	**96**	**56**	**725**	**718**	**1,909**	**6,882**
Hayward								
	Low	38	109	98	141	140	251	16,907
	Medium	0	1	0	1,203	1,200	2,950	91,257
	High	44	78	69	3,668	3,660	7,419	31,866
	Total	**82**	**187**	**167**	**5,011**	**4,999**	**10,620**	**140,030**
Oakland								
	Low	0	100	8	261	260	555	58,615
	Medium	6	646	176	1,777	1,765	3,233	67,946
	High	9	625	49	4,070	3,941	11,043	272,918
	Total	**16**	**1,370**	**233**	**6,107**	**5,965**	**14,831**	**399,484**
San Leandro								
	Low	222	560	265	1,344	1,302	1,677	4,240
	Medium	120	2,348	1,879	5,965	5,603	8,552	42,826
	High	14	1,338	1,077	2,761	2,541	5,236	32,386
	Total	**356**	**4,246**	**3,220**	**10,070**	**9,447**	**15,466**	**79,452**
San Lorenzo								
	Low	0	0	0	0	0	0	0
	Medium	13	200	177	2,888	2,628	5,337	18,602
	High	0	0	0	0	0	0	3,296
	Total	**13**	**200**	**177**	**2,888**	**2,628**	**5,337**	**21,898**
Union City								
	Low	6	1,723	516	1,905	1,905	2,941	10,913
	Medium	348	9,742	1,632	14,469	14,701	22,014	38,747
	High	0	6,475	2,700	8,879	8,894	9,208	17,209

	MHHW		100-year Stillwater		100-year + Wind and Waves		Population
	+ 16"	+ 55"	+ 16"	+ 55"	+ 16"	+ 55"	(for reference)
Total	**353**	**17,940**	**4,849**	**25,253**	**25,501**	**34,163**	**66,869**
All Cities							
Low	402	6,364	3,591	12,780	12,808	19,803	112,548
Medium	1,472	19,803	8,104	39,730	39,516	59,871	293,109
High	78	12,100	5,625	27,554	27,309	44,111	381,212
Total	**1,952**	**38,266**	**17,320**	**80,065**	**79,633**	**123,786**	**786,874**
All Cities Percent of Total							
Low	21%	17%	21%	16%	16%	16%	14%
Medium	75%	52%	47%	50%	50%	48%	37%
High	4%	32%	32%	34%	34%	36%	48%

While SoVI scores provide a necessary indicator of overall social vulnerability within impacted areas, planning and preparation must also be informed by the presence of populations with singular vulnerabilities. Several social groups known to be more likely to experience adverse outcomes in flood events have significant populations in the study area. Under 16" and 55" 100-year storm event plus wind and wave scenarios, approximately 9,100 (33%) and 15,500 (36%) of the households at risk of inundation are occupied by renters, respectively, a population less likely to have the means to reinforce buildings and otherwise prepare for flood events (see Table 16).

Table 16 Renter-occupied households exposed to inundation risk

	MHHW		100-year Stillwater		100-year + Wind and Waves		Renter Households in City (for reference)	Total Households in City (for reference)
	+ 16"	+ 55"	+ 16"	+ 55"	+ 16"	+ 55"		
Alameda	82	2,235	1,319	5,139	5,210	7,245	15,740	30,226
Emeryville	12	39	23	285	283	740	2,499	3,975
Hayward	4	11	10	213	212	579	20,600	44,804
Oakland	3	265	73	1,128	1,106	3,744	88,301	150,790
San Leandro	9	369	290	732	686	1,153	12,078	30,642
San Lorenzo	1	10	9	121	110	229	1,558	7,500
Union City	4	1,142	357	1,497	1,505	1,845	5,278	18,642
Total	**115**	**4,071**	**2,081**	**9,115**	**9,112**	**15,535**	**146,054**	**286,579**

Table 17 Linguistically isolated households exposed to inundation risk

	MHHW		100-year Stillwater		100-year + Wind and Waves		Linguistically Isolated Households in City	Total Households in City
	+ 16”	+ 55”	+ 16”	+ 55”	+ 16”	+ 55”	(for reference)	(for reference)
Alameda	33	421	248	891	904	1,229	2,235	30,226
Emeryville	1	5	3	33	33	87	242	3,975
Hayward	2	4	4	137	137	281	5,000	44,804
Oakland	1	67	27	262	256	725	17,199	150,790
San Leandro	14	165	126	339	322	495	2,764	30,642
San Lorenzo	0	2	2	26	23	47	498	7,500
Union City	21	579	233	861	869	1,096	2,396	18,642
Total	**72**	**1,243**	**643**	**2,549**	**2,544**	**3,960**	**30,334**	**286,579**

Households without a member over age 14 who ‘speaks English well’ are considered by the US Census as “linguistically isolated” (See Table 17). Depending on the social networks available to these households, their lack of an English-speaking adult may prevent the members from having sufficient access to information about preparedness, response, and recovery. Households without a vehicle are at greater risk of harm during a sudden flood event. According to the 2000 Census, 3,800 households without a vehicle reside in the areas at risk of flooding under the most severe scenario considered in this study (Table 18).

Table 18 Households at risk of inundation with no vehicle

	MHHW		100-year Stillwater		100-year + Wind and Waves		Households with No Vehicle	Total Households
	+ 16”	+ 55”	+ 16”	+ 55”	+ 16”	+ 55”	(for reference)	(for reference)
Alameda	21	487	280	1,012	1,025	1,405	2,817	30,226
Emeryville	1	5	3	33	33	86	441	3,975
Hayward	2	5	4	86	86	191	3,449	44,804
Oakland	1	75	20	427	418	1,425	29,544	150,790
San Leandro	4	86	68	179	169	280	2,836	30,642
San Lorenzo	0	1	1	28	25	59	484	7,500
Union City	1	181	72	252	254	334	946	18,642
Total	**30**	**840**	**448**	**2,017**	**2,010**	**3,780**	**40,517**	**286,579**

Table 19 Low-income population at risk of inundation

	MHHW		100-year Stillwater		100-year + Wind and Waves		Low Income Population in City	Population in City
	+ 16”	+ 55”	+ 16”	+ 55”	+ 16”	+ 55”	(for reference)	(for reference)
Alameda	128	2,197	1,218	5,172	5,246	7,340	14,285	72,259
Emeryville	7	22	13	168	167	443	1,814	6,882
Hayward	11	23	20	980	978	2,199	36,067	140,030
Oakland	6	612	97	3,267	3,188	7,474	159,634	399,484
San Leandro	32	625	483	1,352	1,268	2,055	14,485	79,452
San Lorenzo	1	17	15	339	308	631	3,525	21,898
Union City	20	3,098	851	4,243	4,266	5,102	11,270	66,869
Total	**205**	**6,594**	**2,697**	**15,521**	**15,421**	**25,244**	**241,080**	**786,874**

*Low income is defined in this study as people in households earning less than 200% of the national poverty level. In 2011, the threshold for a 4-person household is $22,350.

Low-income residents have fewer means to prepare for, respond to, and recover from flood events. Using a standard measure of poverty, we found that 15,600 to 25,000 people at risk of inundation are living off less than twice the federal poverty threshold, based on the 16-inch and 55-inch storm event plus wind and wave scenarios, respectively (Table 19). This comprises about 20 percent of the population exposed in both scenarios.

According to the Census, more than 300 people living in correctional and nursing and related institutions reside in areas at increased risk of flooding under the most severe scenario (Table 20). This population is almost entirely located in Alameda. The Census data does not reveal the specific type of institution housing the population.

Table 20 Institutionalized population at risk of inundation

	MHHW		100-year Stillwater		100-year + Wind and Waves		Institutionalized Population in City	Population in City
City	+ 16”	+ 55”	+ 16”	+ 55”	+ 16”	+ 55”	(for reference)	(for reference)
Alameda	0	73	40	225	230	294	469	72,259
Emeryville	0	0	0	0	0	0	0	6,882
Hayward	0	0	0	0	0	0	739	140,030
Oakland	0	1	0	5	5	18	2,894	399,484
San Leandro	0	0	0	0	0	0	517	79,452
San Lorenzo	0	0	0	0	0	0	0	21,898
Union City	0	0	0	0	0	0	212	66,869
Total	**0**	**74**	**40**	**230**	**235**	**312**	**4,831**	**786,874**

Table 21 People of color at risk of inundation

City	MHHW + 16"	MHHW + 55"	100-year Stillwater + 16"	100-year Stillwater + 55"	100-year + Wind and Waves + 16"	100-year + Wind and Waves + 55"	People of Color (for reference)	Population (for reference)
Alameda	452	5,226	3,055	11,926	12,108	16,968	27,551	72,259
Emeryville	13	44	26	334	330	878	3,542	6,882
Hayward	35	78	70	2,561	2,555	5,735	72,007	140,030
Oakland	12	1,022	169	4,833	4,713	11,258	260,887	399,484
San Leandro	233	2,014	1,471	4,733	4,451	7,229	35,056	79,452
San Lorenzo	4	50	44	770	696	1,485	6,881	21,898
Union City	274	13,200	3,586	18,465	18,651	24,530	43,452	66,869
Total	1,023	21,634	8,421	43,622	43,504	68,083	449,376	786,874

Race has had significant influence on the effectiveness of past disaster preparedness and emergency response efforts. For instance, perceptions of emergency response workers toward neighborhoods that are predominantly people of color have increased the vulnerability of these communities (Klynman 2007). As shown in Table 21, in the cities in the study area there is a population of about 450,000 people of color (or non-white non-Hispanic population), comprising 57% of the cities' total population. Between 1,000 and 68,000 people of color are exposed to inundation under the various scenarios.

4 Exposure of Workplaces

More frequent flooding caused by sea level rise is likely to cause disruptions to key services, such as transportation, water, energy, and health care. Such disruptions are likely to cause an indirect economic impact, due to lost work days or increased travel times. In addition to the residences that may be exposed to flooding, a number of workplaces will also face increased flood risk. This includes coast-dependent workplaces such as ports and marinas (King et al. 2011), but also the many commercial and industrial buildings in low-lying areas adjacent to the Bay (Heberger et al. 2009). In this section, we describe the data and methods we used to estimate the exposure of workplaces to inundation in the ART study area.

4.1 Data

To estimate workplace exposure to inundation, we used employment information from FEMA's HAZUS database. The software contains a set of databases for each state; California's database can be found on the HAZUS data disc, in a file named CA1.mdb. Each state's database contains a table, "Occup," which includes data on the number of employees in each Census block. The data is aggregated according to the year-2000 census. HAZUS reports two classes of employee: Commercial and Industrial. The field names are WorkingCom and WorkingInd. The values in each field represent the number of employees in each Census Block. The information can be joined to the Census Block GIS file (feature class) via the field CensusBloc.

In the ART study area, the labor force was an estimated 291,000 employees in 2000 (Table 22). About 80% of employees in the ART study area are employed by the commercial sector, with 20% or about 58,000 in the industrial sector. Table 22 also shows households and population (also for year 2000) for reference.

Table 22 Number of employees by city in the ART study region in 2000 (number of households and population in 2000 shown for reference)

	Households	Population	Employees-Commercial	Employees - Industrial	Total Employees
Alameda	30,226	72,259	18,002	4,863	22,865
Emeryville	3,975	6,882	10,605	1,055	11,660
Hayward	44,804	140,030	48,127	18,585	66,712
Oakland	150,790	399,484	117,672	17,926	135,598
San Leandro	30,642	79,452	26,242	10,080	36,322
San Lorenzo	7,500	21,898	1,204	1,008	2,212
Union City	18,642	66,869	11,125	4,350	15,475
Total	286,579	786,874	232,977	57,867	290,844

4.2 Methods

To estimate the number of employees who would be exposed to flooding, we used the same methods that we used to estimate population exposure described in Section 3.2. We had previously determined the percentage of each Census block that is overlapped by the inundation hazard zones. We proceed as before, and use this information to estimate the percentage of workers in each Census block that is exposed to inundation risk. Thus, in a block with 1,000 workers that is 30% inundated, we assume that 300 workers are exposed to inundation risk. We used ArcGIS Spatial Analyst's Zonal Statistics as Table tool to determine the percentage of each Census block that is overlapped by the inundation hazard zone under each of the six scenarios. More details on the specific processing steps are included in Section 5.1.2.

4.3 Limitations

One source of inaccuracy has to do with uncertainties in the input data. Here, we are using the word "uncertainty" to mean that our data is not 100% accurate or up-to-date, not in the layperson's sense that our knowledge is murky. We used FEMA's HAZUS database because it is freely available, fairly well documented, and contains data for every Census block in the United States. We are not aware of similar datasets with such extensive coverage. (Data are available from the US Department of Labor's Bureau of Labor Statistics; however, these are aggregated at the state and county level and do not give the same level of geographic detail.)

HAZUS data represents the year 2000 and is already over a decade old. The employment numbers are estimates created for FEMA by Dunn & Bradstreet, a business listing company, using a proprietary algorithm. Thus, it is difficult to independently confirm the accuracy of the data. The HAZUS manual (FEMA 2006) also states that D&B aggregated some employment data at the census block group and tract level. Thus, the employment numbers may be distributed evenly over a large region, and may not accurately represent employment at a neighborhood scale.

The second source of inaccuracy stems from the analysis methods used. In short, we estimated the percentage of each Census block that is inundated under each flood scenario, and applied the same percentage to the employment. The area-weighted ration method is commonly used in GIS modeling, but has known limitations. For it to be reasonably accurate, one assumes that the variable of interest (in this case, number of employees) is homogeneous and uniformly spread over the surface of the block. When population occurs in clusters, and is not evenly distributed over an area, it means this method will be less accurate.

Finally, our results show only one measure of workplace exposure: the number of affected employees. There are a number of other methods of estimating direct and economic impacts of natural disasters that were beyond the scope of this study.

4.4 Results

Estimates of number of employees exposed to inundation are shown in Table 23. Note that these values represent employment estimates from year 2000. Table 24 reports the percentage of city's employees exposed to inundation, by scenario. Here, the percentage is calculated based on the total number of employees in each city (within the boundaries of the city, not just the portion in the ART study area). The employment data we used from the FEMA HAZUS model breaks down employees into two categories only: commercial and industrial. We report the numbers of employees exposed to inundation by sector in Table 25.

Table 23 Number of employees exposed to inundation, by flood scenario and by city

	MHHW		100-year Stillwater		100-year + Wind and Waves		Total Employees in City (for reference)
	+ 16”	+ 55”	+ 16”	+ 55”	+ 16”	+ 55”	
Alameda	3,310	7,193	6,002	13,446	12,099	15,686	22,865
Emeryville	29	50	36	512	2,436	5,055	11,660
Hayward	973	6,309	4,304	18,540	15,066	22,446	66,712
Oakland	921	11,676	4,584	32,134	29,642	49,229	135,598
San Leandro	110	2,403	1,857	5,030	6,572	9,517	36,322
San Lorenzo	34	605	450	1,328	1,241	1,380	2,212
Union City	198	1,697	1,076	5,979	4,975	6,556	15,475
Total	**5,574**	**29,933**	**18,308**	**76,969**	**72,033**	**109,868**	**290,844**

Table 24 Percentage of city's employees exposed to inundation, by scenario

	MHHW		100-year Stillwater		100-year + Wind and Waves	
	+ 16"	+ 55"	+ 16"	+ 55"	+ 16"	+ 55"
Alameda	14.5%	31.5%	26.2%	52.0%	52.9%	68.6%
Emeryville	0.3%	0.4%	0.3%	21.0%	20.9%	43.4%
Hayward	1.5%	9.5%	6.5%	22.7%	22.6%	33.6%
Oakland	0.7%	8.6%	3.4%	22.0%	21.9%	36.3%
San Leandro	0.3%	6.6%	5.1%	18.9%	18.1%	26.2%
San Lorenzo	1.5%	27.4%	20.3%	57.0%	56.1%	62.4%
Union City	1.3%	11.0%	7.0%	32.0%	32.2%	42.4%
Total	**1.9%**	**10.3%**	**6.3%**	**24.9%**	**24.8%**	**37.8%**

Table 25 Number of employees exposed to inundation, by sector

	MHHW		100-year Stillwater		100-year + Wind and Waves	
	+ 16"	+ 55"	+ 16"	+ 55"	+ 16"	+ 55"
Commercial	4,533	19,980	12,132	49,752	49,560	79,930
Industrial	1,041	9,953	6,176	22,583	22,472	29,938
Total	**5,574**	**29,933**	**18,308**	**72,335**	**72,033**	**109,868**

5 Value of Property Exposed to Flood Risk

We obtained estimates of property values from two sources. First, the Alameda County Assessor's Office provided assessed tax value for parcels, or individual units of land ownership. Second, FEMA's HAZUS model contains a database of replacement value of buildings and contents compiled at the Census Block level. Thus, we analyzed the value of property that may be exposed to future flooding using two different sources of information. In the following sections, we describe each of these analyses, including the data, methods, results, and limitations. At the end of this section, we compare the results obtained using the separate analysis methods, and give thoughts on how to make estimates of property value exposed to climate risks more robust.

5.1 Census Block Analysis with FEMA's HAZUS model database

5.1.1 Data

We used information in FEMA's HAZUS database to estimate the exposure of the built environment to future inundation due to sea level rise. Data on the value of buildings and contents was taken from datasets supplied with the HAZUS model, which was developed for FEMA's Mitigation Division by the National Institute of Building Sciences. HAZUS was designed to help planners estimate the potential losses from natural disasters such as earthquakes, floods, and hurricane winds. HAZUS uses a database called the "General Building Stock Inventory" that contains the value of buildings and contents based on data from a number of sources including the U.S. Census Bureau, Dun & Bradstreet (a business listing service), and the Department of Energy. Values are provided for residential, commercial, industrial, agricultural, religious, governmental, and educational developments in each census block. A detailed description of how this information was compiled is presented in the HAZUS Flood Technical Manual, Chapter 14 (FEMA 2006).

It is important to note that this study evaluates the replacement value of property at risk, not the expected flood damage. In many instances, flooding may not cause complete loss of a property, as the extent of damage depends on the type and quality of construction and depth of flooding. Concrete and steel structures, for example, may be habitable after being inundated while a more typical wooden residential structure may have sodden and rotting drywall and rotting beams. Thus we have purposely reported "assets at risk to flood damage" rather than "expected flood damage."

We follow the HAZUS methods for estimating direct economic losses, based on the repair and replacement of damaged or destroyed buildings and their contents. The HAZUS documentation includes the following under direct losses:

- Cost of repair and replacement of damaged and destroyed buildings
- Cost of damage to building contents
- Losses of building inventory (contents related to business activities)

HAZUS uses a statistical model to estimate rebuilding costs based on square footage, number of stories, building material, and other variables. As we discuss in Section 5.1.3, these values are likely to be significantly lower than market value for most properties. Table 26 shows the total replacement value of buildings and contents in each of the seven cities in the ART study area. This table reports totals for the entire city, not just flood-prone areas; note that values are reported in millions of dollars. The total is $45 billion across the seven cities.

Table 26 Replacement value of buildings and contents (from HAZUS) by sector in the ART study area (in millions of year-2000 dollars).

	Agric.	Religious	Residential	Commercial	Industrial	Govt.	Edu.	Total
Alameda	3.6	68.0	3,004.7	1,028.5	210.3	78.2	56.4	**4,450**
Emeryville	1.3	4.8	254.8	418.3	214.0	9.3	7.7	**910**
Hayward	11.4	107.6	4,262.9	2,268.3	1,295.7	35.9	128.5	**8,110**
Oakland	36.5	667.5	12,964.3	6,198.4	1,695.7	230.0	383.3	**22,176**
San Leandro	5.0	70.6	2,972.6	1,330.9	793.7	14.8	30.4	**5,218**
San Lorenzo	1.2	13.4	857.1	111.4	15.6	0.0	5.2	**1,004**
Union City	9.0	32.4	2,221.5	505.8	460.6	6.2	23.3	**3,259**
Total	**67.9**	**964.3**	**26,537.9**	**11,861.6**	**4,685.5**	**374.4**	**634.8**	**45,126**

5.1.2 Methods

We estimated the portion of the building stock value that is exposed to inundation risk using an area-weighted ratio overlay method, described in detail in Appendix D. The methods are analogous to those used to estimate the population at risk described above in Section 3.2, and are carried out at the Census block level. In brief, if a block contains $100,000 worth of buildings and is 30% inundated, we estimate that $30,000 worth of buildings is at risk. We repeated the analysis for each of the six inundation scenarios, and summarized the results for each of the 7 ART communities. We rounded all results to two significant digits to reflect the approximate nature of the analysis methods.

5.1.3 Limitations

In this section, we described how we estimated the value of property at risk of inundation under six sea level rise scenarios. There are several sources of uncertainty associated with this analysis. First, there are inaccuracies associated with the input data. We have shown previously that HAZUS data underestimates the market value of buildings and their contents (Heberger et al. 2009). We investigated replacement costs for residential buildings at a few locations and found that the replacement costs in HAZUS far underestimate actual market values for residential properties. We estimated that replacement value likely underestimates actual market values by a factor of four or more. In other words, actual losses of property value are likely four times higher than estimates based on replacement cost alone.

Second, some uncertainties are introduced due to the analysis methods. Information about building value is compiled at the Census block level, and we use the assumption common to many GIS analyses that the value is evenly distributed over the area of each block.

Third, our analysis summarizes the value of buildings that are exposed to inundation, but we have not attempted to estimate how the various flooding scenarios could inflict damage to different buildings. It is very difficult to predict whether flood exposure will be damaging. Flood depends on such factors as water depth and velocity, the duration of flooding, and the elevation of the building, along with its materials and quality of construction and maintenance, and the presence of any flood-proofing or other mitigation.

5.1.4 Findings

Below, we present results for the value of property in the inundation hazard zone analyzed using data from FEMA's HAZUS model. Table 27 shows the total replacement cost of buildings and contents exposed to flooding for each of the six scenarios, by city. The total building value in the city is included in the right column for reference. Table 28 reports the value of buildings in the inundation zones as a percent of each city's total building value. Under the highest scenario, more than $10 billion dollars' worth of assets are exposed to flooding. This represents 16% of the total asset value across the 7 cities. The results are even more striking in certain cities, for example Alameda, where nearly 66% of building value is exposed to flooding, or Union City where nearly 50% is exposed.

Table 27 Replacement costs of buildings and contents exposed to inundation, by city and by scenario (millions of year-2000 dollars).

	MHHW		100-year Stillwater		100-year + Wind and Waves		City Total
	+ 16"	+ 55"	+ 16"	+ 55"	+ 16"	+ 55"	(for reference)
Alameda	91	1,017	645	2,142	2,170	2,922	4,450
Emeryville	4	11	6	113	112	316	910
Hayward	75	373	258	958	973	1,506	8,110
Oakland	104	678	256	1,933	1,922	2,975	22,176
San Leandro	22	316	227	780	737	1,140	5,218
San Lorenzo	2	27	22	167	155	282	1,004
Union City	26	716	220	1,143	1,155	1,580	3,259
Total	323	3,139	1,633	7,236	7,224	10,721	45,126

Table 28 Percentage of each city's total building value exposed to potential inundation, by scenario; HAZUS analysis

	MHHW		100-year Stillwater		100-year + Wind and Waves	
	+ 16"	+ 55"	+ 16"	+ 55"	+ 16"	+ 55"
Alameda	2.0%	22.9%	14.5%	48.1%	48.8%	65.7%
Emeryville	0.4%	1.2%	0.6%	12.4%	12.3%	34.7%
Hayward	0.9%	4.6%	3.2%	11.8%	12.0%	18.6%
Oakland	0.5%	3.1%	1.2%	8.7%	8.7%	13.4%
San Leandro	0.4%	6.1%	4.4%	15.0%	14.1%	21.9%
San Lorenzo	0.2%	2.7%	2.1%	16.6%	15.4%	28.1%
Union City	0.8%	22.0%	6.7%	35.1%	35.5%	48.5%
Total	0.7%	7.0%	3.6%	16.0%	16.0%	23.8%

5.2 Analysis Based on Parcels and Assessor's Data

In the previous section, we described our analysis of property (buildings and contents) that are exposed to inundation using data from FEMA's HAZUS model that is compiled at the Census block level. In this section, we describe a similar analysis done with a different dataset. Here, we repeat this analysis with the smaller geographic unit of Parcel boundaries.

Parcels are the basic units of land ownership, and are defined by a plat diagram of its boundaries. Historically, parcel maps (also referred to as a cadastral survey or landbase) have been maintained by local governments to regulate land ownership and as a basis for levying taxes. Today, many counties in California maintain digital databases in GIS format. Our analysis was greatly facilitated by the fact that Alameda County offers free downloads of GIS data, and releases the tax roll data for a nominal fee.

5.2.1 Data

Data from Alameda County Assessor's Office included (a) a GIS file of parcel boundaries, and (b) the property database, a table containing information about land and properties. The county maintains this information for the purpose of levying taxes. Each parcel in the county has a unique identifier, the Assessor's Parcel Number, or APN. The corresponding database is a flat file, or a single table, containing information about each parcel in the county, identified by its APN. The Assessor's office continually updates this database, and publishes new versions periodically. The GIS file of parcel boundaries is a shapefile that we downloaded from the county website (Alameda County 2011). The shapefile's coordinate system (NAD 1983 State Plane California III FIPS 0403 Feet) was not the same as the standard chosen for this project. We re-projected the data to NAD 1983 California Teale Albers as described in section 2.2.2. During the same processing step, we loaded this data as a feature class in an ESRI Personal Geodatabase (.mdb) file.

We purchased the property database (Alameda County 2012) in person at the county offices in Oakland. The data table was in text format. We loaded this data into a table in Microsoft Access, taking care to preserve the proper format (text vs. numeric) for each field.

To estimate property values based on the Assessor's Database, we added all fields related to property value, and *did not* include tax exemptions. We created new columns, or fields, in the data table and set their values through a series of update queries in MS Access. (We wrote queries using a combination of the Access Query Design View and by editing SQL manually. These queries are available on request from the authors.) The new fields included:

- Land
- Improvements (buildings and structures)
- Personal property
- Household personal property

We also created a field for the value of buildings and contents (including improvements and personal property, but not land). We did this for two reasons. First, it is a different measure of possible flood damages that may be of interest. A flood event may damage buildings and property, but may not have an effect on the underlying value land, unless for example the land is badly eroded, or a regulatory agency prohibits rebuilding in flood-damaged areas. Second, this allowed us to compare the results of the parcel-based analysis with the analysis done using the HAZUS model, which estimates the value of flood-affected buildings and contents only, and does not include the value of land.

The assessor's table contained dozens of use categories. These were grouped and simplified into the 23 categories shown here by BCDC staff. This cross-reference from the Alameda County Assessor's Office land use classifications to custom BCDC land use category is shown in Table 41 in Appendix B.

Table 29 summarizes the Assessor's data that we used as the input data in our analysis. Assessed value is reported in millions of dollars. Values are current as of January 1, 2012. The total assessed value of land, buildings, and property in the 7-city ART study area is 86.6 billion dollars. In Table 30, we report the number of parcels and assessed value by city.

Table 29 Assessed value of land and improvements in the 7 cities in the ART study area, by land use type (total within city boundaries; value in millions of dollars, as of Jan 2012)

Land Use	Number of Parcels	Value of Land	Value of Improvements and Property	Total Value
Agriculture	64	17.3	3.3	20.7
Care Facility	192	89.4	370.4	459.8
Cemetery	48	20.3	44.9	65.2
Commercial	7,573	3,394.0	7,829.9	11,223.9
Condominium	24,919	1,456.4	3,408.5	4,864.9
Floating Home	41	0.0	7.5	7.5
Golf Course	33	13.7	20.9	34.7
Grocery	47	54.4	82.3	136.7
Historic Residential	24	1.4	3.2	4.6
Hospital	69	75.8	1,029.2	1,105.0
Hotel	55	72.4	229.7	302.1
Industrial	3,895	2,601.0	5,853.2	8,454.2
Mixed Use	1,508	253.1	636.2	889.3
Mobile Home	1,156	126.0	82.8	208.7
Motel	101	72.3	179.9	252.2
Multi-Family Residential	31,436	4,057.6	9,240.8	13,298.4
Public	6,807	12.3	21.6	33.9
Recreation	32	19.9	22.7	42.7
Residential	203	25.6	55.0	80.5
Rural	61	19.1	6.9	26.0
Salt Ponds	10	1.9	0.0	1.9
School	200	93.7	462.9	556.6
Single Family Residential	152,612	13,861.2	29,198.4	43,059.6
Vacant Commercial	761	231.9	68.9	300.8
Vacant Industrial	772	215.2	28.4	243.6
Vacant Residential	4,674	328.8	47.3	376.1
Vacant Rural	4	0.0	0.0	0.0
Unknown	1,709	168.7	373.1	541.8
Total	239,006	27,283.4	59,307.8	86,591.1

Table 30 Assessed value of land and improvements in the 7 cities in the ART study area, by city (in millions of dollars, as of Jan 1, 2012)

City	Number of Parcels	Value of Land	Value of Improvements and Property	Total Value
Alameda	20,576	2,987	5,889	8,877
Emeryville	5,151	904	2,608	3,512
Hayward	45,733	5,395	10,920	16,315
Oakland	111,230	11,670	26,501	38,171
San Leandro	28,342	3,292	6,598	9,890
San Lorenzo	9,308	759	1,505	2,264
Union City	18,666	2,277	5,285	7,563
Total	239,006	27,283	59,308	86,591

5.2.2 Methods

The analysis methods we used are similar to those used for the Census block-based analysis in the previous section, and described in detail in Appendix D. The main difference was that we used parcel boundaries as the polygon vector file instead of Census blocks. We used the ArcGIS Spatial Analyst tool "Zonal Statistics as Table" to calculate the percentage of each parcel that is inundated by floodwaters. Figure 4 shows an example of how flood percentage was calculated for each parcel.

After calculating the Zonal Statistics, some of the parcels contained "Null" values for flood percentage. This resulted from parcels whose geometry does not overlap the inundation raster. In reality, these are parcels that are far from the shoreline and are not covered by the floodplain rasters. We used ArcMap's Field Calculator to convert Null values to 0 in these fields.

At this point, our analysis method diverged. For the census blocks, we used an area-weighted ratio method to determine the *fraction* of each block's building value that is exposed to inundation. Parcels represent smaller geographic areas. For parcels, we simply determined whether it is exposed to inundation, using a true/false condition.

We created a set of 6 Boolean (true/false) fields in the Parcel attribute table. These new fields indicate whether each parcel was flooded or not. We named these fields as follows:

- b_mhhw16
- b_mhhw55
- b_sw16
- b_sw55
- b_ww16
- b_ww55

In practice, ArcGIS does not allow the creation of a Boolean field in attribute tables, so we created an Integer field, and used 1 to represent flooded, and 0 to represent not flooded. The rule was: if the fraction flooded is greater than 0, then the block is considered flooded. While this rule means that some parcels where only 1% is flooded end up flagged, we felt that this was appropriate. The boundary of the inundation hazard zone is inexact; if the parcel is near that boundary, it is possible that the property is exposed to some flooding.

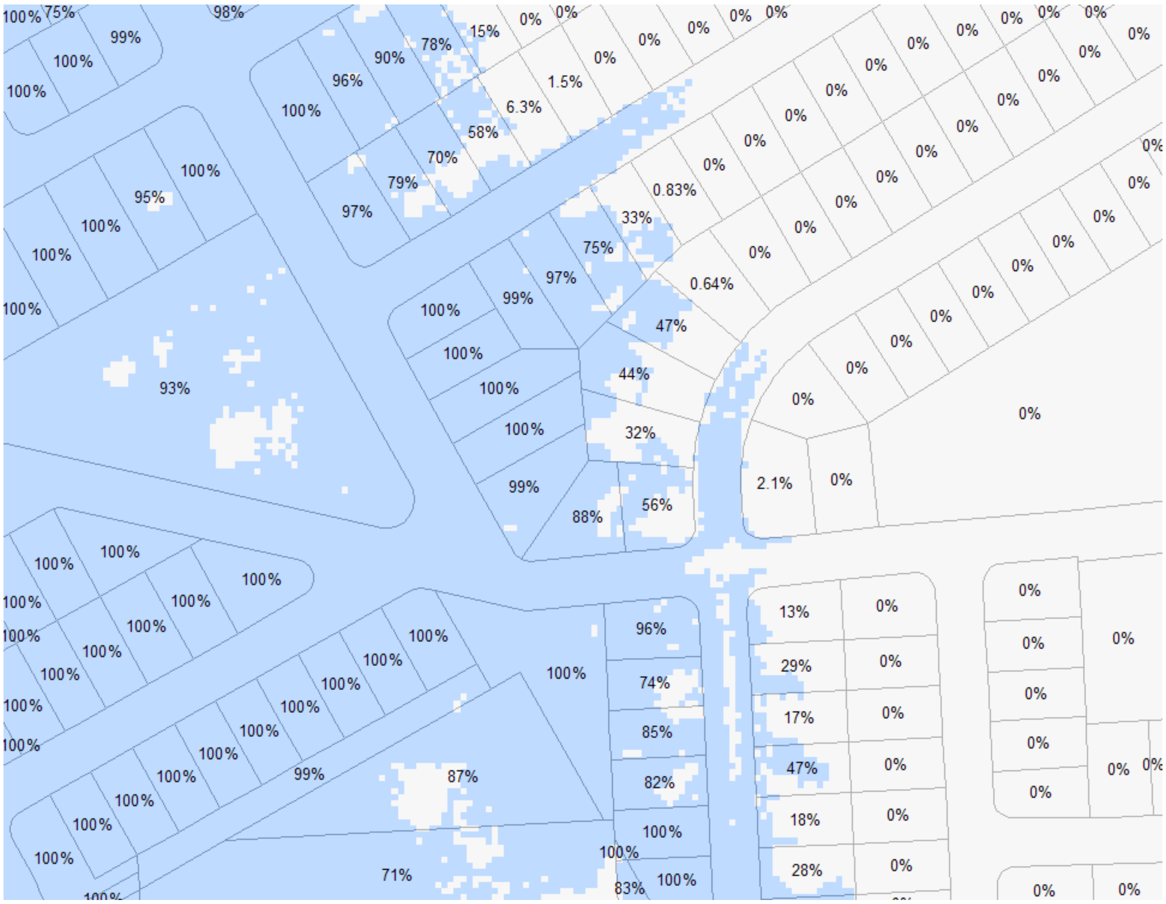

Figure 4 Example of overlay of the flood raster layer (blue shading) with the parcel boundary polygons to determine percent of each parcel in the study area that is exposed to flooding

5.2.3 Limitations

The data presented challenges for conducting analyses for this study. The assessor's database does not include any publicly-owned buildings, so it excludes many police and fire stations, government buildings, park buildings, schools, water treatment plants, etc.

It is likely that assessed values in the database are below the actual market values for many properties in California. Properties are assessed continuously, for example when a home is built or sold, thus the assessments do not all share a base year. California's Proposition 13 (1978), lowered property taxes by assessing property values at a base year of 1975, and prohibited local government from raising the assessed value by more than 2% per year. Proposition 8, passed in the same year, allowed counties to re-assess properties in a declining market. Since the passage of these laws, it has been written into the California Constitution (Amendment 13), that assessed property values should be lower than market value. In a recent study for the California Department of Boating and Waterways, King et al. (2010, p. 27-28) describe other reasons why assessor's data do not always reflect market value. They concluded that the assessor's office estimation of property values does not seem to realistically reflect the market value of personal property and household property, especially at residences. We confirmed this by analyzing the Alameda County Assessor's Office database. In the fields "Personal Property" and "Household Personal Property," over 90% of the records contain a value of 0. Land use categories hospitals, schools, and industrial, are more likely to contain a non-zero value. However, for "single-family residential," the average value of personal property is $8, and average household personal property is $0. Surely, the average resident of Alameda County owns possessions worth more than $8; thus common sense indicates that the county's assessments are unrealistically low.

On close examination, the property values in the Assessor's database seem unrealistically low, especially for single-family residences. Of the 8,951 single-family residential parcels in Oakland, only 20 are assessed at more than $400,000. The highest value for a single-family residential parcel in Oakland is $750,000, for a 1,463 square foot home in the Golden Gate neighborhood of northwest Oakland. The majority of single-family homes are assessed at under $200,000. However, one can easily find dozens of homes in Oakland on sale for over a million dollars by looking at the real estate listings of the local paper or online at zillow.com. This strengthens our conclusion that using Assessor's Office data to estimate property values results in significant underestimates compared with market value.

Finally, the "total net taxable value" may include one or more deductions. In Alameda County, homeowners are eligible for a "homeowner's exemption" of $7,000 if the property is his or her primary residence. Additional exemptions are granted to nonprofits such as schools, hospitals, churches, and other public-benefit organizations. The total exemptions may exceed the value of the property, resulting in a net taxable value of $0.

5.2.4 Findings

The results of the parcel-based analysis are reported below. Table 31 shows the number of parcels subject to inundation city and by flood scenario. Table 32 reports the assessed value of parcels exposed to inundation risk, by city and by scenario. Table 33 reports the percentage of the property value in each city that is exposed to inundation under each scenario.

Table 31 Number of parcels exposed to inundation risk, by city and by scenario

	MHHW		100-yr Stillwater		100-yr + Wind + Waves		Total # Parcels in City
	+ 16"	+ 55"	+ 16"	+ 55"	+ 16"	+ 55"	(for reference)
Alameda	631	5,694	3,600	9,262	9,318	11,857	20,576
Emeryville	9	31	20	141	137	227	5,151
Hayward	121	1,147	769	2,629	2,638	4,223	45,733
Oakland	118	1,415	302	3,255	3,217	5,234	111,230
San Leandro	72	1,467	889	3,736	3,600	5,039	28,342
San Lorenzo	11	79	62	1,319	1,222	2,151	9,308
Union City	26	5,378	1,642	6,824	6,933	9,044	18,666
Total	988	15,211	7,284	27,166	27,065	37,775	239,006

Table 32 Value of parcels potentially exposed to inundation, by city and by scenario (in millions of dollars, assessed value as of January 1, 2012)

	MHHW		100-yr Stillwater		100-yr Wind + Waves		Total Assessed Value in City
	+ 16"	+ 55"	+ 16"	+ 55"	+ 16"	+ 55"	(for reference)
Alameda	370	2,665	1,807	4,589	4,623	5,800	8,877
Emeryville	86	112	89	726	704	1,271	3,512
Hayward	48	1,203	743	2,466	2,470	3,214	16,315
Oakland	182	1,158	375	2,396	2,403	3,017	38,171
San Leandro	8	802	464	1,607	1,561	2,022	9,890
San Lorenzo	1	76	49	373	353	551	2,264
Union City	0	1,859	589	2,964	3,017	3,730	7,563
Total	694	7,875	4,117	15,122	15,132	19,605	86,591

Table 33 Value of parcels potentially exposed to inundation, as percentage of the value of each city's parcels

	MHHW		100-yr Stillwater		100-yr Wind + Waves	
	+ 16"	+ 55"	+ 16"	+ 55"	+ 16"	+ 55"
Alameda	4%	30%	20%	52%	52%	65%
Emeryville	2%	3%	3%	21%	20%	36%
Hayward	0%	7%	5%	15%	15%	20%
Oakland	0%	3%	1%	6%	6%	8%
San Leandro	0%	8%	5%	16%	16%	20%
San Lorenzo	0%	3%	2%	16%	16%	24%
Union City	0%	25%	8%	39%	40%	49%
Total	**1%**	**9%**	**5%**	**17%**	**17%**	**23%**

Table 34 reports the assessed value of land and improvements (including buildings) for flooded parcels, by land use classification.

Table 34 Assessed value of parcels potentially exposed to inundation under scenarios of future sea level rise, by land use classification (in millions of dollars, assessed value as of January 1, 2012).

	MHHW		100-yr Stillwater		100-yr Wind + Waves		Total
	+ 16"	+ 55"	+ 16"	+ 55"	+ 16"	+ 55"	(for reference)
Agriculture	-	1.87	1.87	1.87	1.87	1.87	20.67
Care Facility	10.31	54.91	42.70	58.75	58.75	106.52	459.77
Cemetery	-	-	-	-	-	-	65.21
Commercial	235.20	1,007.02	591.89	2,161.65	2,148.24	2,837.48	11,223.88
Condominium	0.35	0.69	0.38	12.84	13.44	16.00	4,864.86
Floating House	-	-	-	-	-	-	7.48
Golf Course	-	-	-	-	-	-	34.66
Grocery	-	0.09	-	0.09	0.09	16.63	136.71
Historic Residential	-	-	-	-	-	0.24	4.64
Hospital	-	4.81	-	6.56	6.56	6.56	1,105.00
Hotel	-	22.88	8.46	162.41	162.41	165.89	302.12
Industrial	127.46	1,939.04	1,045.13	4,096.34	4,063.17	5,019.93	8,454.16
Mixed Use	0.30	5.40	4.52	23.06	23.06	37.36	889.29
Mobile Home	40.52	46.05	46.05	72.79	72.75	72.79	208.75
Motel	5.49	67.62	32.13	141.56	141.56	154.72	252.16
Multi-Family Residential	95.85	876.21	449.55	1,482.46	1,499.38	1,849.36	13,298.37
Public	0.00	0.01	0.00	2.49	2.49	2.59	33.85
Recreation	17.82	27.59	27.59	27.59	27.59	27.65	42.66
Residential	-	22.03	2.09	36.08	36.08	38.72	80.51
Rural	0.00	0.07	0.00	0.07	0.07	0.07	26.00
Salt Ponds	0.27	0.88	0.88	0.88	0.88	0.88	1.86
School	-	3.43	2.99	28.31	31.51	41.88	556.58
Single Family Residential	130.88	3,630.13	1,792.75	6,560.51	6,596.16	8,925.85	43,059.63
Vacant Commercial	26.45	78.79	35.32	113.24	113.24	118.32	300.81
Vacant Industrial	2.57	66.62	29.38	107.76	107.54	133.41	243.60
Vacant Residential	0.61	18.46	3.47	24.87	24.89	29.90	376.10
Vacant Rural	-	-	-	-	-	-	-
Unknown	-	-	-	-	-	-	541.79
Total	694.09	7,874.58	4,117.14	15,122.16	15,131.71	19,604.61	86,591.11

*Total for all parcels within the boundaries of the 7 cities in the ART study area

5.3 Comparison of Results

In this section, we analyze the results of our analysis of property value exposed to inundation using two different sources of information, as described above in Sections 5.1 and 5.2.

The replacement value of buildings and contents derived from FEMA's HAZUS Database is 31% less than the assessed value of improvements, and property from the Alameda County Assessor's Office (Table 35). (The values in Table 35 summarize the value of buildings and contents within the boundaries of each of the 7 study-area cities, not just the portion in the study area near the shoreline.). We believe that HAZUS tends to smooth values out, causing it to assign relatively lower values to property near the waterfront. The parcel database may contain a more accurate representation of high-value commercial and industrial buildings, which tend to be clustered near the waterfront.

Table 35 Comparison of the total value of buildings and contents in ART study cities from two data sources: FEMA's HAZUS model database and Alameda County Office of the Assessor (in millions of dollars)

	Replacement value of buildings and contents from FEMA's HAZUS Database (in millions of year-2000 dollars)	Assessed value of Property and Improvements (excludes Land) from the Alameda County Assessor's Office, Jan 1, 2012	Percent Difference
Alameda	4,449	5,889	+32%
Emeryville	910	2,608	+187%
Hayward	8,110	10,920	+35%
Oakland	22,176	26,501	+20%
San Leandro	5,218	6,598	+26%
San Lorenzo	1,004	1,505	+50%
Union City	3,259	5,285	+62%
Total	45,126	59,308	+31%

Further, a previous Pacific Institute study (Heberger 2009) concluded that FEMA's estimates of replacement value were significantly lower than actual market value. This indicates limitations to using public datasets to accurately estimate property values. All of the results reported here are likely much lower than the actual *market value* for properties. The HAZUS database reports the estimated cost to rebuild structures and to replace their contents. The Assessor's Office database is assembled for the purpose of levying taxes; it is not intended to accurately reflect market value. In a recent study, economists from San Francisco State noted that Assessor's "values are prone to underestimating the market value of land and should therefore be considered conservative" (King et al. 2011).

Based on the limitations in each of these datasets, we conclude that each is likely to underestimate property values. As these were the most readily-available public datasets, we proceeded with the analysis. However, this limitation should be kept in mind when interpreting the results.

6 Community Assets and Liabilities Exposed to Flood Risk

We use the term "community assets and liabilities" to describe a class of geographic features that can be represented as *points* on a map and in a GIS database. In order to assess community vulnerability and adaptation needs, we looked at a wide a range of features that represent locations and facilities that may be exposed to flood risk in the future. In this section, we describe the data and methods we used to determine which of these facilities may be exposed to inundation under each sea level rise scenario.

6.1 Data

We created a GIS database of community assets and liabilities as a Point Feature Class in an ESRI Personal Geodatabase (PGDB). *Community Assets* represent features that are important to the welfare of the community. In particular, we focused on locations which are home to or serve vulnerable populations. Examples include Child Care Facilities, Food Banks, Homeless Shelters, Schools, and Senior Housing. *Community Liabilities* include facilities where toxic waste or other dangerous substances are present, and which may be released or mobilized during a flood or other natural disaster.

Table 36 shows a full listing of the classes of community assets that we researched and included into our database. We were limited by the availability of publicly-available data. In a few cases, we developed new data layers by researching the location of certain features via internet searches and phone calls. We divided the 20 different types of features into 5 major types:

- Community Assets and Vulnerable Populations
- Contaminated Sites
- Critical Facilities
- Emergency Response
- Health care

Table 36 Data sources for community assets and liabilities

Data Set	Source
Community Assets & Facilities with Vulnerable Populations	
Child Care Facilities	California Community Care Licensing Division
Food Banks	California Community Care Licensing Division
Group Homes	California Community Care Licensing Division
Homeless Shelters	California Community Care Licensing Division
Schools	FEMA HAZUS
Senior Housing	California Community Care Licensing Division
Jails	Internet research; manually entered addresses
Contaminated Sites	
Cleanup Program Sites	BCDC
DTSC-listed sites	BCDC
Leaking Underground Storage Tanks	BCDC
Military Sites	BCDC
RCRA-listed sites	EPA Envirofacts (via BCDC)
Landfills and Waste Facilities	BCDC
Critical Facilities	
Critical Facilities – City and County	Association of Bay Area Governments (ABAG)
Critical Facilities – Special District	Association of Bay Area Governments (ABAG)
Emergency Response	
Fire Stations	FEMA HAZUS
Police Stations	FEMA HAZUS
Health Care	
Hospitals	FEMA HAZUS
Health Care Facilities	CA Dept. of Public Health
Long-Term Care Facilities	CA Dept. of Public Health

Critical facilities were identified by the Association of Bay Area Governments (ABAG 2010). ABAG identifies these as “several types of facilities are critical to the functioning of our region after disasters and during the recovery process.” The types of data included in their database are:

- Health-related facilities (based on a list of licensed facilities from the California Office of Statewide Health Planning and Development)
- Schools (location information on public and private K-12 schools, community colleges, colleges, and universities based on a combination of addresses from Thomas Bros. and the individual facilities)
- Critical facilities (owned by cities, counties, and special districts other than K-12 school districts)
- Highway and road structures, including freeway interchanges, small bridges over creeks, and toll bridges (location information based on data from Caltrans)

Contaminated sites include sites that are listed by the California Department of Toxic Substances Control (DTSC) and by the US EPA under the Resource Conservation and Recovery Act (RCRA). RCRA is a federal law that was passed in 1976 that requires all Treatment, storage, and disposal facilities (TSDFs) that manage hazardous wastes to have a permit in order to operate. Other contaminated sites include leaking underground storage tanks, landfills, and active cleanup sites.

We merged the 20 individual GIS data files to create a single “asset database” containing 2,656 points. The locations of the facilities in our community assets database are shown in Figure 5. Table 37 lists the number of facilities in our database, by city and by type. It should be noted that our database is not complete; it does not necessarily cover all of the area inside the boundaries of each of the 7 study communities. This is due to two reasons. First, the data that we received from BCDC was clipped to the study area, and did not include the eastern portions of Hayward and Union City. Second, with the data sets that we developed via independent research, we focused our efforts on the area in and near the inundation hazard zone. This should be kept in mind when interpreting the results in this section.

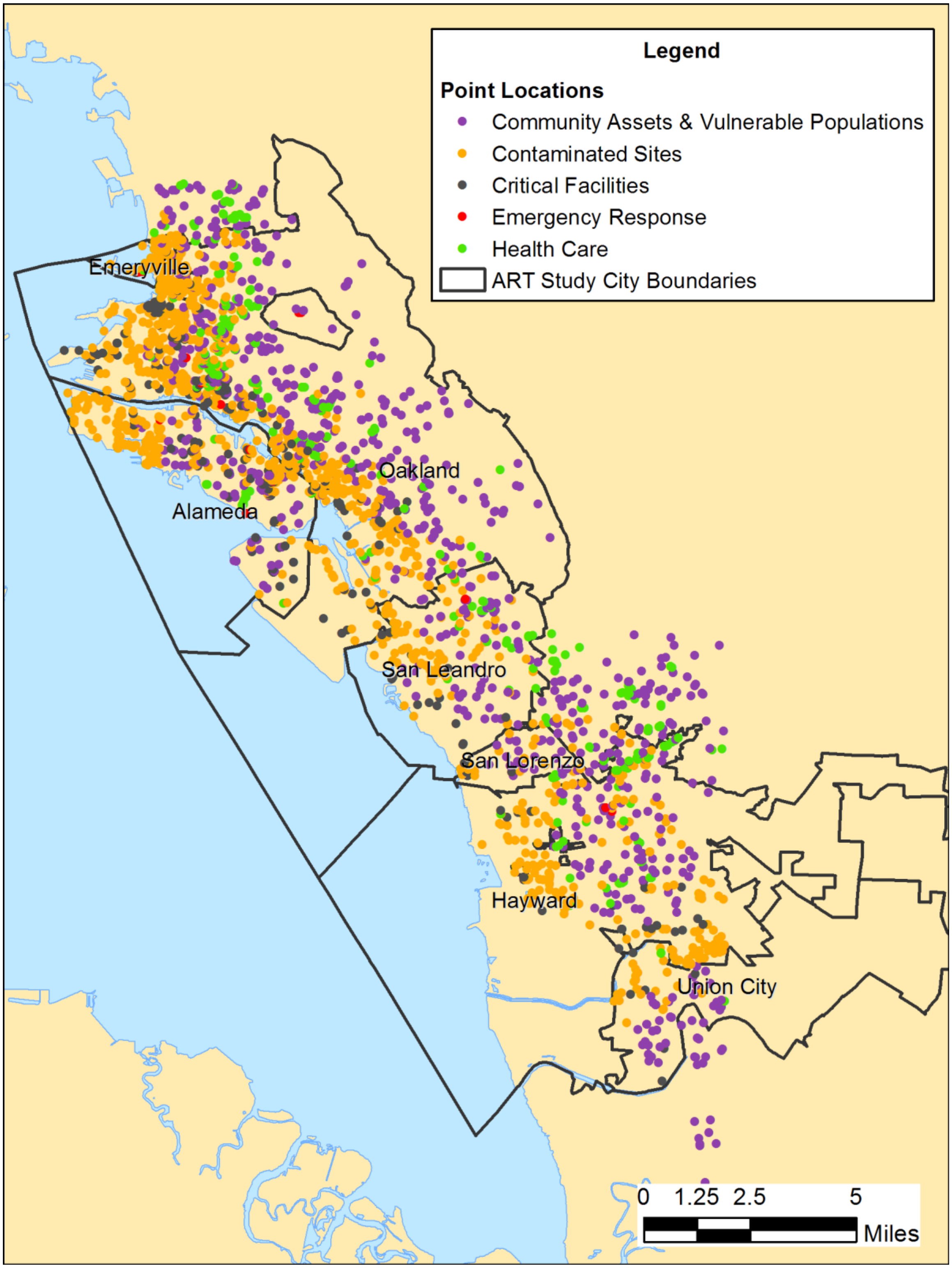

Figure 5 The locations of the community assets and liabilities in the ART study area, shown by major type.

Table 37 Number of Community Assets and Liabilities in project database, by city and by type.

	Alameda	Emeryville	Hayward	Oakland	San Leandro	San Lorenzo	Union City	Total
Community Assets & Vulnerable Populations								
Child Care Facilities	31	4	35	149	26	11	5	261
Food Banks	2	0	7	15	4	2	1	31
Group Homes	0	0	4	19	2	0	1	26
Homeless Shelters	0	0	2	12	0	0	0	14
Jails	1	0	1	1	1	0	0	4
Schools	29	4	43	83	25	14	7	205
Senior Housing	12	1	46	47	24	9	25	164
Contaminated Sites								
Cleanup Program Sites	19	42	41	151	30	3	5	291
DTSC-listed sites	7	18	10	66	6	0	1	108
Leaking Undg. Storage Tanks	32	37	66	201	24	15	15	390
Military Sites	124	0	5	10	0	0	0	139
RCRA-listed sites	15	46	69	77	23	1	7	238
Landfills and Waste Facilities	4	2	2	9	4	0	1	22
Critical Facilities								
City and County	48	6	18	47	5	0	4	128
Special District	15	6	15	138	15	0	3	192
Emergency Response								
Fire Stations	2	1	0	5	0	0	0	8
Police Stations	3	1	2	6	1	0	0	13
Health Care								
Health Care Facilities	9	4	38	120	26	2	3	202
Hospitals	1	0	2	4	3	0	0	10
Long-Term Care Facilities	7	0	16	21	8	0	0	52
Total	**361**	**172**	**422**	**1181**	**227**	**57**	**78**	**2,498**

6.2 Methods

Because of the large file sizes of the inundation hazard zone rasters datasets, we initially encountered some difficulty in performing an overlay analysis with the point layers. To complete the analysis, we used the procedure described below, which worked reliably, and which we verified to be accurate. The first steps were to verify the accuracy of the point locations and to make some adjustments to improve their accuracy.

6.2.1 Correcting Point Locations

In reviewing a subset of the 2,656 points in the asset database, we found that most points were slightly inaccurate, while some were up to ¼ mile from their true location. We manually edited a few dozen points with obvious errors and updated the location of many points that had a street address by using the Google Maps Geocoding API. We did this by using a short script written in Python (see Appendix E).

We had some concern that automatically querying Google's service may be a violation of their terms of service, so we contacted a Google Maps administrator who gave us permission to proceed (Christian Adams, personal communication, January 11, 2012). Google's algorithms locate most points at parcel centroids, rather than clamped to a road. While we found this to improve the locations considerably, we did not attempt to verify the precise location for all 2,656 points. Geocoding routines seem to be the least accurate for buildings on large lots, such as high schools and water plants.

We also made several corrections to the attribute table. Some records included incorrect entries, for example listing the name of the city as "Haywood" rather than "Hayward." Other records incorrectly used neighborhood names, such as "Alameda Point," rather than the city name "Alameda."

6.2.2 Adjusting Overlapping Points

Further, a number of the points were overlapping (i.e. they had identical coordinates) after geocoding. This was mostly a problem with the wastewater layers. We found that overlapping points and polygons caused some of ESRI's Spatial Analyst tools to fail.

Several of the datasets we received from public agencies contained overlapping points, which had to be adjusted slightly in order to perform our analysis. This appears to be the result of multiple records with the same address. For example, the Critical Facilities database we received from the Association of Bay Area Governments (ABAG) contains several entries at the East Bay Municipal Utility District's wastewater treatment plant, as shown in Figure 6. There were four facilities represented by overlapping points with identical coordinates: the Administration Building, Fuel Location, Warehouse, and Field Services.

When we attempted to perform an overlay analysis in ArcGIS to determine which locations overlap the inundation hazard zone, the program produced an error and stopped unexpectedly. A little research revealed that this issue occurs with overlapping features with coincident geometries. The same issue occurs regardless of geometry type (e.g. for points, polylines, and polygons.). In order to proceed, we "nudged" the points by a small distance (about 5 feet). Thus, the points remain in essentially the same location, and the geoprocessing tools can run without errors.

Figure 6 Example of multiple points occurring in a cluster at the EBMUD wastewater plant.

Note that ArcGIS has a built-in "Disperse Markers" tool that performs a similar function. However, this tool only adjusts the drawing layer in ArcMap, and not the underlying data. In other words, the point coordinates are not adjusted, but the program displays a cluster of points rather than a single dot where multiple points overlap.

We wrote a pair of custom functions in Excel VBA to disperse overlapping markers. These functions, listed in Appendix B, move a set of overlapping points by a small distance so that they are no longer overlapping. It does this by creating a new, revised pair of latitude and longitude coordinates that are slightly offset from the original. An example of its application is shown in Table 38. In this example, there are 17 points with the identical latitude and longitude coordinates. The function leaves the first point it encounters in the original position. It takes the rest of the remaining points, and moves them outward in concentric rings, at a set distance from the original, as shown in Figure 7. After we made minor adjustments to overlapping points so that each point had its own unique coordinates (even though several were very close to one another), the geoprocessing tools operated as expected and produced good results.

Table 38 Example of the disperse markers code.

PointID	Latitude	Longitude	Latitude-Revised	Longitude-Revised
1	37.8255160	-129.2925440	37.82551600	-129.29254400
2	37.8255160	-129.2925440	37.82553721	-129.29252279
3	37.8255160	-129.2925440	37.82554600	-129.29254400
4	37.8255160	-129.2925440	37.82553721	-129.29256521
5	37.8255160	-129.2925440	37.82551600	-129.29257400
6	37.8255160	-129.2925440	37.82549479	-129.29256521
7	37.8255160	-129.2925440	37.82548600	-129.29254400
8	37.8255160	-129.2925440	37.82549479	-129.29252279
9	37.8255160	-129.2925440	37.82551600	-129.29251400
10	37.8255160	-129.2925440	37.82551600	-129.29248400
11	37.8255160	-129.2925440	37.82555842	-129.29250158
12	37.8255160	-129.2925440	37.82557600	-129.29254400
13	37.8255160	-129.2925440	37.82555842	-129.29258642
14	37.8255160	-129.2925440	37.82551600	-129.29260400
15	37.8255160	-129.2925440	37.82547358	-129.29258642
16	37.8255160	-129.2925440	37.82545600	-129.29254400
17	37.8255160	-129.2925440	37.82547358	-129.29250158

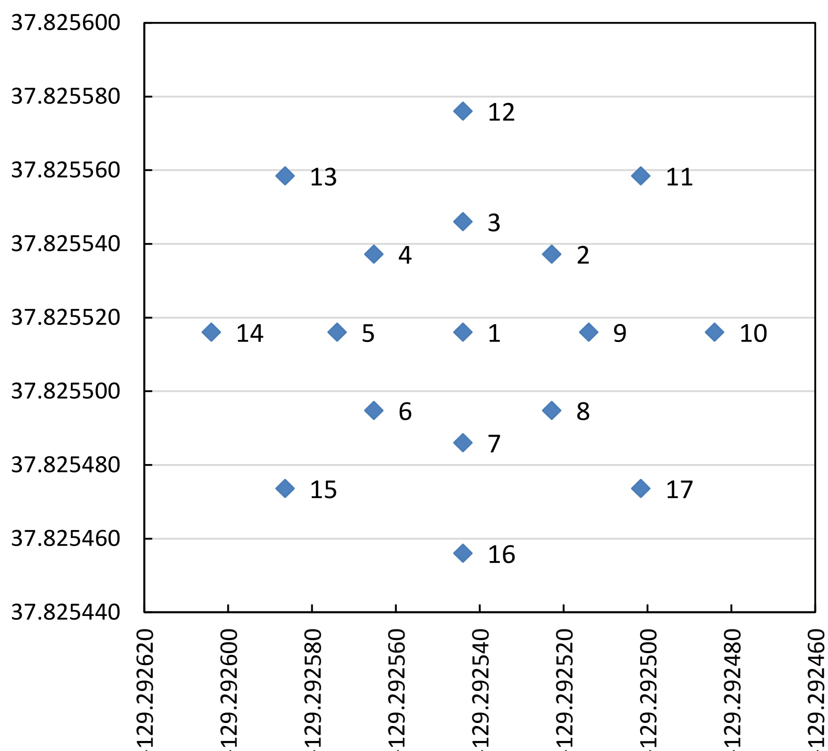

Figure 7 Demonstration of the disperse markers tool.

6.2.3 Converting Points to Polygons

First, we converted the point feature class to circular polygons with a 25 m radius using the Buffer tool. The circular polygon approach also helps compensate somewhat for the problem of inaccurate or arbitrary placement of point features to represent polygon features. We had previously experimented with the approach of overlaying the points with the inundation raster. This approach extracts a raster value to a point layer. Theoretically, this would result in exactly the information we were looking for: is the point inside or outside of the inundation hazard zone.

We found, however, that overlaying points with the inundation raster resulted in occasional false negatives and false positives. A false negative (structure is not in the inundation zone) is shown in Figure 8. In this example, the floodwaters cover over ¾ of the building, but the point representing the building lies just outside the inundation zone. A false positive is shown in Figure 9. Here, the actual building is outside of the inundation hazard zone. However, the point representing the building is inaccurate, and is not located directly above the building. Rather, it is located along the adjacent road. (This facility's address is on Edes Road, and the geocoding algorithm located the point along the polyline that represents Edes Road.) This is common with points that have been automatically geocoded by computer.

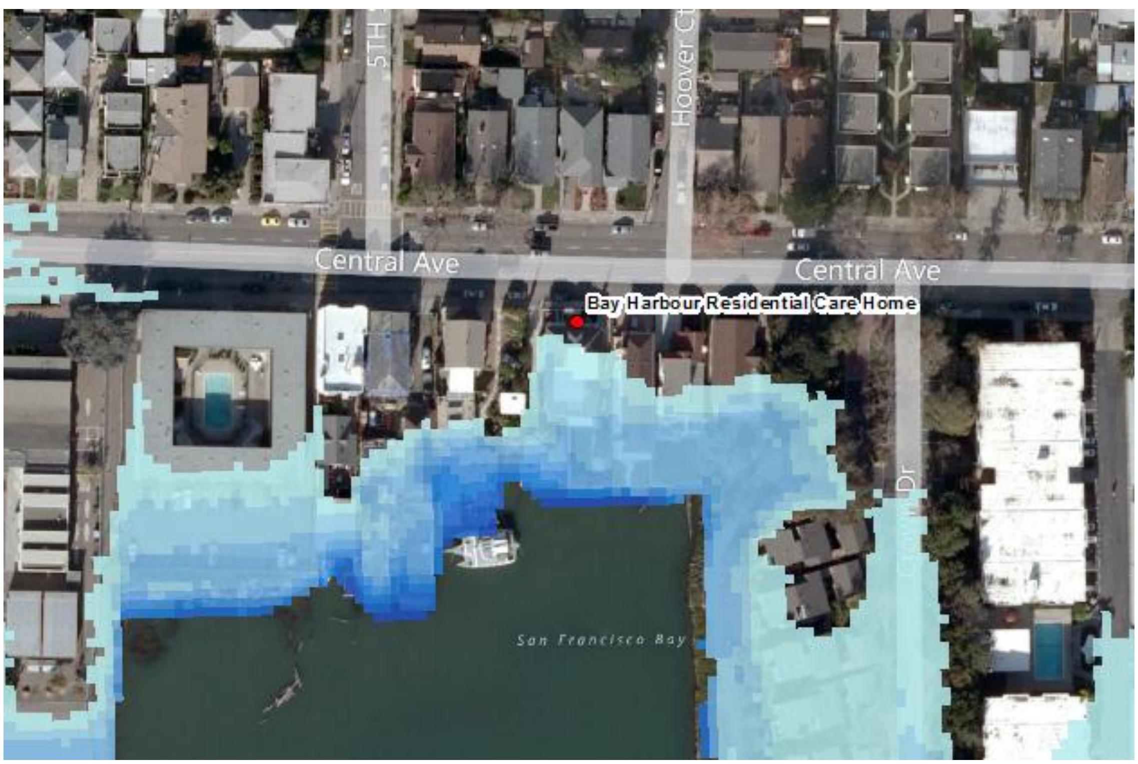

Figure 8 Example of a situation where a simple point-based analysis results in a false negative.

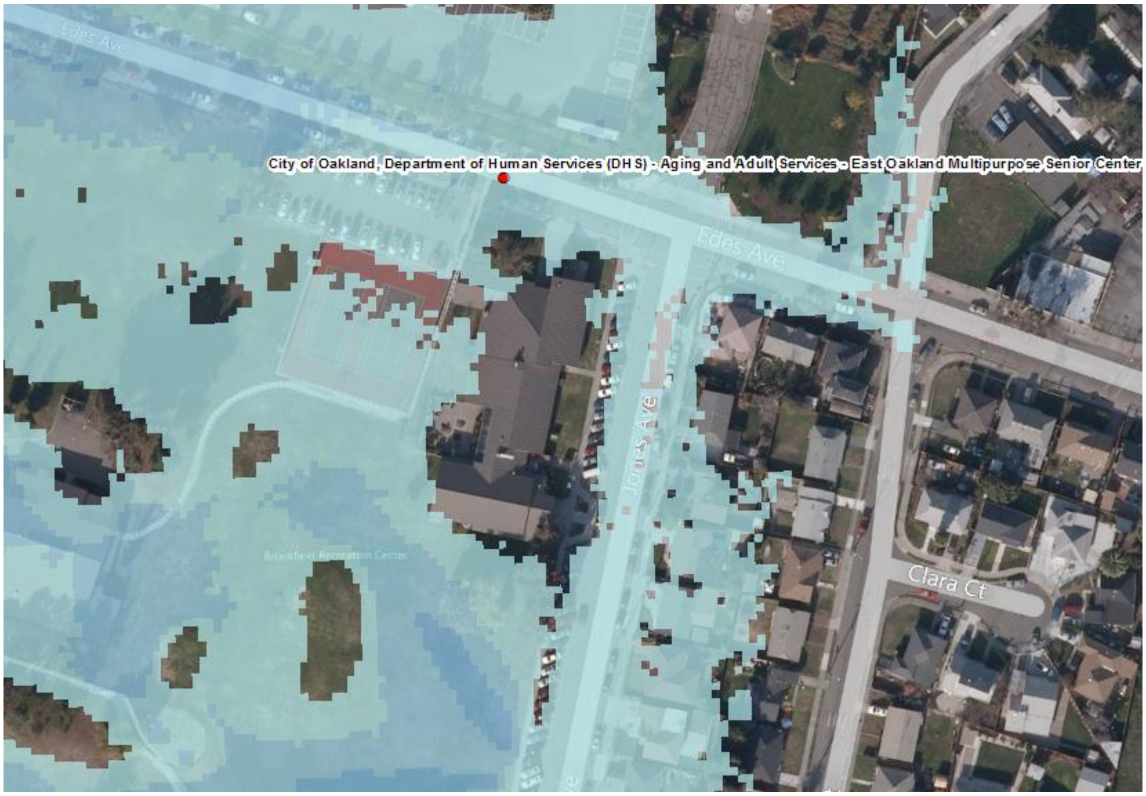

Figure 9   Example of a false positive when doing a simple analysis based on point locations.

The 25m radius is arbitrary. Various assets have different size footprints, thus a single value could not accurately represent all of the features we considered. A diameter of 50 meters (or about 164 feet) approximates the size of a building in the study region. Some buildings, such as single-family residences, may be somewhat smaller, while government buildings may be larger. An example of the points with a 25-m buffer is shown in Figure 10. Note that there are several instances where two or more points very nearly overlap, but have been adjusted so that they are slightly offset from one another. There are over 10 critical facilities (all related to stormwater) that were located at a single point on Embarcadero West between Alice Street and Jackson Street.

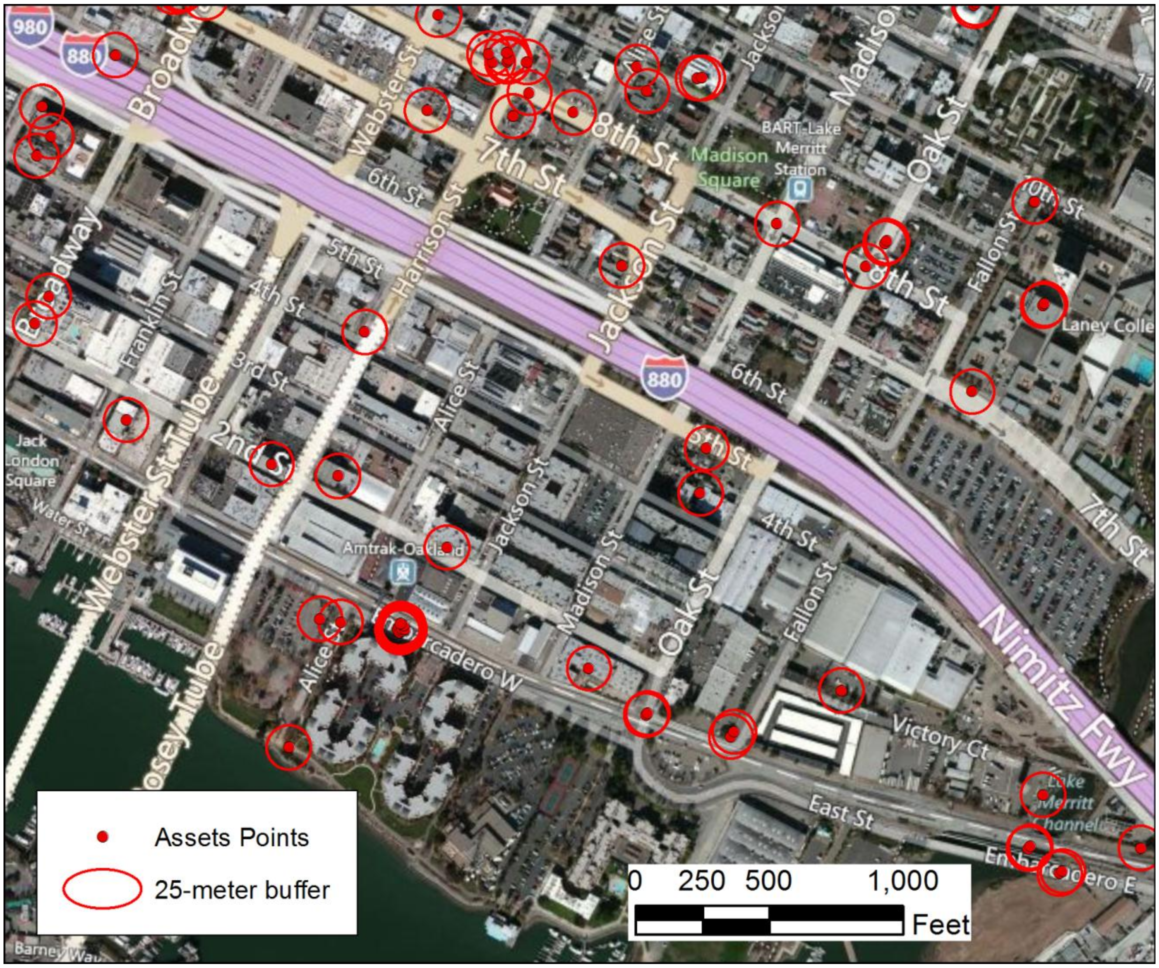

Figure 10 Points in the Community Assets database with a 25-m buffer.

6.2.4 Overlay Analysis

We used the simplified Boolean inundation rasters that we created as described in Section 2.2.3. In these layers, every cell has a value of 1 (flooded) or 0 (not flooded).

We used the ArcGIS Spatial Analyst "Zonal Statistics to Table" tool to summarize the raster values that fell within the 25 m circles representing each facility. The result is the percentage of each circle that is inundated. We considered any circle with a flood percentage greater than zero to be at risk of flooding.

We updated the asset database table to include fields representing the percent inundated and a Boolean (true/false) inundation, using the procedure described in Appendix D. These fields were used when creating Pivot Table summaries of the results in Microsoft Excel.

6.3 Limitations

Various sources were used for gathering data on community assets, the accuracy of which could not be verified. Sources such as 211.org were the best available source for data on service providers such as shelters and emergency food outlets. These sources are intended for connecting clients with services and Pacific Institute could not verify the frequency or methodology with which the information is updated. Some locations for service providers were intentionally withheld by 211.org out of privacy and safety concerns. These include shelters that serve individuals experiencing domestic violence. Some locations of community assets may also be inaccurate due to datasets that include administrative offices rather than solely facilities that directly serve the community.

Some of the data layers that we obtained rely on voluntary reporting by local governments. For example, it appears that some jurisdictions reported many more “critical facilities” than others. Water-related infrastructure for example, appears to be well-represented in the database, but there are fewer entries representing electrical infrastructure or communications. It seems that the definition of “critical” is subjective, making it impossible to fully capture a definitive database of critical facilities.

Lastly, the analysis method simply screens a location for potential flood exposure. It does not address whether individual facilities are elevated above the potential flood elevation or otherwise armored or flood-proofed.

6.4 Findings

The tables below show the number of community assets at risk by city and grouped into four categories. For this analysis, facilities are represented as points in the Geographic Information System.

Table 39 shows the number of assets for each of the six sea-level rise scenarios modeled for the ART project. It appears that there are a large number of critical facilities that are at risk of flooding. This should be tempered somewhat by the observation that the dataset from the Association of Bay Area Governments (ABAG) often included multiple points that are a part of the same facility. For example, there are over a dozen points at the site of EBMUD's wastewater treatment plant in Oakland.

Table 39 Community assets at flood risk in the ART project area sea level rise scenarios

	MHHW		100-yr Stillwater		100-year + Wind & Waves		Total Number of Facilities* (for reference)
	+16"	+55"	+16"	+55"	+16"	+55"	
Community Assets & Vulnerable Populations							
Child Care Facilities	0	12	6	26	26	37	261
Food Banks	0	0	0	2	2	4	31
Group Homes	0	1	0	1	1	1	26
Homeless Shelters	0	0	0	2	2	2	14
Jails	0	0	0	0	0	0	4
Schools	0	12	5	24	24	35	205
Senior Housing	0	18	5	28	28	46	164
Contaminated Sites							
Cleanup Program Sites	12	58	29	97	96	128	291
DTSC-listed sites	2	36	10	68	68	78	108
Leaking Underground Storage Tanks	4	49	17	109	109	142	390
Military Sites	3	60	41	121	121	124	139
RCRA-listed sites	1	51	20	110	110	153	238
Landfills and Waste Facilities	3	8	7	14	14	18	22
Critical Facilities							
Critical Facilities - City and County	10	36	28	58	59	79	128
Critical Facilities - Special District	9	91	39	144	145	154	192
Emergency Response							
Fire Stations	0	3	2	3	3	3	8
Police Stations	0	1	1	3	2	3	13
Health Care							
Health Care Facilities	0	9	3	19	19	25	202
Hospitals	0	0	0	0	0	0	10
Long-Term Care Facilities	0	2	0	7	7	7	52
Total	**44**	**447**	**213**	**836**	**836**	**1039**	**2,498**

*Note that the total number of facilities may not represent all facilities in each study-area city, as discussed in the text.

In Table 40, we show the number of assets exposed to inundation risk by city, with each row showing a different category of community asset. This analysis reflects the number of facilities at risk under the scenario representing the 100-year storm event plus wind and waves, plus a 55” sea-level rise. Tables like this one can easily be produced for each of the six inundation scenarios by making a small change to a Pivot Table in an MS Excel workbook available from the authors.

Table 40 Community assets at risk under the highest scenario of sea-level rise and flooding (100-year storm event plus wind and waves, with 55 inch sea level rise), by category and by community

	Alameda	Emeryville	Hayward	Oakland	San Leandro	San Lorenzo	Union City	Total
Community Assets & Vulnerable Populations								
Child Care Facilities	14	–	2	10	3	4	4	37
Food Banks	1	–	–	3	–	–	–	4
Group Homes	–	–	–	–	–	–	1	1
Homeless Shelters	–	–	–	2	–	–	–	2
Schools	14	–	1	8	4	3	5	35
Senior Housing	12	1	5	3	5	3	17	46
Contaminated Sites								
Cleanup Program Sites	12	6	11	83	9	2	5	128
DTSC-listed sites	6	13	4	52	2	–	1	78
Leaking Undg. Storage Tanks	15	16	16	74	4	4	13	142
Military Sites	114	–	–	10	–	–	–	124
RCRA-listed sites	13	22	39	57	15	1	6	153
Landfills and Waste Facilities	4	2	1	8	2	–	1	18
Critical Facilities								
City and County	27	2	14	29	3	–	4	79
Special District	13	1	11	112	14	–	3	154
Emergency Response								
Fire Stations	1	1	–	1	–	–	–	3
Police Stations	2	1	–	–	–	–	–	3
Health Care								
Health Care Facilities	9	4	2	6	2	–	2	25
Long-Term Care Facilities	7	–	–	–	–	–	–	7
Total	**264**	**69**	**106**	**458**	**63**	**17**	**62**	**1,039**

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Acronyms and Abbreviations

ABAG	Association of Bay Area Governments
APN	Assessor’s Parcel Number
ART	Adapting to Rising Tides
BCDC	Bay Conservation and Development Commission
CSC	Coastal Services Center, a division within NOAA
DPH	California Department of Public Health
DTSC	California Department of Toxic Substances Control
EBMUD	East Bay Municipal Utility District
FEMA	Federal Emergency Management Agency
FIPS	Federal Information Processing Standards
GCS	Geocentric Coordinate System
GIS	Geographic Information System
HAZUS	Geographic information system-based natural hazard loss estimation software package developed and freely distributed by the Federal Emergency Management Agency (FEMA).
MHHW	Mean Higher High Water
NAD83	North American Datum of 1983
NOAA	National Oceanic and Atmospheric Agency
RCRA	Resource Conservation and Recovery Act of 1975
SLR	Sea Level Rise
SoVI	Social Vulnerability Index
TSDF	Treatment, Storage, and Disposal Facility
USGS	United States Geological Survey
WWTP	Wastewater treatment plant

Appendix A: "The SoVI Recipe"

Reprinted from Hazards and Vulnerability Research Institute (January 2011). Retrieved March 19, 2012, from http://webra.cas.sc.edu/hvri/docs/SoVI_32_recipe.pdf.

1. Collect the input variables. SoVI variables are derived primarily from the US Census Bureau using the Census Data Engine with some ancillary data from the Geographic Names Information System (GNIS). Alternate data sources may include City and County Databook or individual county offices.

2. Normalize all variables as either percentages, per capita values, or density functions (i.e. 'per square mile').

3. Verify accuracy of the dataset using descriptive statistics (i.e. min/max, mean, standard deviation). Missing values can be replaced by substituting the variable's mean value for each enumeration unit. The statistical procedure will not run properly with missing values. Census units with population valuesof zero should be omitted.

4. Standardize the input variables using z-score standardization. This generates variables with a mean of 0 and standard deviation of 1.

5. Perform the principal components analysis (PCA) using a varimax rotation and Kaiser criterion for component selection. This rotation reduces the tendency for a variable to load highly on more than one factor. Next, set parameters for the extraction of factors. This can be aided by the examination of a scree plot for significant drops in Eigenvalue as the number of components included in the analysis increases. While some disjoints in the scree are anticipated (such as those that occur between the first few components) subsequent decreases in Eigenvalue indicate appropriate thresholds for factor extraction.

6. Examine the resulting factors. Determine the broad representation and influence on (i.e. increase or decrease) social vulnerability for each factor by scrutinizing the factor loadings (i.e. correlation between the individual variable and the entire factor) for each variable in each factor.

7. Factors are named via the choosing of variables with significant factor loadings (or correlation coefficients)--usually greater than .500 or less that -.500. Next, a directional adjustment (or cardinality) is applied to an entire factor to ensure that the signs of the subsequent defining variables are appropriately describing the tendency of the phenomena to increase or decrease vulnerability.

Factor 1 below is an indicator of class and poverty. As shown in the table, the dominant factors that theoretically **increase** vulnerability (people over age 25 w/o a diploma, percent in poverty) have a significant **positive** factor loading. Conversely, the other 2 dominant factors, while still being indicators of socioeconomic status (percent employment and per capita income), theoretically **decrease** vulnerability, and exhibit a **negative** factor loading. Thus, the cardinality of this factor remains positive (+) as the signs on the factor loadings for the individual variables is consistent with their tendency on social vulnerability.

Factor 2 is an indicator vulnerable age groups (i.e. the old and the young). As you can see, both the old and the young, as well as their proxies embody the dominant factors. In examining the variables' factor scores, we see that they exhibit both positive and negative factor loadings, but since all of the variables (i.e. kids under 5, elderly over 65, median age, and social security beneficiaries) have tendency to **increase** vulnerability, we apply an absolute value to Factor 2 to dissolve the negative sign on the factors that increase vulnerability, and maintain the cardinality of the variables with non-negative loadings.

Alternatively, some factors may exhibit significant **positive** factor loadings on variables that theoretically **decrease** vulnerability. Factor 4 below is one such example, with positive loadings on mean rent, mean house value and percent rich. To adjust the sign of this factor so that those variables appropriately represent their tendency to decrease social vulnerability, a negative cardinality is applied, and the factor is multiplied by -1.

8. Save the component scores as a separate file.

9. Place all the components with their directional (+, -, ll) adjustments into an additive model and sum to generate the overall SoVI score for the place.

10. Map SoVI scores using an objective classification (i.e. quantiles or standard deviations) with 3 or 5 divergent classes so illustrate area of high, medium, and low social vulnerability.

Appendix B: Land Use Classification Cross-Reference

Table 41 Cross reference relating land use classification used in this study (BCDC Category) to the land use classifications in the Alameda County Assessor's office database

BCDC Category	Assessor's Land Use Classification (Use Code)
Agriculture	Rural property used for agriculture, 10+ acres
Care Facility	Medical-Residential Care Facility (SFR)
	Assisted living unit
	Nursing or boarding home
	Skilled Nursing Facility
Cemetery	Cemetery
Commercial	One story store
	Commercial Imps on Residential Land
	Miscellaneous improved commercial
	Department store
	Discount store
	Restaurant
	Shopping Center
	Shopping Center-Community
	Shopping Center-NBHD without anchor (strip mall)
	Shopping Center-Power Center
	Commercial or Industrial Condominium
	Commercial or Ind Condo Common Area
	Nurseries
	Church
	Other institutional property
	Lodgehall and/or clubhouse
	Historical commercial
	Church Home
	Car wash
	Commercial repair garage
	Automobile dealership
	Parking lot
	Parking garage
	Service Stations
	Funeral home
	Bank
	Medical - Dental building
	Veterinarian Office
	One to five story office building
	Over five story office building
	Bowling alley
	Walk-in theater
	Drive-in theater
Condominium	Condominiums - single residential living unit
	Condominium - residential live/work unit
	Condominiums - single res unit, first sale
	Condominium - res live/work unit, first sale
	Condominium - single res unit, R&T 402.1
	Condominium Common Area
	Condominium - res live/work, common area or use

	Condominium - urban res unit above, common area or
	Condominium-office, common area or use
Floating Home	Floating home
Golf Course	Golf course
Grocery	Supermarket
Historic Residential	Historical residential
Hospital	Hospital (convalescent or general)
	Medical clinic/outpatient surgery
Hotel	Hotel
Improved Rural	Improved rural land, non-renewal Williamson Act
Industrial	Warehouse
	Warehouse-Self Storage
	Light industrial
	Industrial Flex/R&D use
	Heavy industrial
	Misc. industrial (improved); no other ind code
	Quarries, Sand and Gravel
	Terminals, trucking and distribution
	Wrecking yards
Mixed Use	Store on 1st floor, with offices, apts/lofts 2nd/3
Mobile Home	Mobile home on SFR land
	Mobile home in a mobile home park
	Mobile home park
Motel	Motel
Multi-Family Residential	Planned development - Townhouse
	Townhouse Style - Condominium
	Planned development - Townhouse, R&T 402.1
	Planned Development - Townhouse, Common Area
	Townhouse Style - Condominium, Common Area or use
	Double or duplex type - two units
	Triplex; double or duplex with single family home
	Four living units; e.g. fourplex or triplex w/SFR
	Four residential living units, R&T 402.1
	Res property of 2 units, lesser quality than 2200
	Res property of 3 units, lesser quality than 2300
	Res property of 4 units, lesser quality than 2400
	Res property of 2,3 or 4 units with rooming house
	More than 1 mobile home, or M/H w/other res units
	Vacant apartment land, capable of 5 or more units
	Vacant apartment land, R&T 402.1
	Vacant apartment common area
	Five or more single family res homes
	Residential property converted to 5 or more units
	Restricted residential income property
	Fraternities and sororities
	Multiple residential building of 5 or more units.
	Residential high-rise (7 or more stories)
Public	Exempt Public Agency
	Property leased to a public utility
	Property owned by a public utility
	Vacant land necessary part of institutional prop.
	Government owned property - vacant land

	Improved government owned property
Recreation	Other recreational activity, e.g. rinks, stadiums
Residential	Tract land, R&T 402.1
	Partially complete residential tract home
	Tract residential PC, R&T 402.1
	Residential Imps on Commercial Land
	Residential Imps on Industrial Land
	Condominium-industrial, common area or use
	Live-Work condominium, R&T 402.1
	Cooperatives (divided)
	Cooperatives (undivided)
Rural	Vacant rural-res homesites, may incl misc. imps
	Improved rural-residential homesite.
	One or more mobile homes on rural home site.
	Rural property with significant commercial use
	Rural property with significant industrial use
	Rural property in transition to a higher use
Salt Ponds	Salt Ponds
School	School
Single Family Residential	Single family residential homes used as such
	Single family residential home, R&T 402.1
	Single family residential (tract) common area
	Single family res home with non-economic 2nd unit
	Single family res home with slight commercial use
	Single family res home with slight industrial use
	Single Family Res - Duet Style, R&T 402.1
	Single family res land with/subj. to communal imps
	SFR Detached Site Condominium , Common Area or use
	Single family res home converted to boarding house
	Planned development tract SFR with common area
	Planned development tract SFR, R&T 402.1
	Planned development tract SFR, Common Area
	Modular/manufactured single family res unit (home)
	Two, three or four single family homes
Unknown	Unknown Use
	Secured PI
Vacant Commercial	Vacant commercial land (may include misc. imps)
Vacant Industrial	Vacant industrial land (may include misc. imps)
Vacant Residential	Vacant residential tract lot
	Vacant residential land, zoned 4 units or less
	Vacant residential land, R&T 402.1
Vacant Rural	Vacant rural land, not usable even for agriculture
	Vacant rural land, non-renewal Williamson Act

Appendix C: Excel/VBA Function to Disperse Overlapping Point Coordinates

Below, we list two short functions written in Visual Basic for Applications (VBA) for Microsoft Excel to disperse overlapping points. This code is described in Section 6.2.2.

```
Option Explicit

'The purpose of these two functions was to move overlapping points where
'you have a lat, lng pair. It is analagous to the Disperse Markers tool in ArcGIS.
'The list has to be sorted for it to work properly.
'It is not very sophisticated and could be improved.

Function LatRev(rng As Range, Optional dist As Double = 0.0003)
    Dim i As Long
    Dim mult() As Variant

    mult = Array(0, 0.707, 1, 0.707, 0, -0.707, -1, -0.707, 0)

    i = 0
    Do
      If rng.offset(-i - 1, 0).Value <> rng.Value Then Exit Do
      i = i + 1
    Loop

    LatRev = rng.Value

    If i > 0 Then
      LatRev = LatRev + (1 + Int(i / 9)) * dist * mult(i Mod 9)
    End If
End Function


Function Lngrev(rng As Range, Optional dist As Double = 0.0003)
    Dim i As Long
    Dim mult() As Variant
    mult = Array(1, 0.707, 0, -0.707, -1, -0.707, 0, 0.707, 1)

    i = 0
    Do
      If rng.offset(-i - 1, 0).Value <> rng.Value Then Exit Do
      i = i + 1
    Loop

    Lngrev = rng.Value

    If i > 0 Then
      Lngrev = Lngrev + (1 + Int(i / 9)) * dist * mult(i Mod 9)
    End If
End Function
```

Appendix D: Overlay Analysis Methods

The next several paragraphs describe the steps we used to calculate the proportion of the region's population that is exposed to flood risk. We used a form of geographic analysis called "area-weighted interpolation." For a theoretical overview of this method, see for example the *Handbook on Geographic Information Systems and Digital Mapping* (United Nations Statistical Division 2000, p. 107–112). For this discussion, we use the example of population data which is linked to Census Blocks that are represented as polygons on maps or in a GIS database. However, this same procedure can be used to analyze any variable which is linked to polygons (e.g. parcels).

We begin by using ArcGIS to calculate the percentage of each Census block that is inundated in each scenario. In other words, we are performing a form of overlay analysis to determine what fraction of each Census block is covered by cells in the inundation raster that represents a flooded condition. The methods described here can be used for any variable that is an attached to polygons (e.g. property value, number of low-income households, etc.)

There are a number of possible ways to approach this problem, but we had the most success using the ArcGIS Spatial Analyst tool "Zonal Statistics as Table." The Zonal Statistics tool, "Summarizes the values of a raster within the zones of another dataset and reports the results to a table" according to ESRI's description. The feature zone data is the feature class containing the Census block polygon boundaries. We used the binary floodplain rasters that we created previously (described in Section 2.2.3) as the input raster.

Under Statistics type, we chose MEAN, which "calculates the average of all cells in the value raster that belong to the same zone as the output cell." Because these raster layers contain only two possible values (1 for flooded areas, 0 for dry areas), the average of the 0s and 1s is a value between 0 and 1 that represents the fraction of the Census Block that is covered by floodwaters.

We also checked the option "Ignore NoData in calculations." The meaning of this option is: "Within any particular zone, only cells that have a value in the input Value raster will be used in determining the output value for that zone. NoData cells in the Value raster will be ignored in the statistic calculation." In other words, this tool will ignore all Census blocks that fall outside of the edge of the raster datalayer. It will also not attempt to do a partial calculation for blocks near the edges of the raster. This option is important because the block boundary file covers all of Alameda County, while the flood layers cover only a limited geographic area.

For the zonal statistics tool to give the expected results, it is important to set certain Environment Settings. In ArcToolbox, under Environment Settings Raster Analysis, Cell Size should be set to "Minimum of Inputs." This is because during the analysis, vector files are converted to temporary rasters. To achieve the best accuracy, these temporary rasters should have the same cell size as the input raster. Checking this option ensures that this happens.

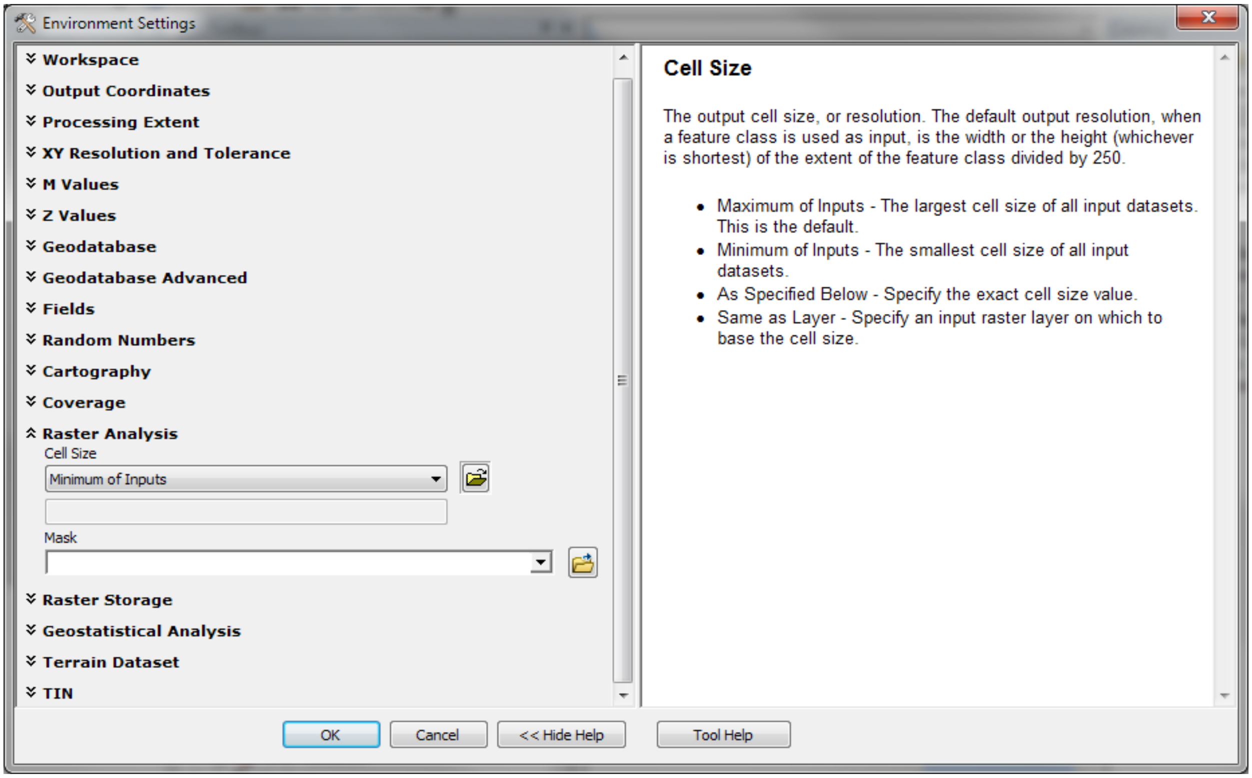

Figure 11 Environment settings dialog box in ArcGIS.

For each zonal statistics calculation, we used the Census block ID code as the Zone Field. The block ID works well because it is a unique identifier that is associated with every Census block in the database. The ID is a 15-digit code that contains all of the information needed to determine its state, county, tract, and block group (Figure 12). Note that these are not numbers, but rather numeric codes that consist entirely of the digits 0–9. Because the codes sometimes start with 0, great care needs to be taken not to import these ID numbers into a spreadsheet or database as a number, or the opening zero will be dropped and valuable information will be lost.

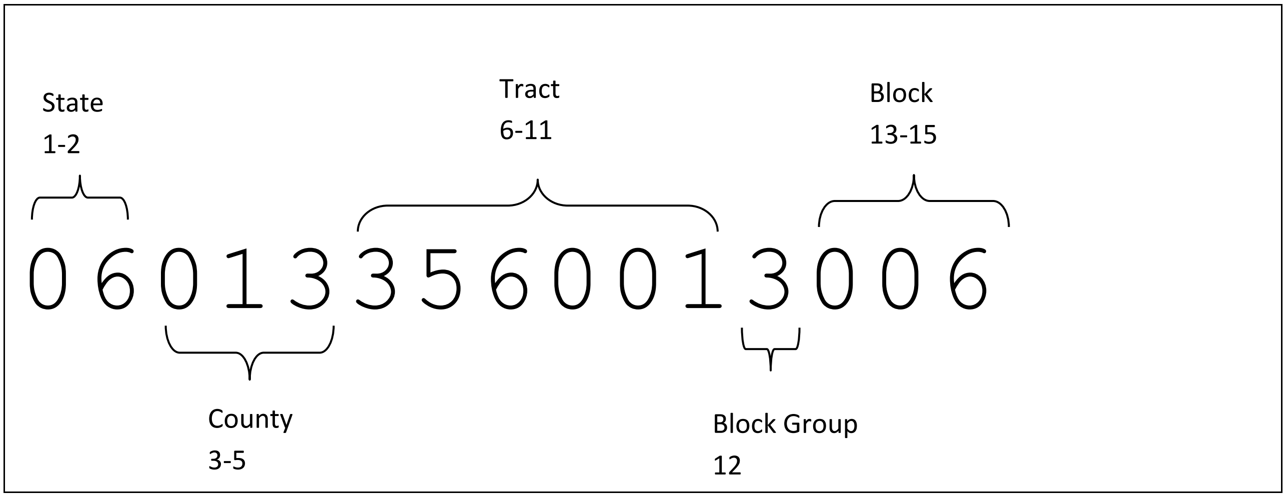

Figure 12 Decoding Census Block IDs.

We repeated the zonal statistics calculation for each of the six flood layers. We stored the output tables in a Microsoft Access database, and carefully named them to avoid confusion. We named the files:

- fld_mhhw16
- fld_mhhw55
- fld_sw16
- fld_sw55
- fld_ww16
- fld_ww55

We then opened the Census block feature class attribute table directly in ArcMap. We created 6 new fields with the same names as the tables above (fld_mhhw16 etc.), with the data type "floating point number." We set up a series of table joins to join the Census block attribute table with the flood percentage table, basing the join on the field representing the Census block ID. We used the ArcGIS Field Calculator to insert the values from the zonal statistics tables into the block attribute table. At this point, we verified that the blocks had been assigned proper values by looking carefully at the layer, as is shown in Figure 4.

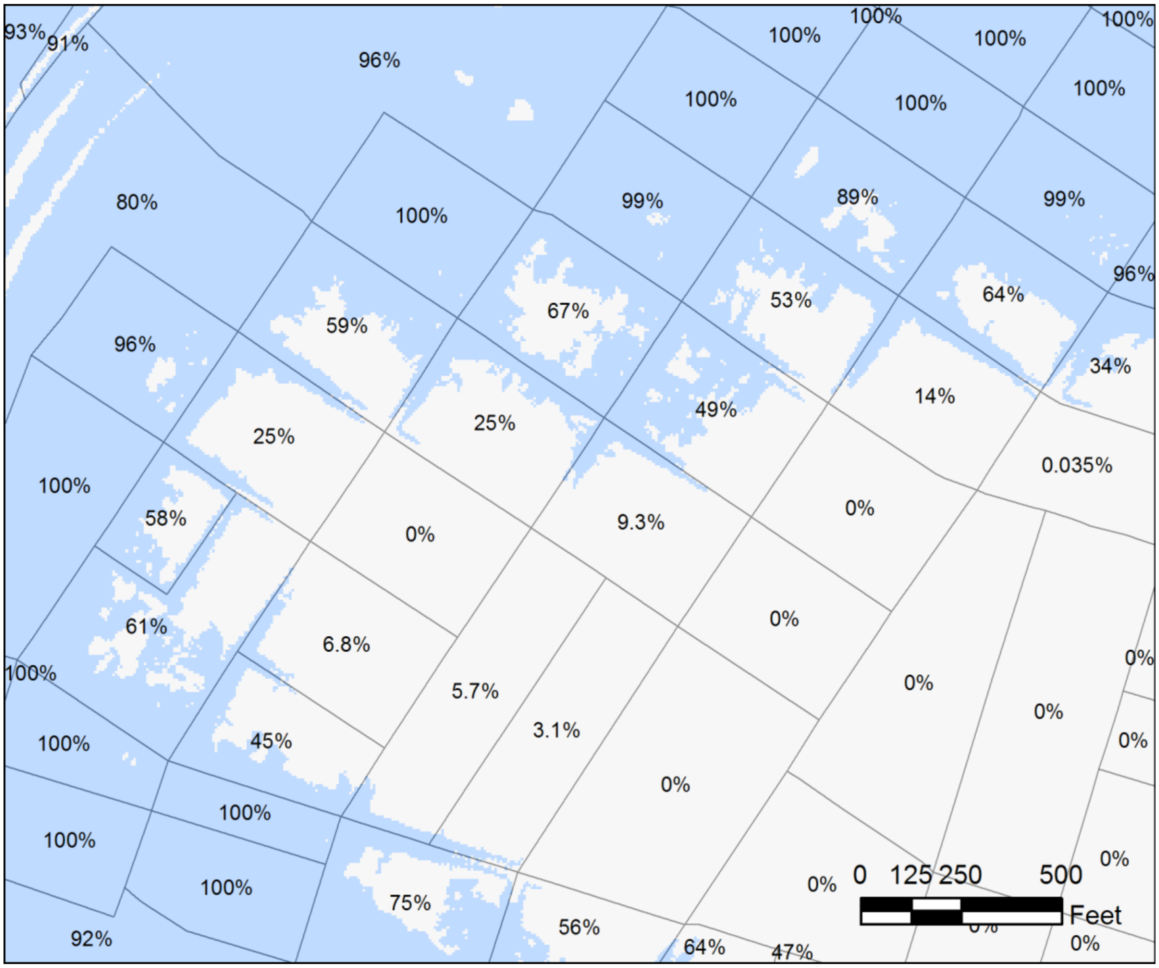

Figure 13 Example of overlay of the flood raster layer (blue shading) with the Census block boundary polygons to determine percent of each block in the study area that is exposed to flooding

After the fields representing flooding were populated, we summarized the data using Pivot Tables in MS Excel. Pivot Tables are a powerful way to analyze and summarize data that is in a tabular or database format. It allows the user to quickly create “cross tabulations,” and is a feature that is included in most spreadsheet packages. One of the main advantages to using the older Access-based personal geodatabase format to store geographic feature data is the ability to read data directly in MS Excel and create Pivot Table summaries. Geodatabases and Excel workbooks are available from the authors for analysts wishing to create custom data summaries.

It is important to note that the area-weighted interpolation method of overlay analysis is prone to inaccuracies. It requires one to assume that the variable of interest is evenly distributed within each of the target area’s polygons. For example, we assume that the population is evenly distributed over a Census block. This assumption may be a valid approximation in dense urban areas where the housing stock shares similar densities. It is easy to find examples where portions of Census blocks are unpopulated. We partially overcame this difficulty by performing a clip to remove the portion of blocks covered by ocean.

Figure 14 shows an example of a Census Block that is partially flooded. However, the floodwaters are on a golf course and neither buildings nor people appear to be threatened. In this example, the Census Block in Hayward has a population of 580 and is 14.3% inundated. Area-based weighting gives a population exposed to inundation of 83 people. A close look at the inundation zone shows that there are no homes at risk in this Census Block. This is an example of where the area-weighting method *overestimates* the population exposure. Likewise, there are instances where the method is likely to underestimate exposure.

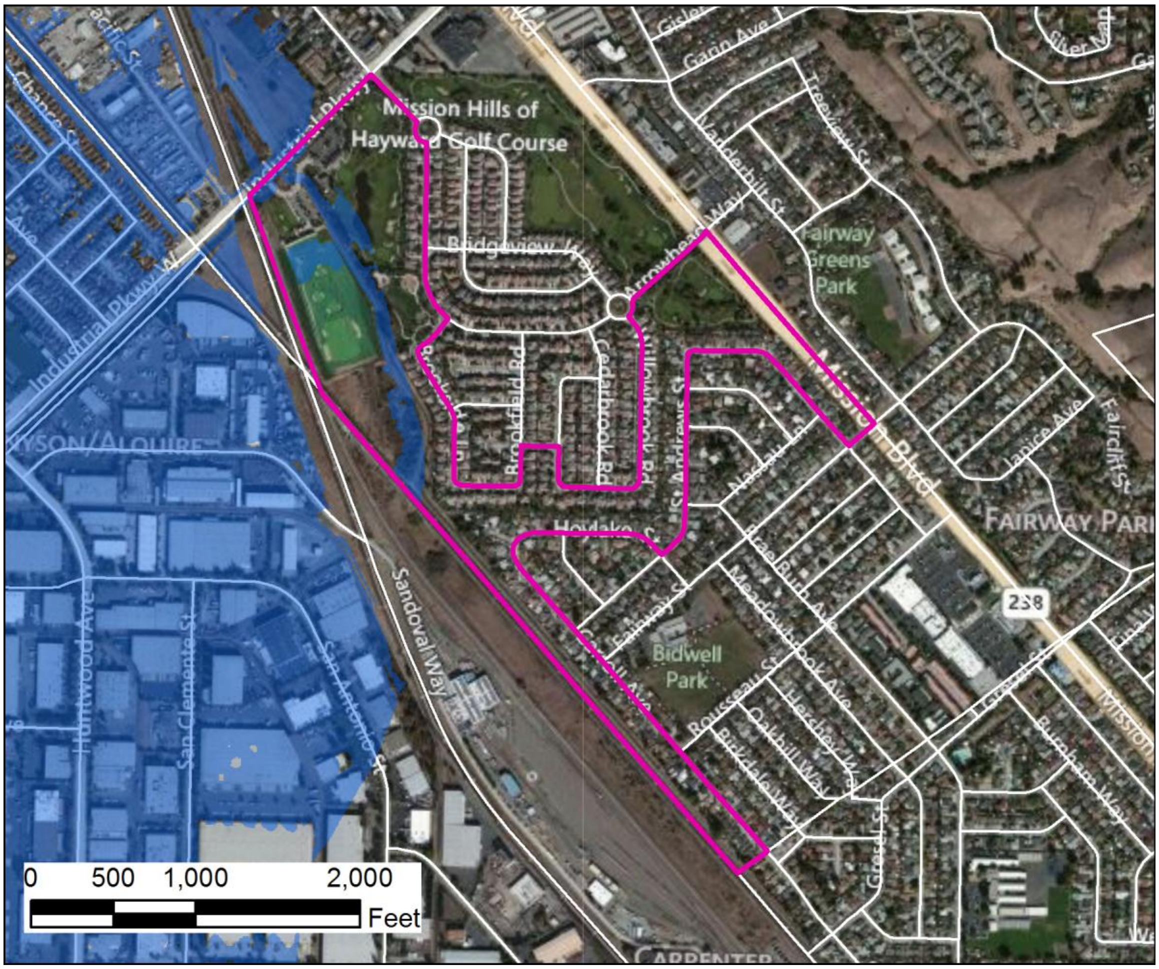

Figure 14 **Example of a partially flooded census block where buildings or population do not appear to be at risk**

Appendix E: Python Script for Batch Geocoding

Below is the listing for a Python program to geocode locations, or get their latitude and longitude coordinates, based on a list of addresses using the Google Maps Geocoding API. Please note that this service was used by permission, and is ordinarily intended for use via interactive websites displaying a Google Map, as described in Google's terms of service (Google 2011). The use of this code is described in Section 6.2.1.

It takes a tab-delimited file with fields for ID, Address, City, State, and Zip Code, like the following in **addresses.txt**:

```
107    35000 Eastin Court        Union City   CA    94587
105    31600 Alvarado Blvd       Union City   CA    94587
112    31600 Alvarado Blvd       Union City   CA    94587
115    3841 Smith Street         Union City   CA    94587
404    1995 Industrial Pkwy West Hayward      CA    94544
359    27836 Loyola Avenue       Hayward      CA    94545
403    1275 W. Tennyson Road     Hayward      CA    94544
```

The script produces a file called **results.txt** with a set of latitude and longitude coordinates keyed to the input ID numbers.

```
107    -122.0696955 37.5658896
105    -122.0730684 37.5917172
112    -122.0730684 37.5917172
115    -122.0776437 37.5966091
404    -122.0755872 37.6176350
359    -122.0923618 37.6251261
403    -122.0788514 37.6314539
```

Here is the Python script:

```
import urllib
import time

def geocode(address):
      # This function queries the Google Maps API geocoder with an
      # address. It gets back a csv file, which it then parses and
      # returns a string with the longitude and latitude of the address.

 # This isn't an actual maps key, you'll have to get one yourself.
```

```
 # Sign up for one here: http://code.google.com/apis/maps/signup.html
	mapsKey = '***APIKEY***'
	mapsUrl = 'http://maps.google.com/maps/geo?q='

 # This joins the parts of the URL together into one string.
	url = ''.join([mapsUrl,urllib.quote(address),'&output=csv&key=',mapsKey])

	#print url
 # This retrieves the URL from Google, parses out the longitude and latitude,
 # and then returns them as a string.
	coordinates = urllib.urlopen(url).read().split(',')

	#Sometimes the google API returns 0...
	#if so, pause for one second and try it again
	print coordinates

	if coordinates[1] == "0":
		print "retrying..."
		time.sleep(1)
		coordinates = urllib.urlopen(url).read().split(',')

	coorText = '%s\t%s' % (coordinates[3],coordinates[2])
	return coorText

h = open('c:/py/addresses.txt', 'r')
o = open('c:/py/results.txt', 'w')

for line in h.readlines():

	data = line.rstrip().split('\t')
	print data[1:]
	address = '%s, %s, %s %s' % tuple(data[1:])
	try:
		tmp = [data[0], geocode(address)]
		o.write( '\t'.join(tmp) )
		o.write('\n')
	except:
		pass
```