Examining the effect of Flood Insurance's exclusion of homeless people on their mental health

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NS50: Empirical Analysis

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Glossary

1) Flood Health Vulnerability Index: the result combination of Social and Demographic, Exposure, Health and Housing Vulnerability indicators of a census blockgroup
2) Census Blockgroup: the geo-id attached to locations in the city on this website's map
3) Poverty index: Proportion of all individuals below 200% of the Federal poverty rate
4) Mental Health index: Age-adjusted hospitalization rate per 100,000 residents due to schizophrenia and other psychotic disorders
5) Homeless index: Homeless population, per 1000 residents
6) Exposure areas: Census blockgroups that have an overall high-risk index in terms of Elevation, Sea Level Rise and Precipitation level
    a) Elevation index: Minimum elevation in feet
    b) Sea Level Rise index: Proportion of the land area in the 100-year flood plain with 36-inches of sea-level rise
    c) Precipitation; Proportion of land area with over 6 inches of projected precipitation-related flood inundation during an 100-year storm

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Background and Justification

The "SF Sea Level Rise, Flooding, and Health" (San Francisco Department of Public Health, 2016) dataset reported the heath-vulnerability level of San Francisco's 578 census blockgroups toward flood inundation. The vulnerability is ultimately determined by the Flood Health Vulnerability Index, which is the score accumulation of 16 other indexes. The report's objective is to identify the highest-vulnerable community to allocate resources and impose risk management. The report's result shows which census blockgroups are most vulnerable (Appendix - Figure 7); however, the causes are unclear. Therefore, this paper explains what possibly gives rise to this highest vulnerability group to create more specific and practical measurements.

Exploratory Data Analysis

Poverty has been the main population characteristic that determines flood health vulnerability (Hallegatte et al., 2020; Appendix - Figure 8). [1]

[1] #dataviz: I effectively used 2 data visualizations: The first one to give an outline view about the overall correlation, the second to zoom closer to the two groups that are explanatory to the bigger question of the report: What gives rise to the highest vulnerable community? The caption was described in 3 parts: Describe the graph, describe the trend, provide interpretation and implication.

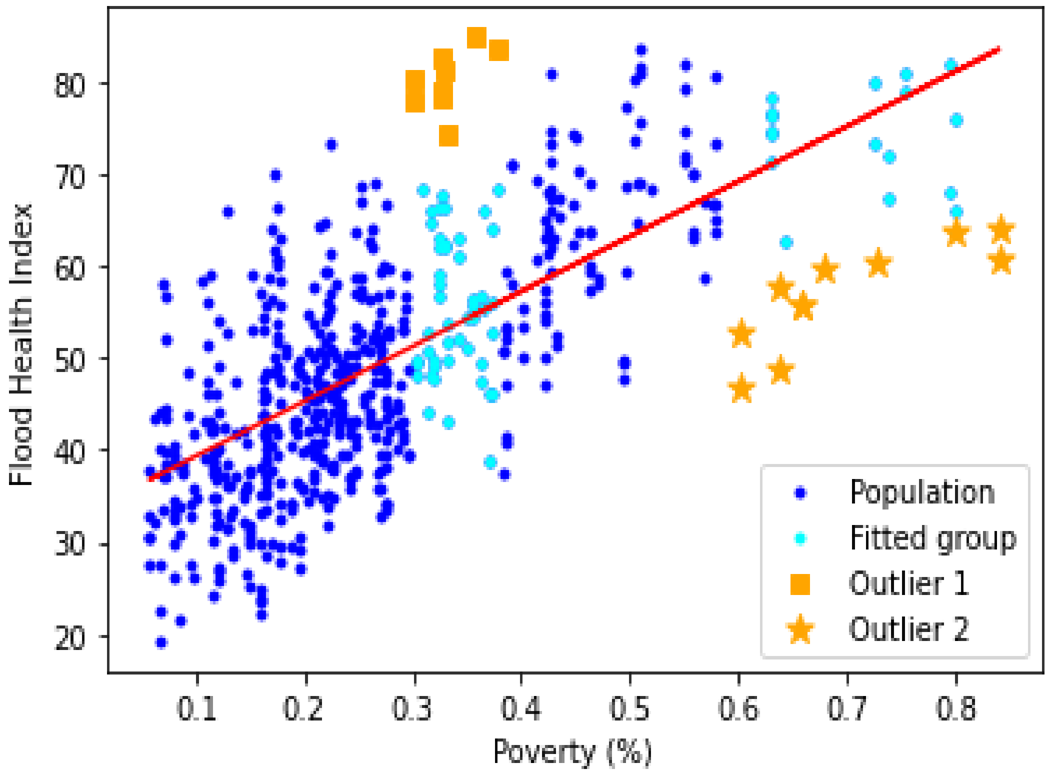


Figure 1. The relationship between poverty and Flood Health Index per 578 census blockgroups in San Francisco in 2016. The two variables have a strong, positive, and linear correlation. There are two outliers in poverty categories 0.3 – 0.4 and 0.6 – 0.9. The most significant pattern is the highest flood-vulnerable group (Outlier 1) since it does not fit the supposed prediction of the trendline: “The highest vulnerability being the poorest group”.

In an attempt to explain the cause of the highest-vulnerable group, Figure 1 begs the explanation of the vulnerability difference between the Outlier group and the Fitted group of the same poverty category 0.3 – 0.4. Mental health could be the explanation head start since mental health and poverty are heavily intertwined as influential pre-existing conditions (Escobar Carías et al., 2022) and flood consequences (Appendix - Figure 9).

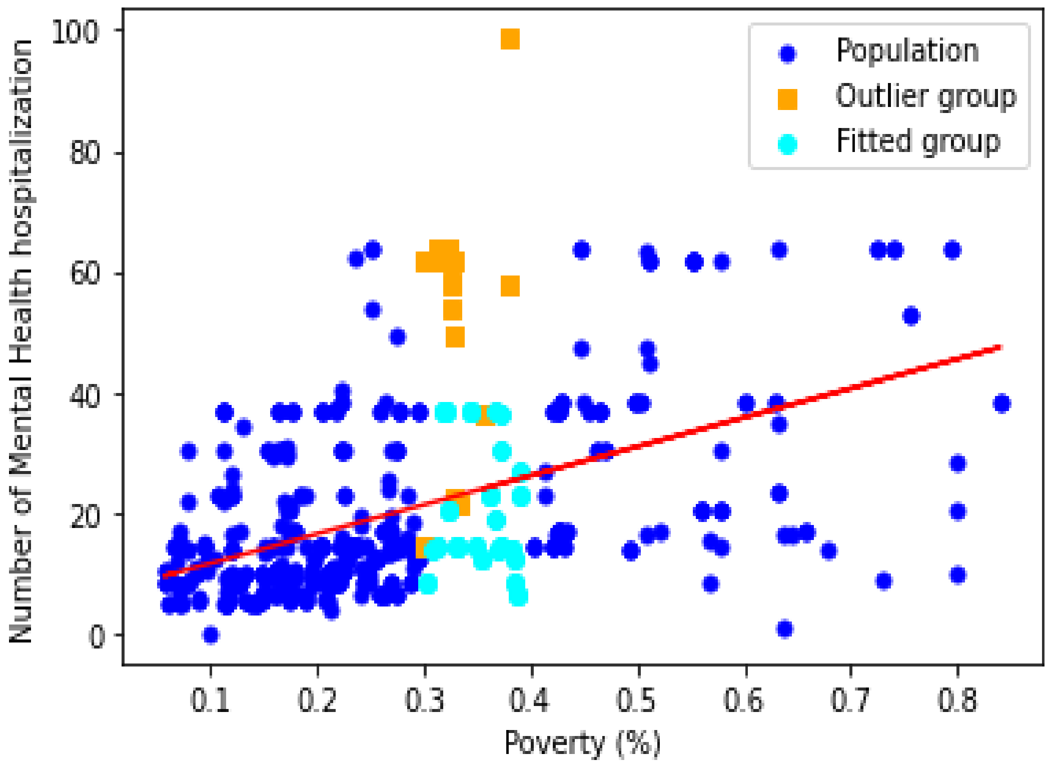


Figure 2. The relationship between poverty and mental health hospitalization per 578 census blockgroups in San Francisco in 2016. There is a positive and linear correlation between the two variables. In the explanatory poverty category 0.3 – 0.4, the number of mental health hospitalizations for the Outlier group is higher than that of the Fitted group, which indicates that the difference in mental health hospitalization between these two groups might explain the relative difference in their Flood Health Index.

Figure 2 inspired this paper's research question: "Why did the Outlier group have significantly higher mental health hospitalization than the Fitted group of the same poverty category 0.3 - 0.4?" Other differences are considered to understand this Outlier group more comprehensively.

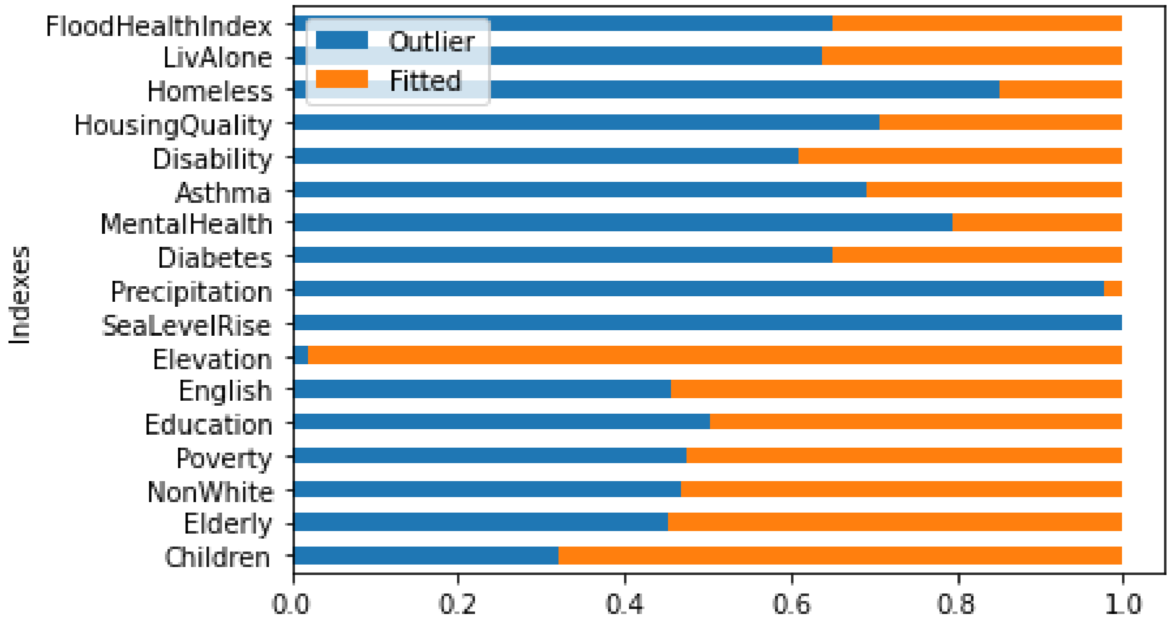
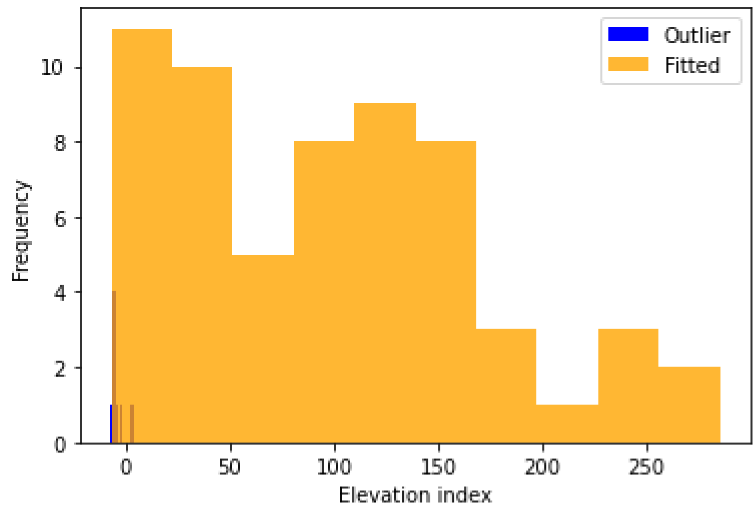
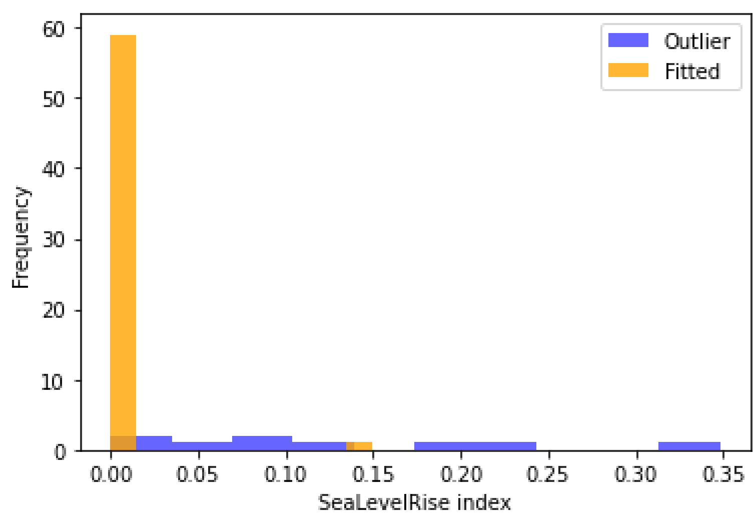


Figure 3. The differences across 17 indexes between Outlier and Fitted group. In each group, each index's range of values is converted into proportion (%) by taking the dividend of their mean and the sum of two groups. The graph indicates that indexes with the highest differences are mental health, homeless, precipitation, sea level rise, and elevation. Therefore, the Outlier group has a significantly higher mental health hospitalization, a higher proportion of homeless people, higher precipitation and sea level rise, and lower minimum elevation than the Fitted group.

Since the values of the three exposure indexes are small, their proportions are inaccurately shown. A closer view is needed.


Outlier
Fitted
Frequency
Elevation index


Outlier
Fitted
Frequency
SeaLevelRise index

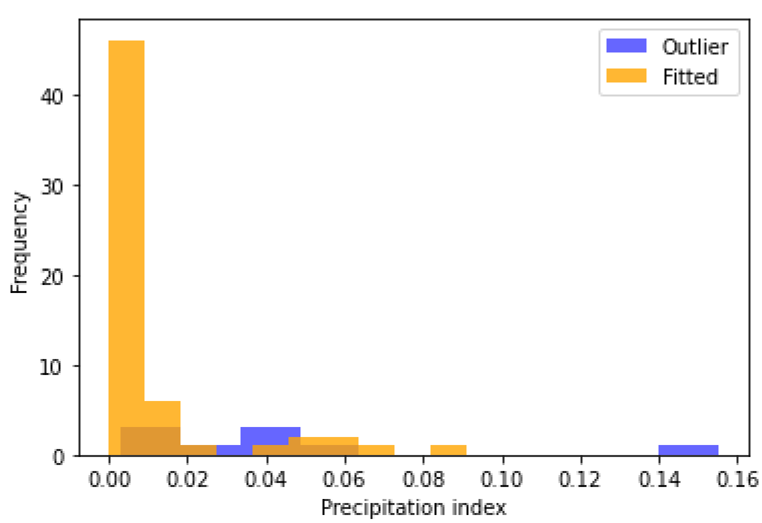

Outlier
Fitted
Frequency
Precipitation index

Figure 4. Distributions of Outlier and Fitted group across 3 exposure indexes: Elevation, Sea Level Rise, Precipitation. Elevation index experienced the largest difference between Outlier and Fitted group: most census blockgroups in Outlier group have negative minimum elevation. Two other indexes also experienced large differences between Outlier and Fitted group. However, since measurements of them are in the proportion of risky precipitation area and the proportion of risky sea-level-rise area, increases of 0.15 - 0.35 % in the land area are relatively insignificant compared to the rise in elevation in feet.

Overall, the data visualization shows that the upsurge of mental health hospitalization in the Outlier group can be explained by its higher proportion of homeless people and lower elevation.

Study objectives [2]

The relationship between homelessness and elevation is proven: homeless people are disproportionately displaced in lower-elevation areas (Hallegatte et al., 2020). Moreover, mental health, homelessness, and elevation can be tied together by the Flood Insurance policy - the most used flood management practice worldwide (Tariq et al., 2013). There is no research found on another type of flood insurance except one with coverage of housing and in-house furniture (FloodSmart | the National Flood Insurance Program, 2019). Research has found that holding Flood Insurance can effectively reduce mental illness: the higher the house's elevation, the lower the insurance cost (Mulchandani et al., 2019). This Flood Insurance policy's property security

[2] #Evidence-based: I applied multiple research from scholarly resources to provide background information for 3 overarching topics; mental health, poverty and flood. The evidence was nicely structured through glossary, data visualization and appendix. Most significantly, I actively searched for the gap in knowledge in current research and found out an important topic remains uncovered.

and economic advantage mostly benefit the Fitted group - the one with more homeowners and higher elevation levels, which explains its lower mental hospitalization. Thus, the effect of its exclusion on homeless people is unclear: The researcher found no article on the inaccessibility of homeless people to this Flood Insurance, which inspired my hypothesis to fill that gap:

> "If homeless people are centered around low elevation areas (Outlier group), they will have higher mental health hospitalization because Flood Insurance, which only covers housing damage cost for housed people, excludes homeless people from recovery of other flood consequences, thus deteriorating their mental health." [3]

Assumption: [4]

- Homeless people do not receive Flood Insurance
- Flood Insurance help reduce mental health hospitalization
- Exclusion from flood recovery measurements would lead to high mental health hospitalization of homeless people
- Decreased mental health leads to increased mental health hospitalization

Prediction:

- In this outlier group, Homeless people will have higher mental health hospitalization than housed people with Flood Insurance
- Housed people without Flood Insurance will have higher mental health hospitalization than housed people with Flood Insurance

[3] #hypothesis development: I conducted intensive research on the current gap in knowledge to create a hypothesis that can give new research direction. The hypothesis was found by combining and analyzing interesting variables that I found out in data visualization: homeless, mental health, elevation.
[4] # plausibility: Most assumptions are found based on existing research that I have identified. There are multiple assumptions. The one that was not found based on research articles is "Homeless people do not receive Flood Insurance", which is also reasonable because homeless people do not own a house and are often excluded from public services.

Study methods [5]

The research proposes the observational study method because mental health development from a disaster could not be seen in a short-term limit of an interventional study and could not be ethically experimented on. The variables are defined as follows: (1) Exposure/ independent variables (categorical variables) are: Homeless - no Flood Insurance, Housed - without Flood Insurance, and Housed - with Flood Insurance. (2) Outcome/ dependent variable (ordinal variable) is two dichotomy groups of mental health hospitalization numbers (0 - no mental health hospitalization, 1 - have at least one mental health hospitalization) (Whaley, 2004). There are multiple confounding variables detected: age group, sex, ethnic group, pre-existing illness, deprivation score (index of multiple deprivations (IMD)), economic status, education, and local authority. To account for those confounders and establish causal conclusions, the researcher does not use cross-sectional surveys. Since exposure variables are targetable categorical variables and the search for control cases with no mental health hospitalization (if using a case-control study) might be hard to recruit, the research will use a cohort study. A retrospective approach is used for being less expensive, less time-consuming, and the fact that outcomes of mental health hospitalization could often occur before the study begins (University of Oxford).

<u>Procedure</u>

The three exposure groups will be drawn from a random sample of 9 census blockgroups from the Outlier group. Although the proportion of homeless people is larger than housed people in these census blockgroups, even distribution for three groups should be met, and age is

[5] #Observational study: I explained and used the concept of retrospective cohort study, a type of observational study to demonstrate my understanding: how data was collected in current time and trace back history to collect longitudinal data from exposure variables to outcome variables. A detailed procedure on participant recruitment, data collection, variables, and data analysis is provided.

controlled (19–59 years) for recruitment. The recruitment of two exposure groups of housed people is done by random telephone directories; however, recruitment of homeless people information is done through homeless shelters. Pairs of participants are created with differences in exposure variables but similar in some demographic characteristics to minimize variability caused by extraneous variables and balance the groups (Brazauskas R, Logan BR, 2016).
With cohort retrospective study and the survey method, participants of each exposure group were asked about their current demographic information as a baseline for adjustment of confounding variables. They are asked about their past exposure when the flood happened 6-8 months prior to the time of the study, based on their response to 2 questions: "Were you homeless or housed?" and "Were you having Flood Insurance?". Then, they are asked to rate their total numbers of mental health hospitalizations since that flood till now (using official media records) into two categories (yes/no) as specified in the variable definition. Finally, their demographic information will be collected when the flood happened. Additionally, an open-text question asks participants to explain how the flood had affected their mental health.

Logistic regression analysis will clarify the association between housing and Flood Insurance status and mental health hospitalization and adjust confounding variables. Crude and adjusted odd ratios are calculated to conclude the causal relationship between exposures and outcomes: the odds of the outcome given the occurrence and absence of exposure (Szumilas, 2010).

Limitations

Although the collection of data relies on official medical records, there could still be chances of recall bias. There could also be selection bias. Moreover, the hospitalization variable cannot capture the actual mental health level of the population since homeless people with mental illness still have less access to hospitalization.

Expected outcomes

Consistent result

After using results from the adjusted odds ratio, one possible outcome is: Homeless people were five times more likely than housed people with Flood Insurance to experience mental health hospitalization.

This shows that Flood Insurance is likely to be the cause, not just a correlation of the mental health outcome of homeless people.

Inconsistent result [6]

The second exposure group "Housed - without Flood Insurance" helps ensure that the test results can be compared fairly and are not skewed. Suppose there is little difference in the mental health hospitalization between the homeless and this control group (both are high). In that case, there could be strong evidence that Flood Insurance is a cause of the mental health increase of homeless people. However, if there is little difference in the mental health hospitalization of this control variable with "Housed people with Flood Insurance", there could be chances that homeless people have higher mental hospitalization not because they are excluded from Flood Insurance, it was just because they have more direct consequences of flood than housed people.

Overall, investigating the effect of Flood Insurance's exclusion of homeless people can call for a re-examination of this discriminatory policy on vulnerable groups. Being the

[6] #testability: My inconsistent outcome can falsify the hypothesis in multiple ways. Implied in the consistent hypothesis, the first way to falsify is the "Homeless people do not have higher rates of mental health hospitalization than other groups" which denied Flood Insurance being the cause. For the second one, I effectively identified a falsification does not seem obvious: "Homeless people have higher rates of mental health hospitalization than other groups", but the difference is insignificant.

highest-flood-vulnerable group, yet they may be left behind. More research could investigate in detail how the exclusion of Flood Insurance influences homeless people's mental health.

Word count: 1296 words

Reflection

I received comments that my hypothesis needed to be more specific and clear and provide new insights. Therefore, I tried to comprehensively analyze the variables provided in the report and explore interesting insights on new variables: homeless and elevation. This new investigation allowed me to develop an overarching Flood Insurance policy that provides a new research direction for the current gap in scientific knowledge.

Appendix

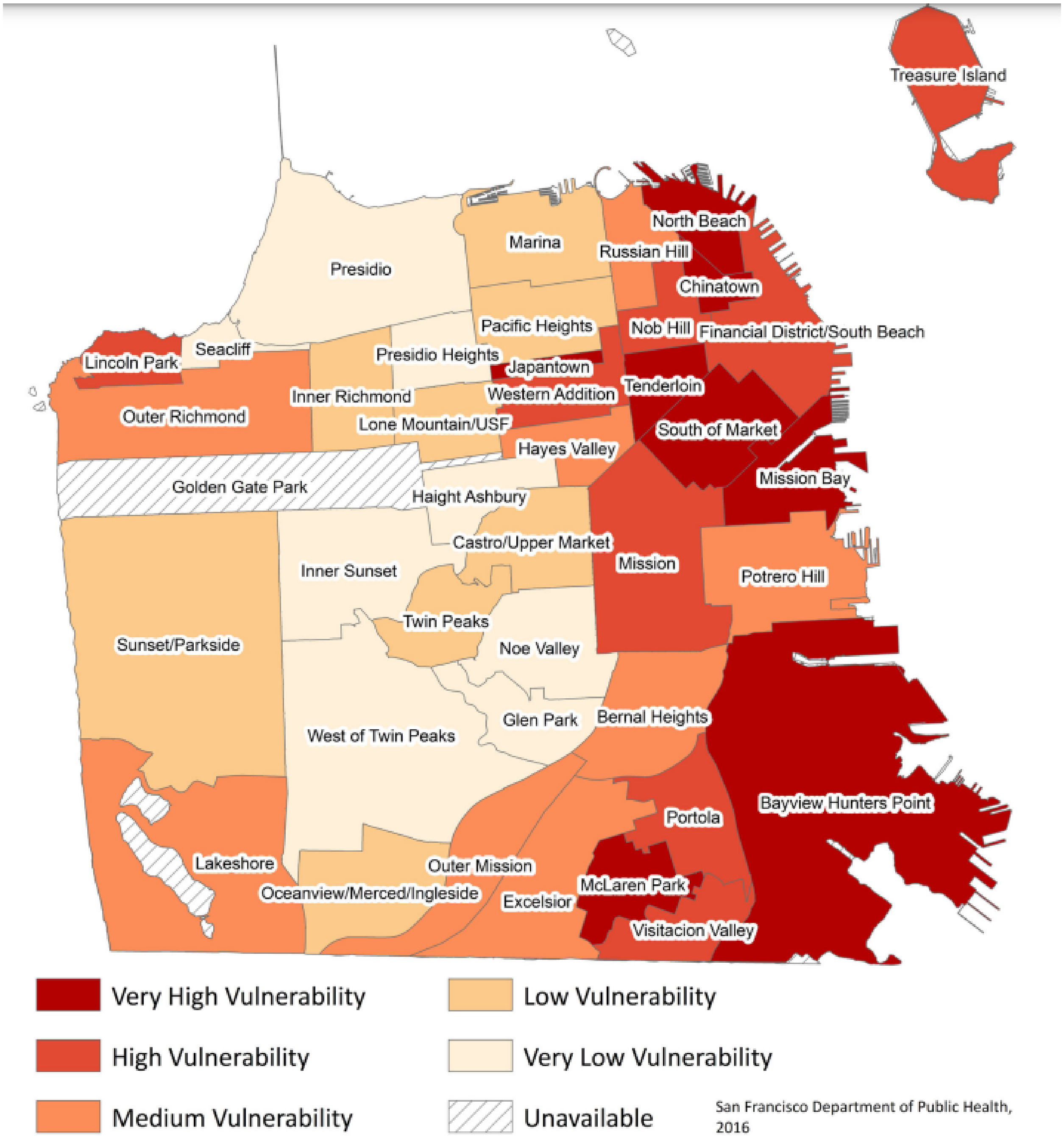


Figure 7 (San Francisco Department of Public Health, 2016)

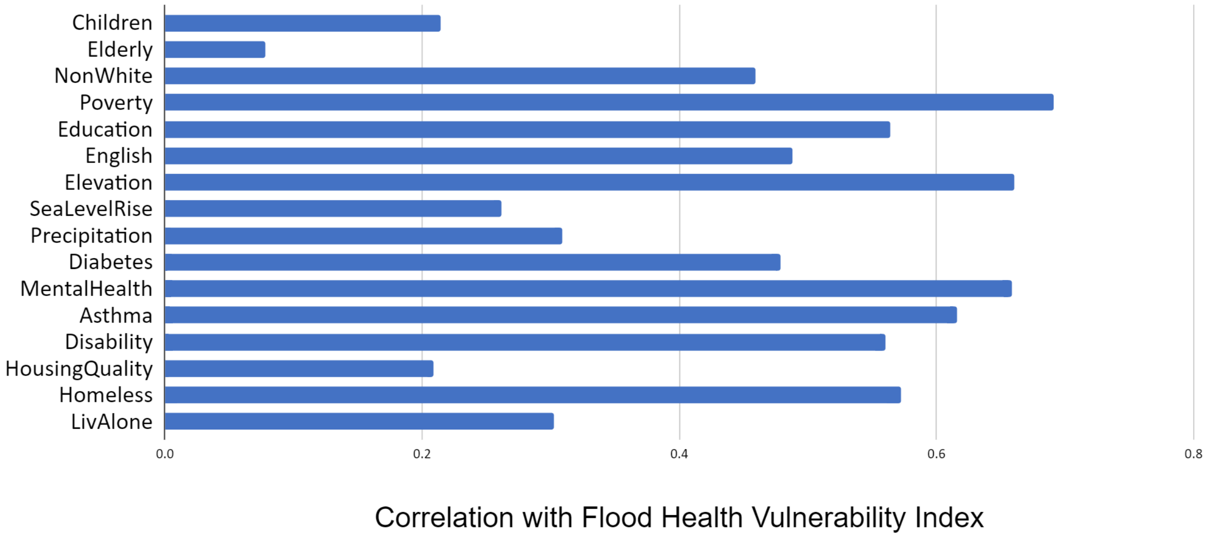


Figure 8

Figure 15. Flood Inundation and Extreme Storm Health Pathways

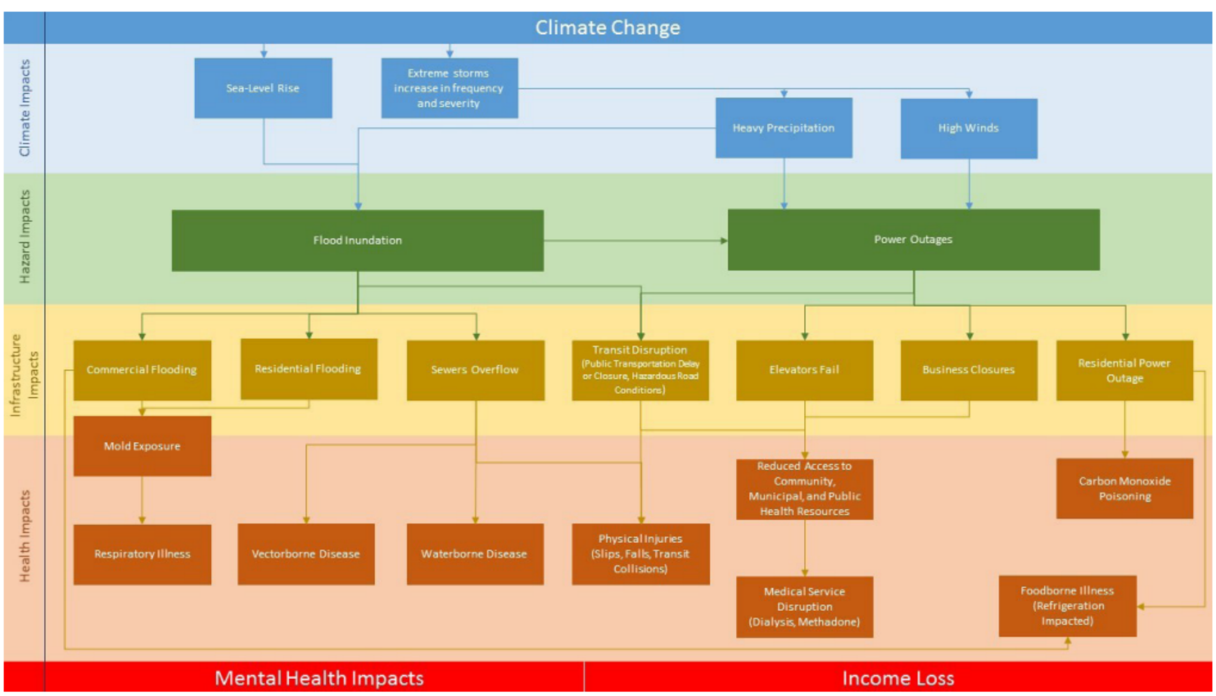


Figure 9 (San Francisco Department of Public Health, 2016)

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