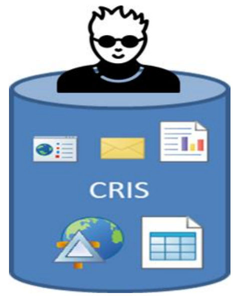
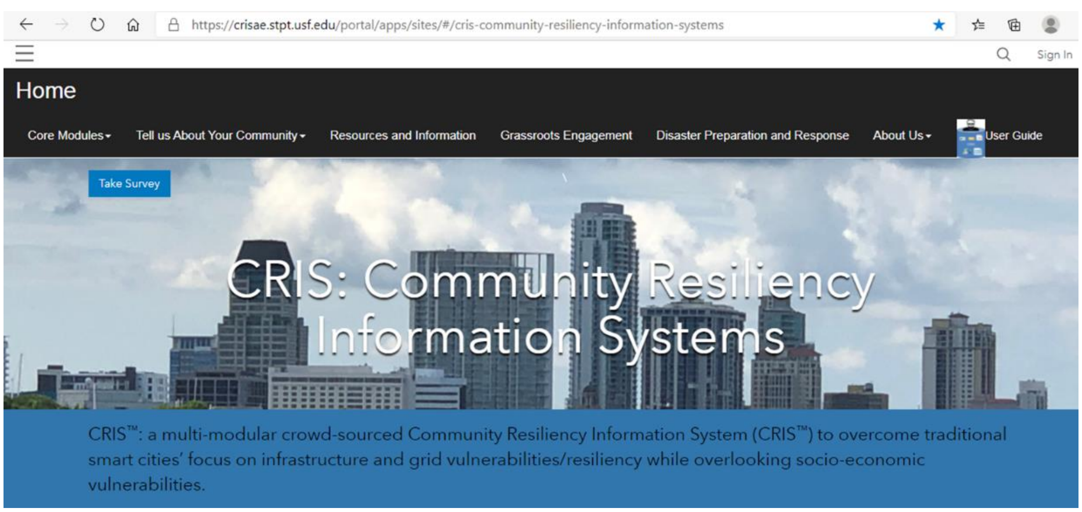
Community Resiliency Information System (CRIS)



Project Report



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Acknowledgements

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Key Websites

Webpage: CRIS (community Resiliency Information Systems)

https://crisae.stpt.usf.edu/portal/apps/sites/#/cris-community-resiliency-information-systems

Webpage: Initiative on Coastal Adaptation and Resilience (iCAR)

iCAR | USF St. Petersburg Campus

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Executive Summary

Project Overview:

Everyone will be impacted by natural disasters but not in the same way. Our ability to cope with disasters varies from individual to individual and community to community. Resiliency and effective/timely recovery efforts require comprehensive planning at the neighborhood level before and after a disaster occurs. This cannot be done without understanding the unique needs of diverse neighborhoods. Prior work undertaken by us (https://www.usfsp.edu/icar/sample-page/) shows that 1) major concerns of communities and access to resources/information vary based on socioeconomic background and levels of biophysical vulnerability; 2) there is a need for customized information and targeted resources to foster preparedness, adaptation and resiliency; and 3) analysis of crowdsourced data shows the potential to increase participation in governance even in marginalized communities. Thus, we propose the development and implementation of a multi-modular crowdsourced Community Resiliency Information System (CRIS). CRIS, integrated with webGIS allows scalable and customizable information to facilitate localized decision making using information generated "by the people", ensuring participation of diverse communities. CRIS can identify neighborhood level socioeconomic and biophysical vulnerabilities, which can then be combined with crowdsourced data using embedded survey tools to identify unique needs of each community in the context of preparedness, resiliency and adaptation.

Key Findings

Based on the preliminary sample, we found the following patterns, which were generally expected based on past research:

i) The neighborhoods that had the most responses were coastal; however, overall response was fairly evenly spread throughout more than two dozen neighborhoods.

ii) The largest percentage of responses came from people who lived in areas that were not under direct threat of storm surge due to category 1 storm as modeled by SLOSH.

iii) The use of the City of St. Petersburg's social media for engaging residents did not appear to be successful in connecting with poor and minority neighborhoods. Engaging poor and minority communities through CRIS will require on the ground organizing and training of community leaders.

iv) The majority of responses are from homeowners in more affluent neighborhoods. Most people claim to have enough resources to recover from a major storm and the majority has homeowner's and flood insurance.

v) While only a third of respondents had experienced flooding, more than half were concerned about flooding in the future.

vi) Nearly 70% of respondents had experienced damage from a major storm.

vii) ANL data when scaled at neighborhood level can be useful for neighborhood level resilience planning related to flood and other extreme weather related events.

viii) 64% of respondents are increasingly concerned about a hurricane strike in the area; however a strong majority of people feel they have the resources to cope with a disaster, which reflects the demographics of this pilot sample.

The more unexpected findings:

Based on preliminary responses, the <u>more unexpected findings</u> include**:**

i) 50% of respondents *did not feel confident* that they knew which government agency to reach out to; this indicates a weakness in communication channels between residents and officials, which CRIS can help to remedy.

ii) Nearly *one in five respondents* had a member of their household with special needs; identifying these households and clusters will be important for emergency planners. This finding indicates how CRIS can help emergency planners identify previously invisible needs at the community level. About 14% of respondents indicated that they care for a disabled household member. Once participation is increased in poorer neighborhoods, these data can be aggregated and used by emergency planners for more efficient and targeted policies.

iii) The most frequent concern voiced by residents was loss of power after a major storm, which resonates with previous research conducted after Hurricane Irma. Loss of power has the potential to disproportionately impact poorer communities. While fear of water and wind damage was also important, emergency planners must address the community's concern about recovering from power outages.

iv) The concern about the possible negative impacts of loss of power is further enforced by the higher numbers of people from non-coastal communities who indicate that they evacuate when a storm watch is issued. Paying attention to the economic impacts of sustained power outages is important for emergency planners in the region.

1. Project Description:

Through our past research and community engagement activities (Dixon et al., 2020, Johns et al., 2020) we identified a need for a Community Resiliency Information system (CRIS). A detailed vision of CRIS can be found in Dixon and Johns (2019). CRIS is a customizable crowdsourced integrative knowledge network, with a two-way communications designed to enhance communities' resilience in the context of climate change, natural disasters and extreme weather events that is integrated with Geographic Information Systems (GIS). We proposed and developed a web-based customizable scalable information system using crowdsourced data along with readily available public data to help cities make better decisions before, during, and after a disaster, as well as in their day-to-day operations for short, medium and long-term planning. Situations such as those associated with Hurricane Michael (where structures were completely obliterated and economic functions severely impaired) require different information and resources to help with recovery and resilience building when compared to Hurricane Irma, where power loss was a major problem. The customizable and scalable information system that allows for multi-stage scenario-based action plans to address specific challenges at neighborhood levels, can help recovery and foster resiliency. Figure 1 shows vision of CRIS.

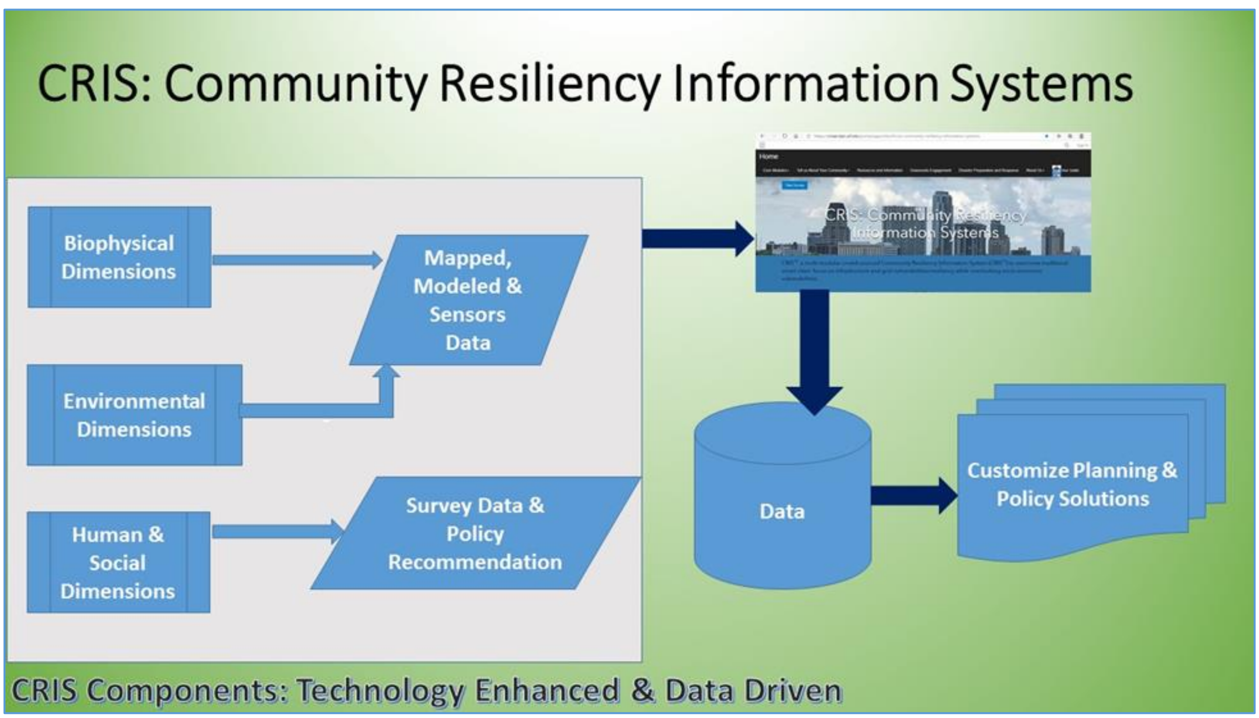


Figure 1. Vision for CRIS

CRIS helps analysis of questions such as: 1) What are the common and unique critical needs in neighborhoods based on their socioeconomic and biophysical vulnerabilities? 2) How do the health and economic characteristics of residents vary across communities, creating specific vulnerabilities to extreme weather events? 3) How does risk of exposure to environmental and chemical hazards (dog parks, hurricane facilities of concerns - toxic release inventories (TRIs), industrial facilities) vary by neighborhood? 4) How and why do diverse neighborhoods vary in their recovery time following an extreme weather event, in terms of economic recovery, job loss, emotional and physical health, and property restoration and repair? 5) What information and resources do communities need and how do they vary?

CRIS integrated with a webGIS in which neighborhood level socioeconomic, environmental and biophysical vulnerabilities can be mapped and combined with crowdsourced data gathered from embedded surveys and open-ended menus to identify the unique needs of each community in the context of preparedness, resiliency and adaptation. The prototype of CRIS is fully equipped with custom programming that allows for geotagged information to be uploaded through smartphone technology to CRIS using focused questions designed to identify needs of specific communities. CRIS, by virtue of being fully online can foster transparency and accessibility of information.

Census data, biophysical data (slope, flood, storm surge, etc.), environmental hazard data, existing health data and crowdsourced data (community-based qualitative data) can be used to create a multi-faceted comprehensive needs-assessment at the neighborhood scale to facilitate customizable local solutions and resource allocation for resiliency. A set of qualitative research techniques can be used with CRIS to obtain detailed assessments of each neighborhood in terms of economic insecurity, health challenges, resource needs and social capital.

2. Significance of the Project

The current explosion of communication technology and big data creates unprecedented opportunities for data-driven decision making in urban and environmental arenas. Smart cities often miss the "citizen element," and require a holistic approach to creating smart solutions that manage diverse actors and their interactions in a complex urban system (Ersoy, 2017).

Traditionally, smart cities focused on infrastructure and grid vulnerabilities and not socioeconomic vulnerabilities in the context of its 'smartness' and resiliency. Integration of information to enhance resiliency and reduce inequity with CRIS can become one of the pillars of a smart city, producing a Holistic Smart City (HSC). CRIS moves the smart city beyond a mere infrastructure/grid smartness to create an interactive space for information exchange, democratic participation and a collaborative resilience-building process.

CRIS fosters a two-way communication between government and communities by creating a grassroots, community-based, technology-enhanced needs assessment and disaster-response information system. Among other benefits, CRIS has the potential to foster social capital at the neighborhood level by increasing grassroots knowledge and access to resources and information, fostering preparedness, adaptation, and resiliency/recovery, and aiding decision-makers in resource allocation and customized communications.

Further, CRIS augments Bloomberg Initiatives and Integrated Sustainability Action Plan (ISAP) efforts, helping the City of St Petersburg to be at the forefront of resilience efforts, particularly in ensuring equity and healthy communities, building an HSC. The results obtained via this project will support the Tampa Bay Regional Resiliency Coalition agreement that was signed on Oct 1, 2018 by providing a ready-to use methodology for comprehensive needs analysis.

The CRIS' modular approach facilitates organization of critical information which can then be used before, during and after an event. Results of this project also provide baseline data before an event so impacts of the disaster can be calculated. CRIS provides baseline data for holistic impact-analysis of future disasters/events (pre-post comparisons). CRIS includes a module on how to engage grassroots via qualitative methods.

NRC (2012) identified key elements of a resilient nation in 2030, an important component of which is availability of "information on risks and vulnerability to individuals and communities is transparent and easily accessible to all". This proposed project (using iCAR's momentum – annual workshops https://www.usfsp.edu/icar/events/) with the webportal, CRIS, will connect communities to decision-makers and serve road map to achieve resiliency goals set for 2030.

3. Methods for CRIS Development:

A prototype of CRIS developed for selected neighborhoods in City of Saint Petersburg is shown in Figure 2.The prototype can easily be applied to other communities. Figure 3 shows architecture of CRIS. Figure 4 shows examples of implementation and integration of core modules. Figure 5 shows various mapping and data display modules. Figure 6 shows the details of the survey module and Figure 7 shows dynamic display of aggregated survey results via CRIS. Figure 8 shows SmartPhone Interface. The data used for biophysical, socioeconomic and environmental modules are obtained from various data sources federal agencies and complied at neighborhood level for the study area. Appendix A provided details of these datasets. Appendix B provided summary of CRIS architecture.

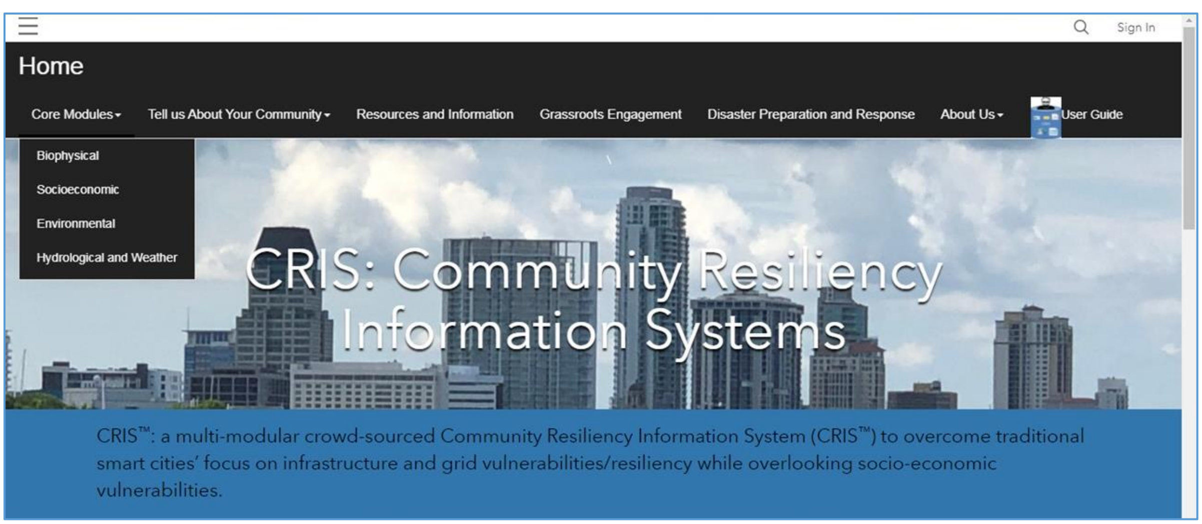


Figure 2. Prototype of CRIS

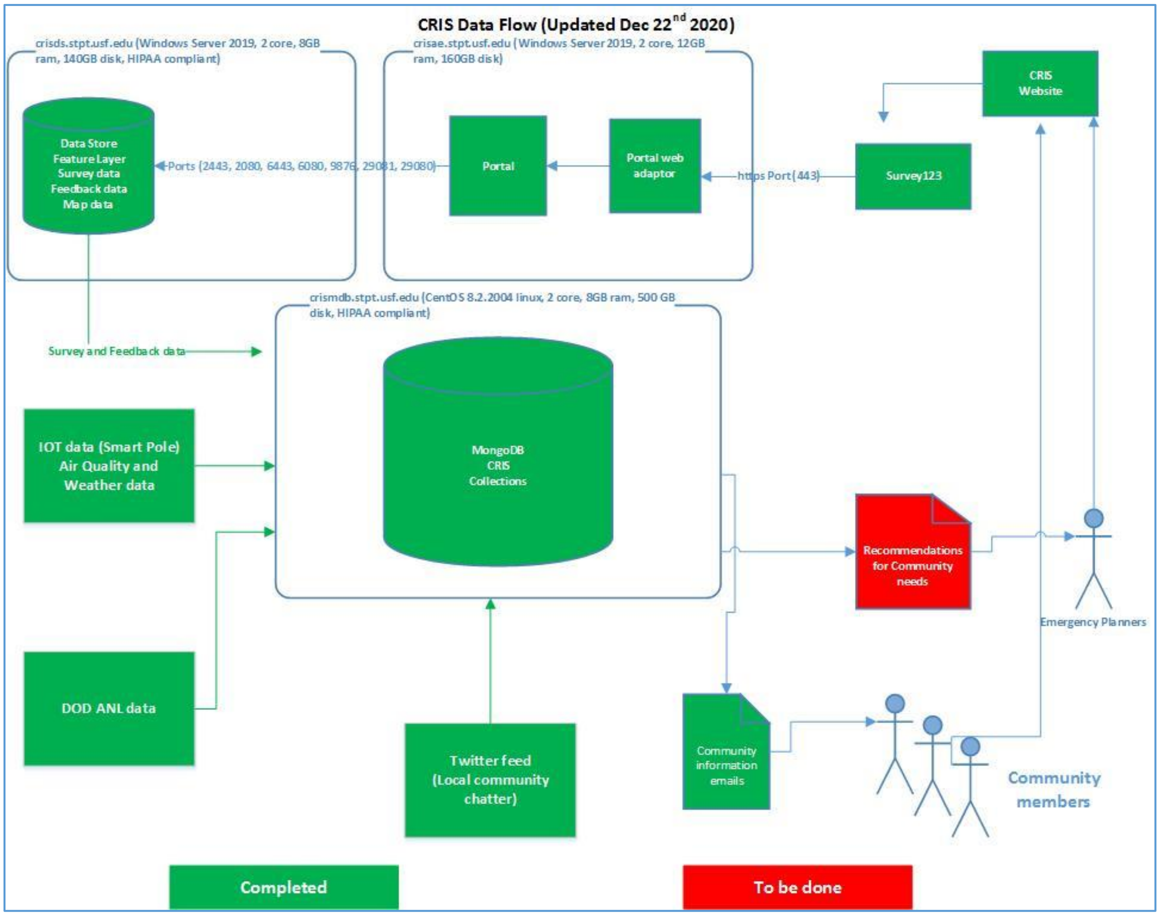
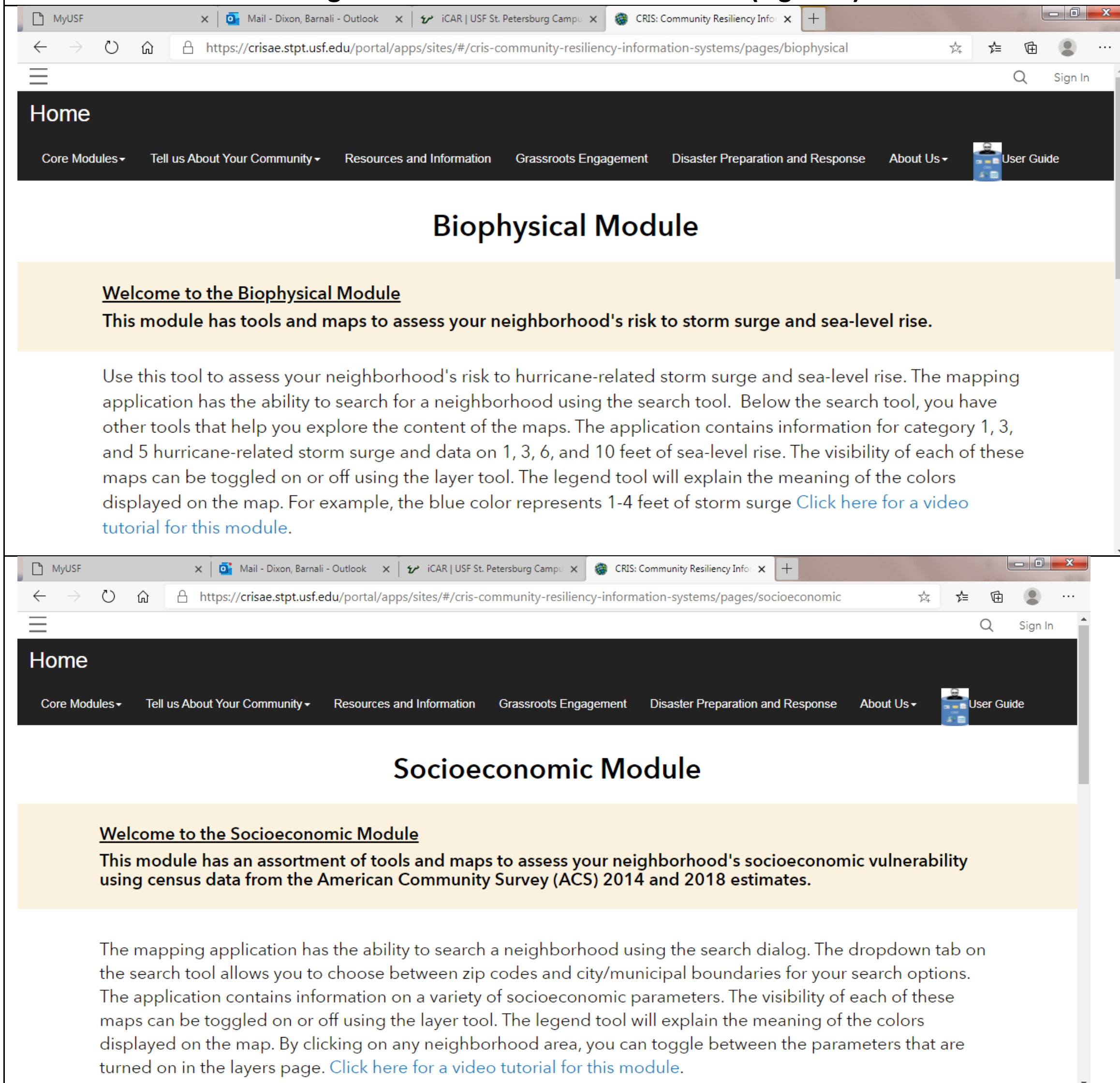


Figure 3. Architecture for CRIS. Recommendations will be made after adeuqate data collection that was hindered by COVID19 related restrictions that prevented in-person interaction with the communities

Images of Various Modules within CRIS (Figure 4)



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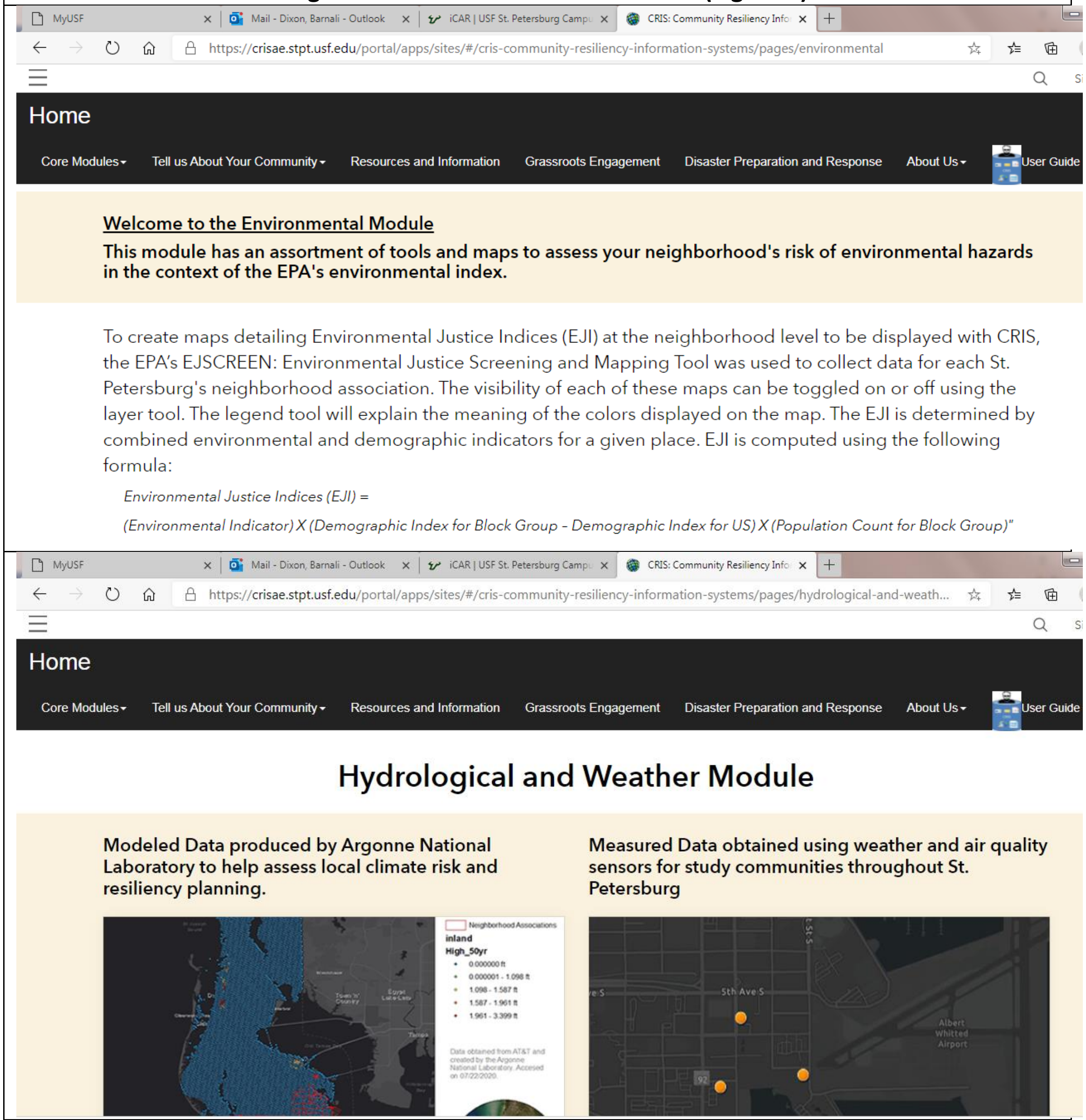

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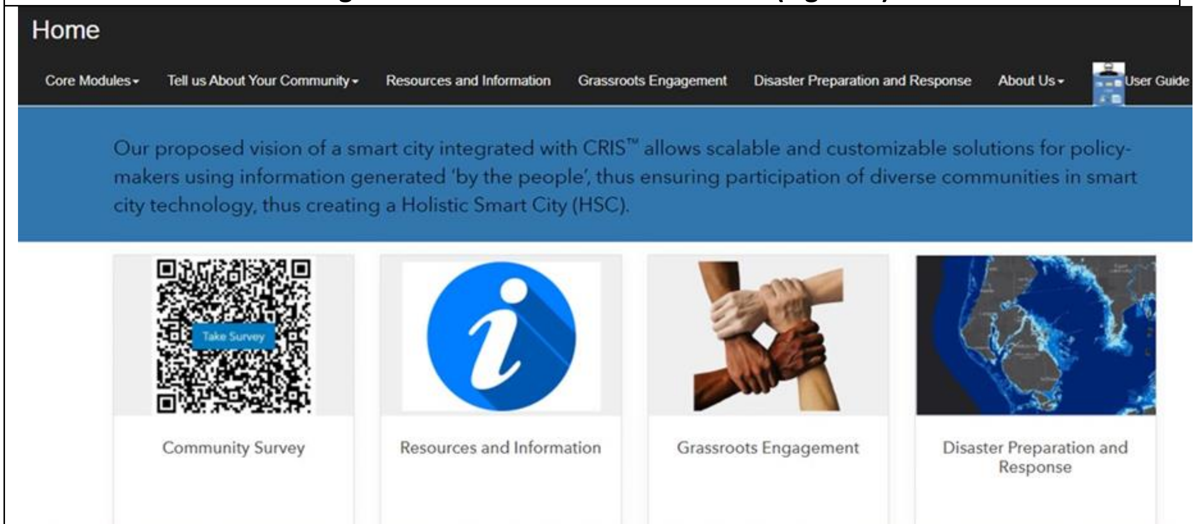

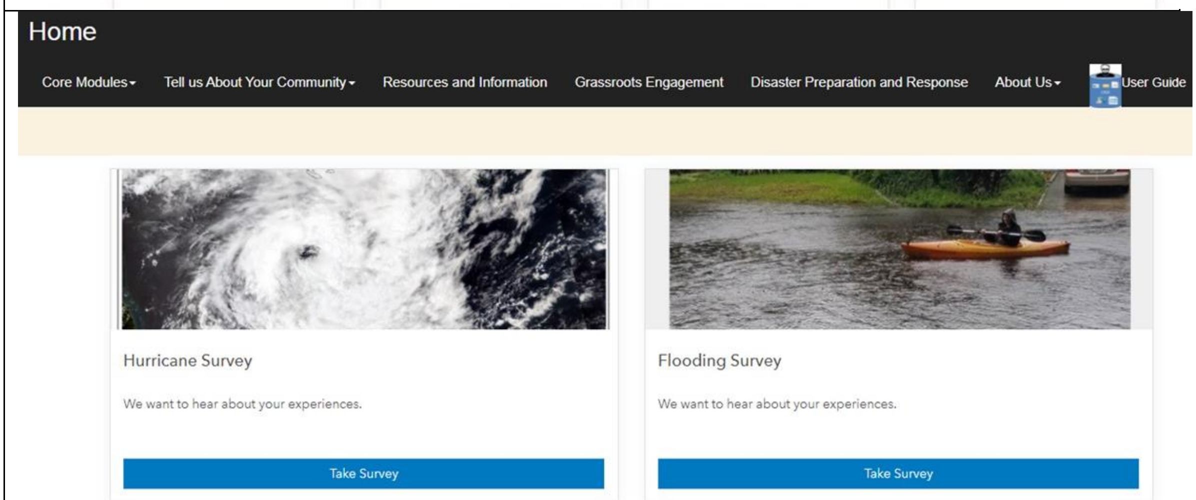

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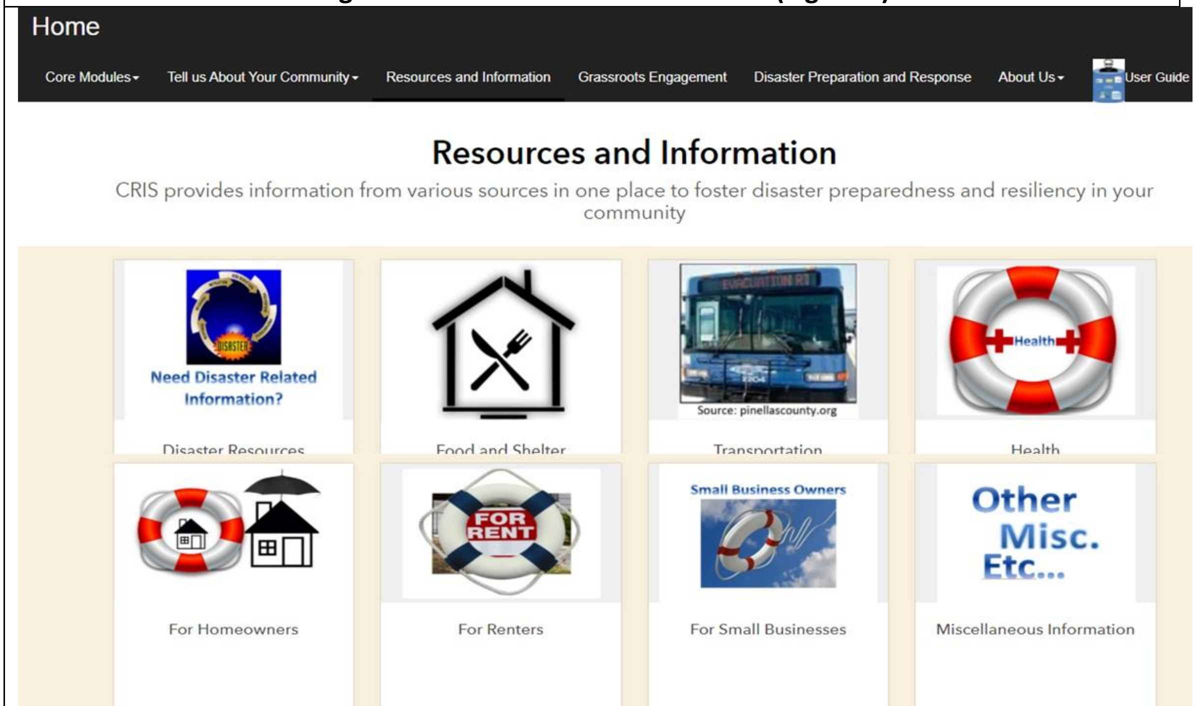

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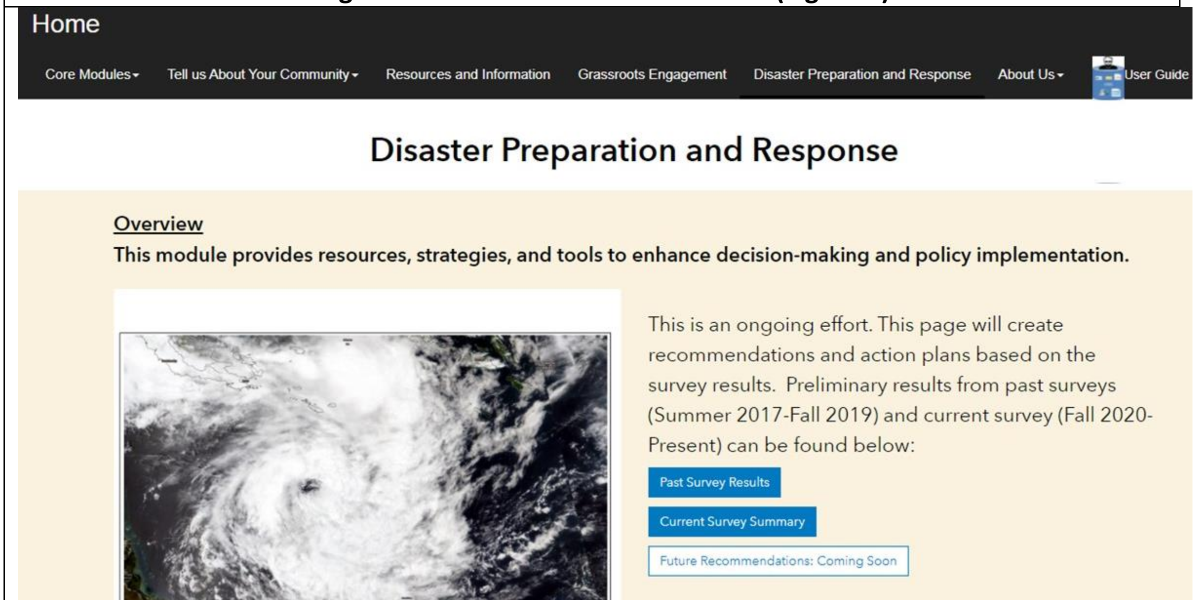
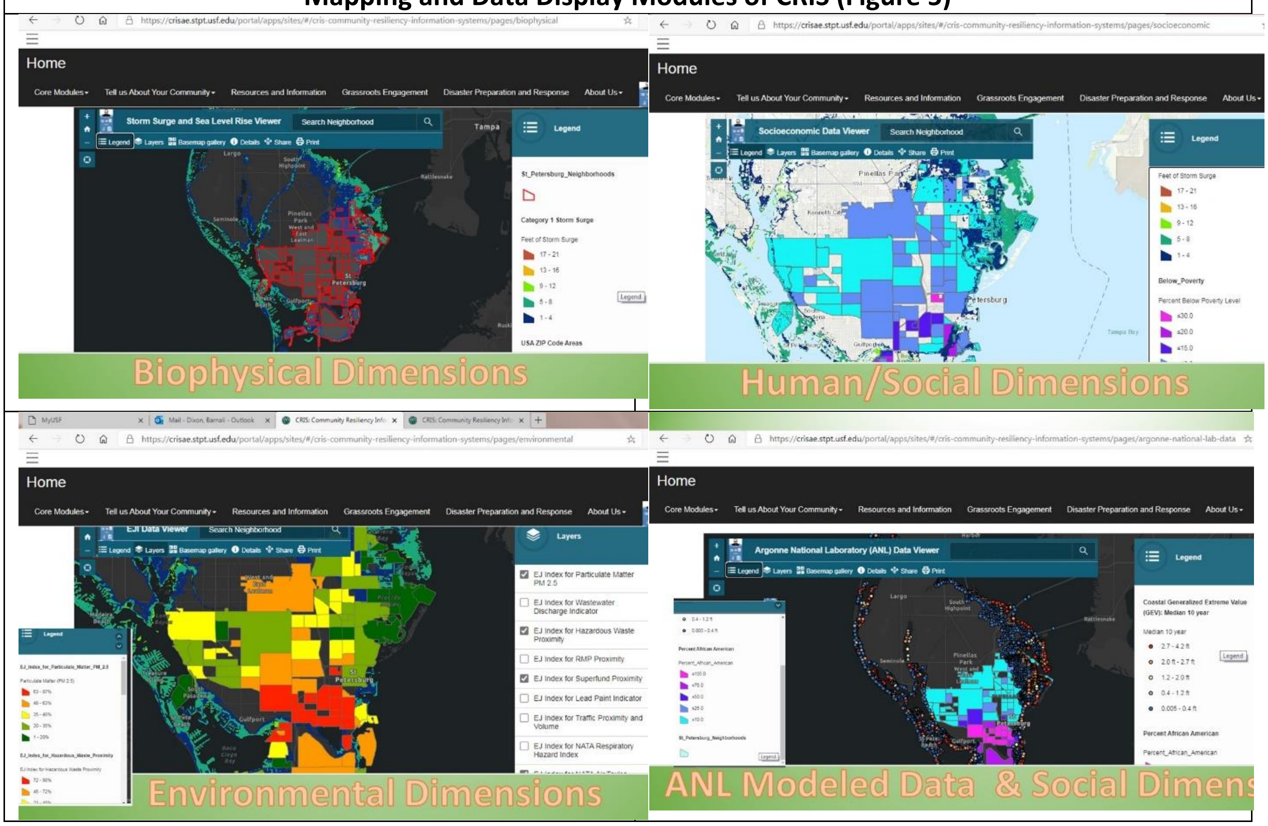


Figure 4. Images of Various Modules of CRIS

The Figure 5 shows various mapping & data display modules incorporated with CRIS. These displays facilitate analysis of overlaid data at neighborhood level from disparate sources when tied to a location.

Mapping and Data Display Modules of CRIS (Figure 5)



Mapping and Data Display Modules of CRIS (Figure 5)

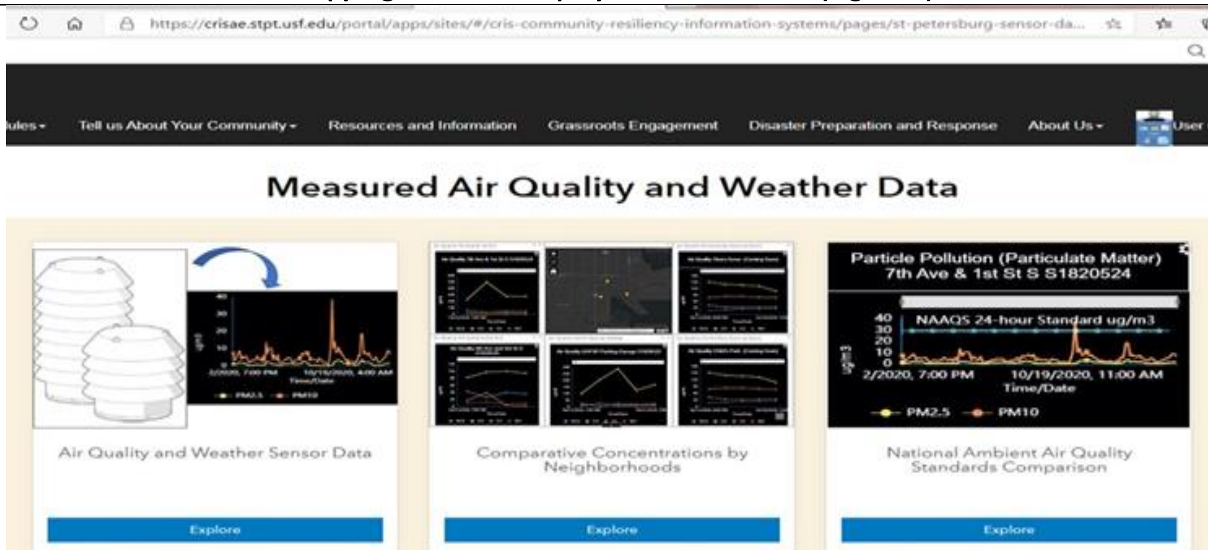


Figure 5. Various Mapping and Data Display Modules of CRIS

Figure 6 shows details of the survey module and Figure 7 shows dynamic display of aggregated survey results. These surveys are designed to track if someone is taking the survey more than once. This allows for assessment of a respondent's needs that changed over time so officials can take this into consideration of the new information to allocate resources that can foster resiliency.

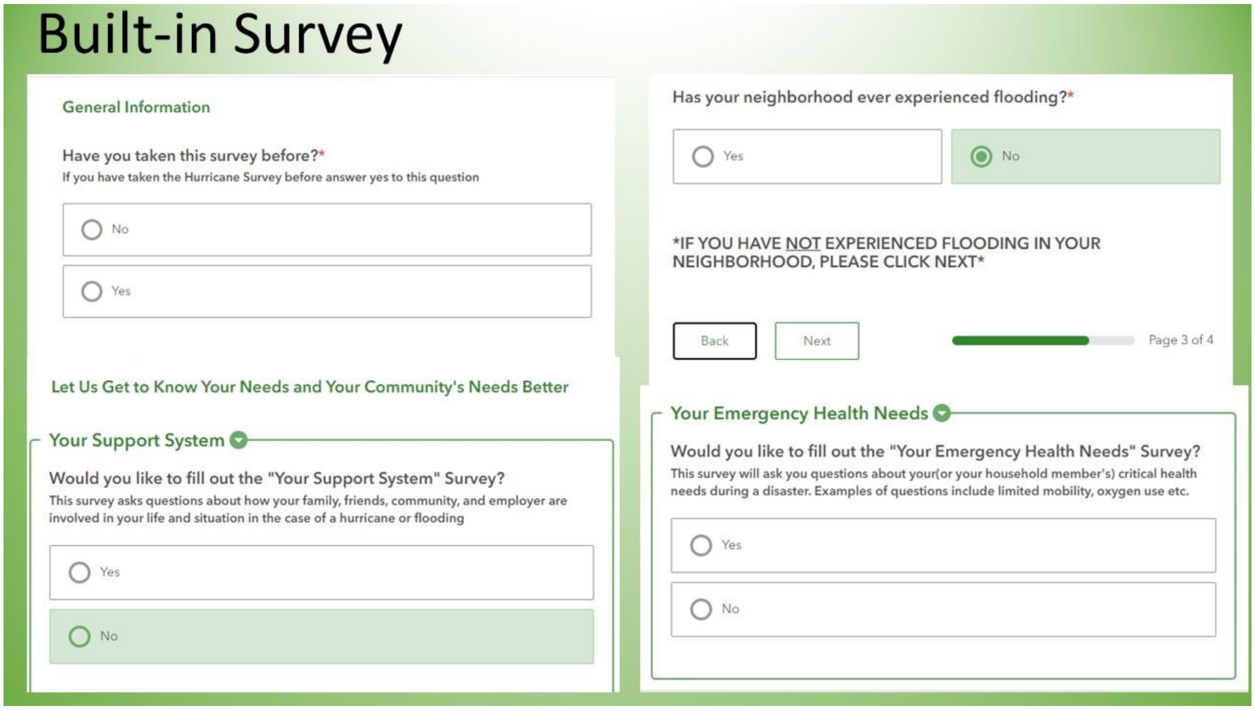


Figure 6. Built-in Survey module for CRIS

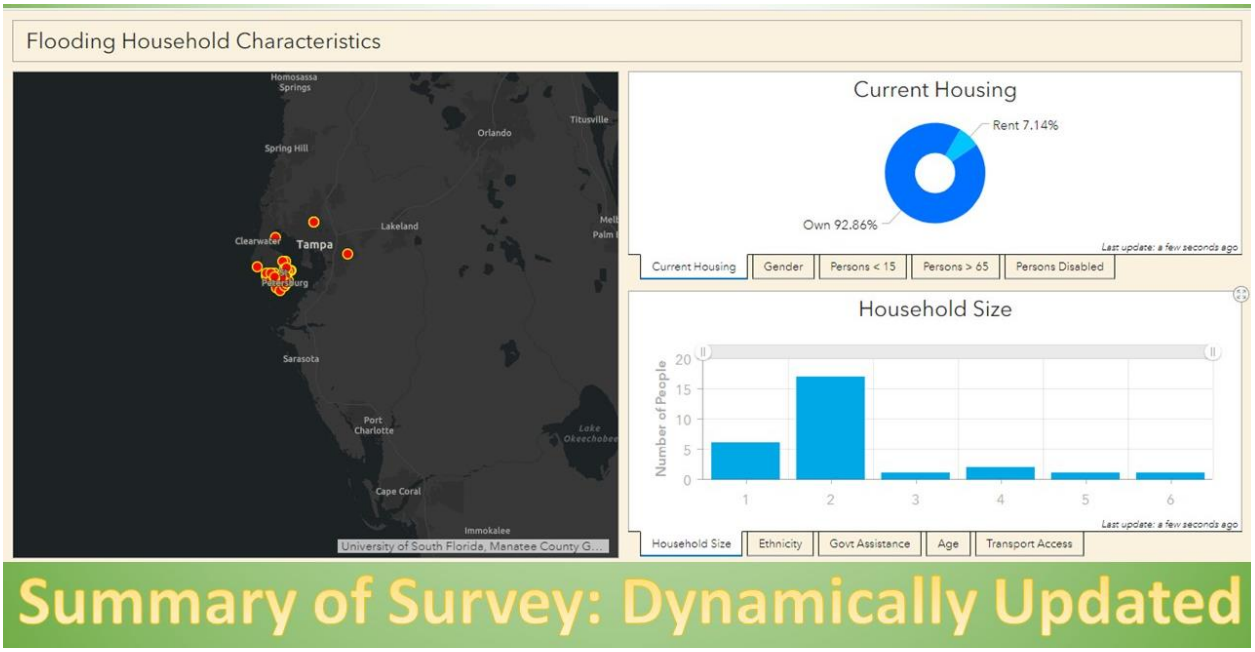
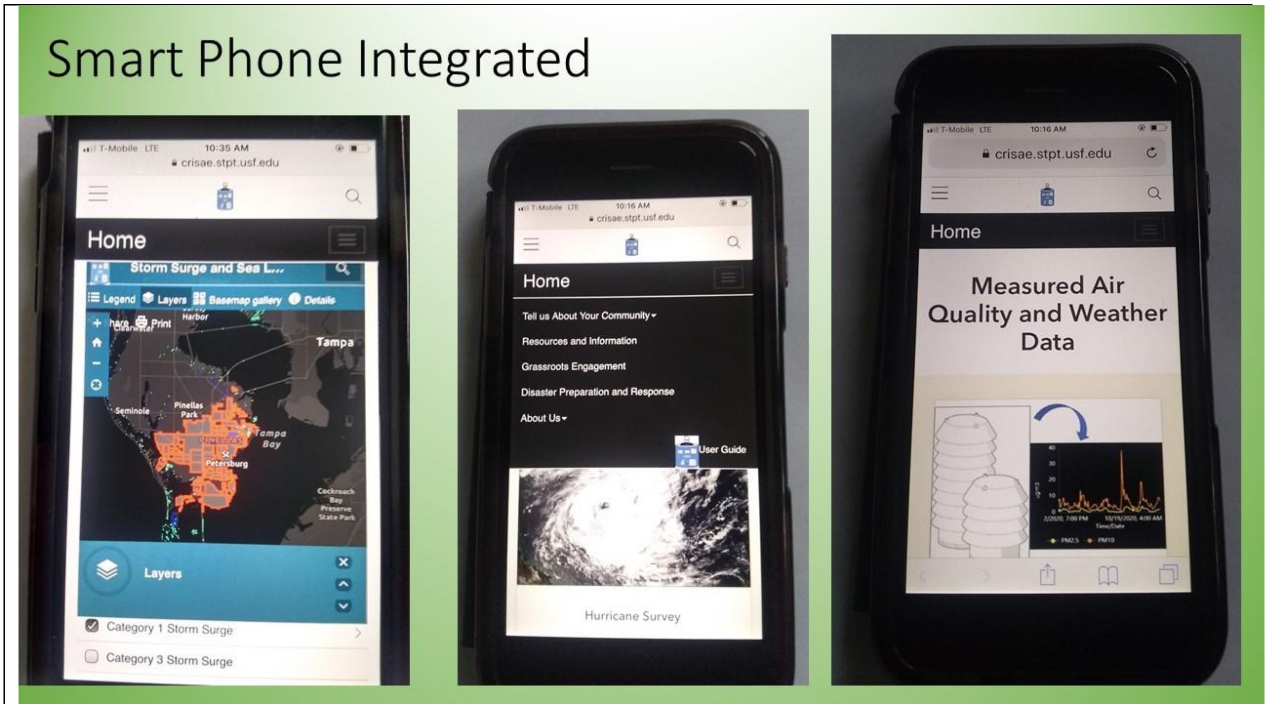
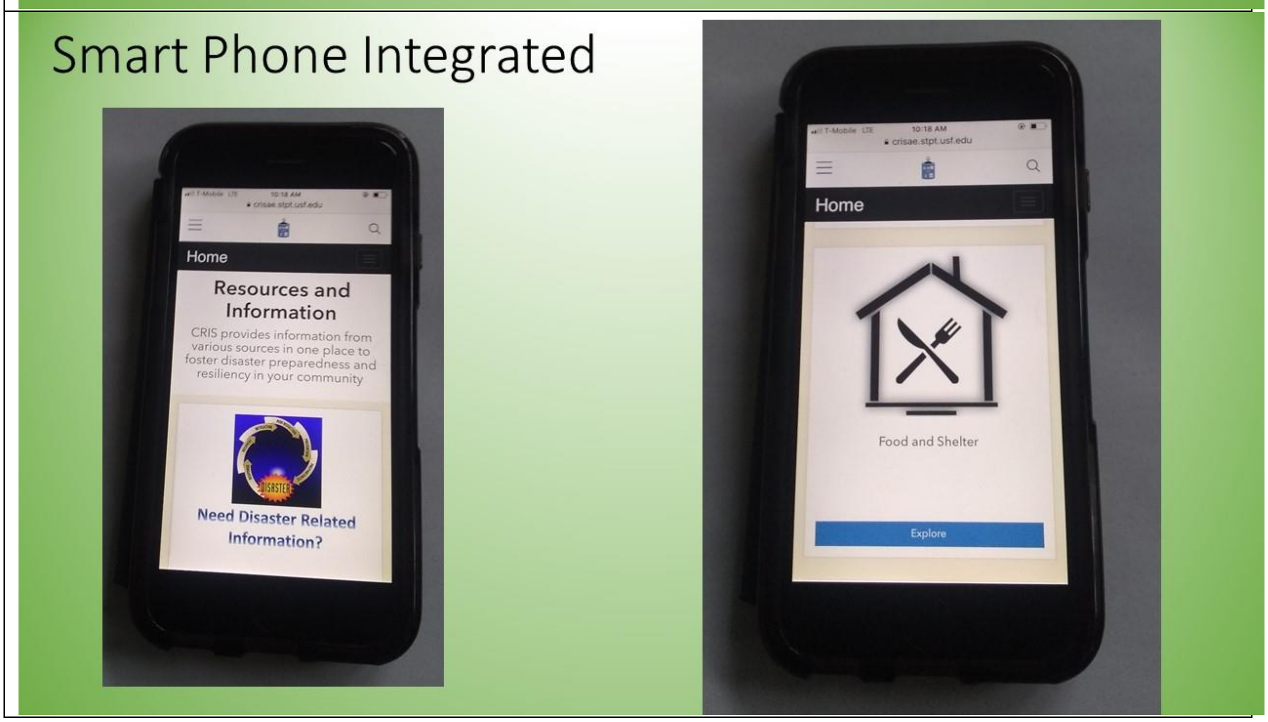


Figure 7. Dynamically Updated Survey Results

Figure 8 shows smartphone interface for CRIS.


Smart Phone Integrated
crisae.stpt.usf.edu
Home
Storm Surge and Sea L...
Legend
Layers
Basemap gallery
Details
Print
Tampa
Seminole
Pinellas Park
Tampa Bay
St. Petersburg
Cockroach Bay Preserve State Park
Layers
Category 1 Storm Surge
Category 3 Storm Surge
Home
Tell us About Your Community
Resources and Information
Grassroots Engagement
Disaster Preparation and Response
About Us
User Guide
Hurricane Survey
Home
Measured Air Quality and Weather Data


Smart Phone Integrated
crisae.stpt.usf.edu
Home
Resources and Information
CRIS provides information from various sources in one place to foster disaster preparedness and resiliency in your community
Need Disaster Related Information?
Home
Food and Shelter
Explore

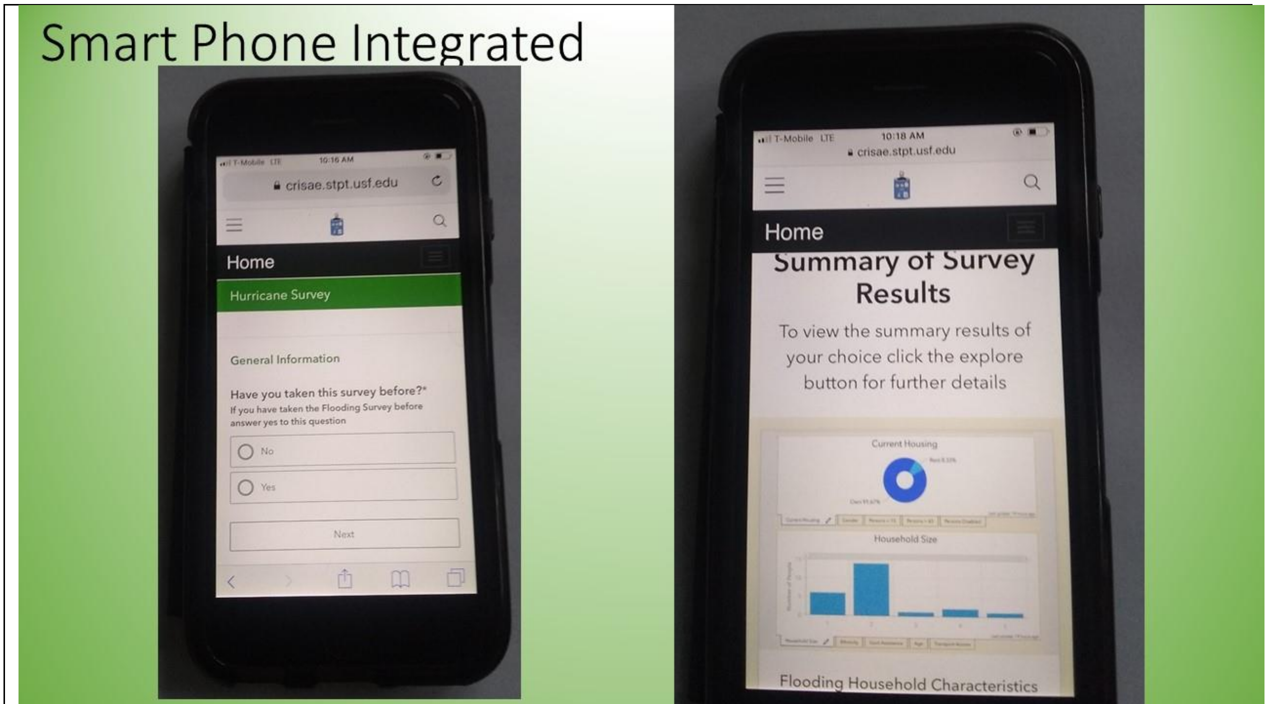


Figure 8. Smartphone Interface of CRIS

4. Results and Discussion

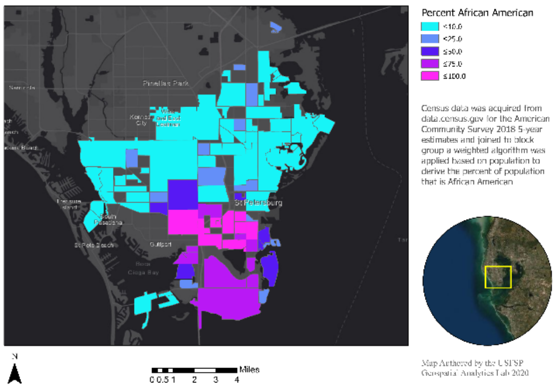
Sections below discuss maps and survey results. Maps are available via CRIS and survey results obtained from in-built survey within CRIS.

4.1 Mapping Results

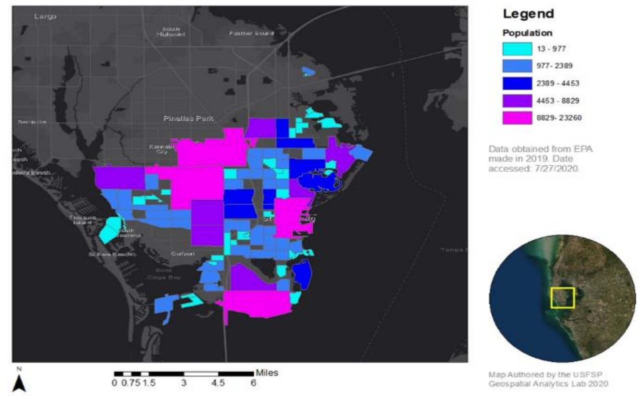
Figure 9 shows resultant maps of biophysical and socioeconomic vulnerabilities as well as environmental justice (EJ) indicators. It should be noted that higher percentages of minority and low-income neighborhoods are located within close proximity of environmental hazards. About 70% of the study area is predicted to be inundated by 1- 4 ft and 29% by 5-8 ft of storm surge with Category 1 storm using SLOSH model (acronym for Sea, Lake, and Overland Surges from Hurricanes model), respectively. The same model predicted 60% of the area to be inundated by 17-21 ft storm surge during Cat 5 storm. While only 11% of the study area is predicted to be inundated by 1ft SLR by NOAA prediction, 6ft of SLR inundate 40% of the study area. About 31% of the study area is characterized by AE (1% annual flooding) whereas about 44% of the study area is characterize by X (minimal flood hazards). However, the issues of SLR and storm surge may change the risk of the areas with minimal flood hazard to other flooding categories.

Mapping Results Available via CRIS (Figure 9)

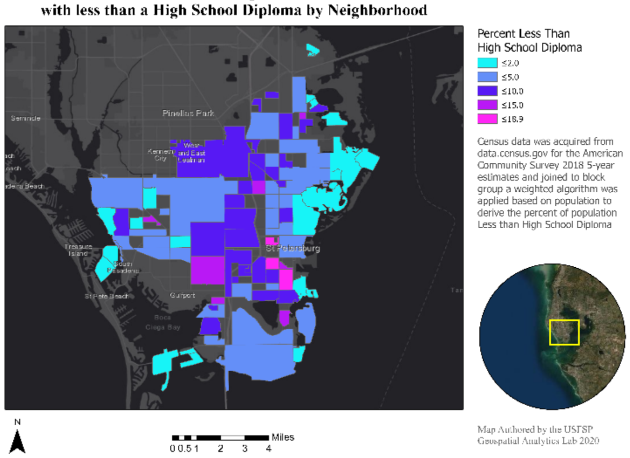
African American Percent of the Population by Neighborhood



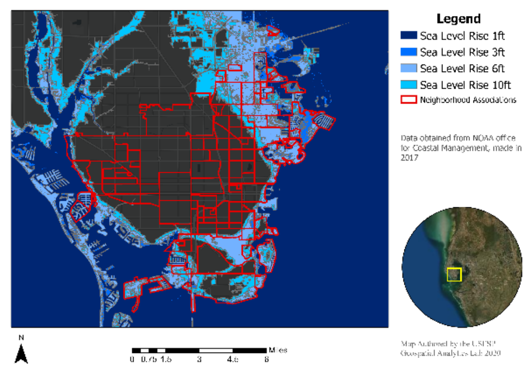
Population



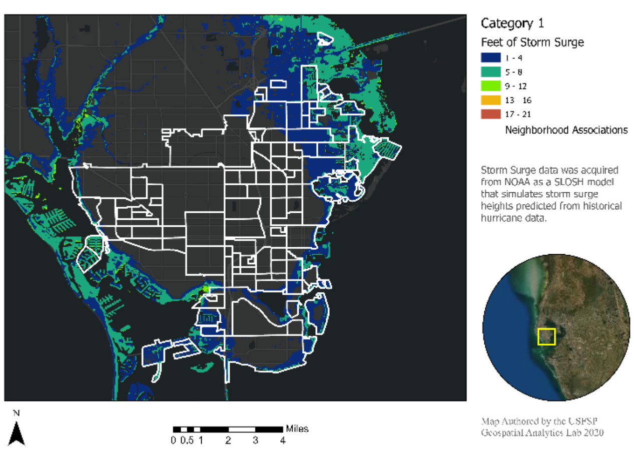
Percent of the Population >25 with less than a High School Diploma by Neighborhood



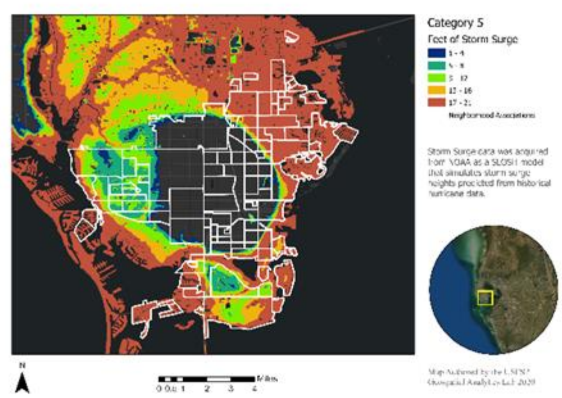
St. Petersburg, FL Sea Level Rise



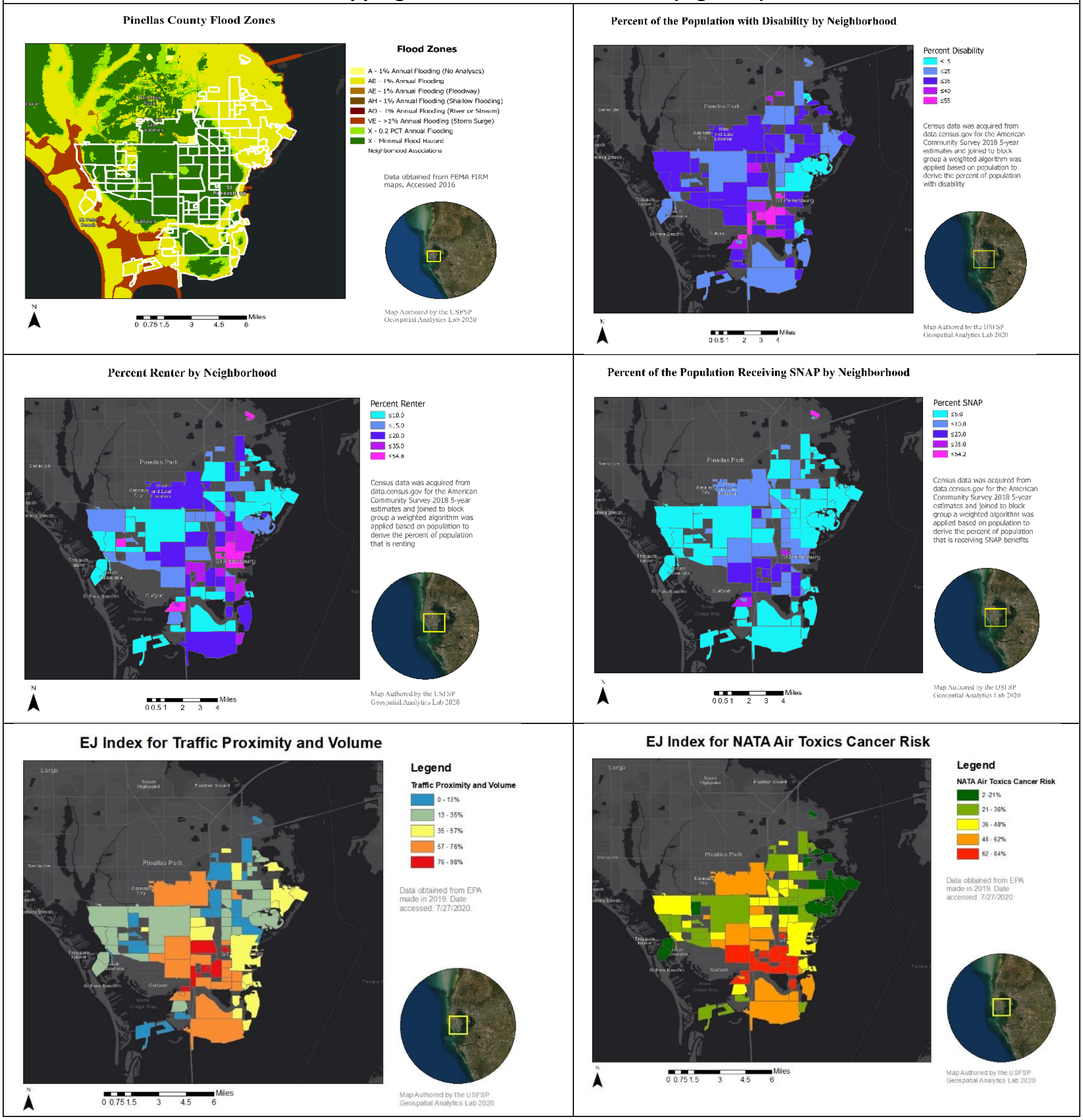
Storm Surge Category 1 with Neighborhoods



Storm Surge Category 5 with Neighborhoods



Mapping Results Available via CRIS (Figure 9)



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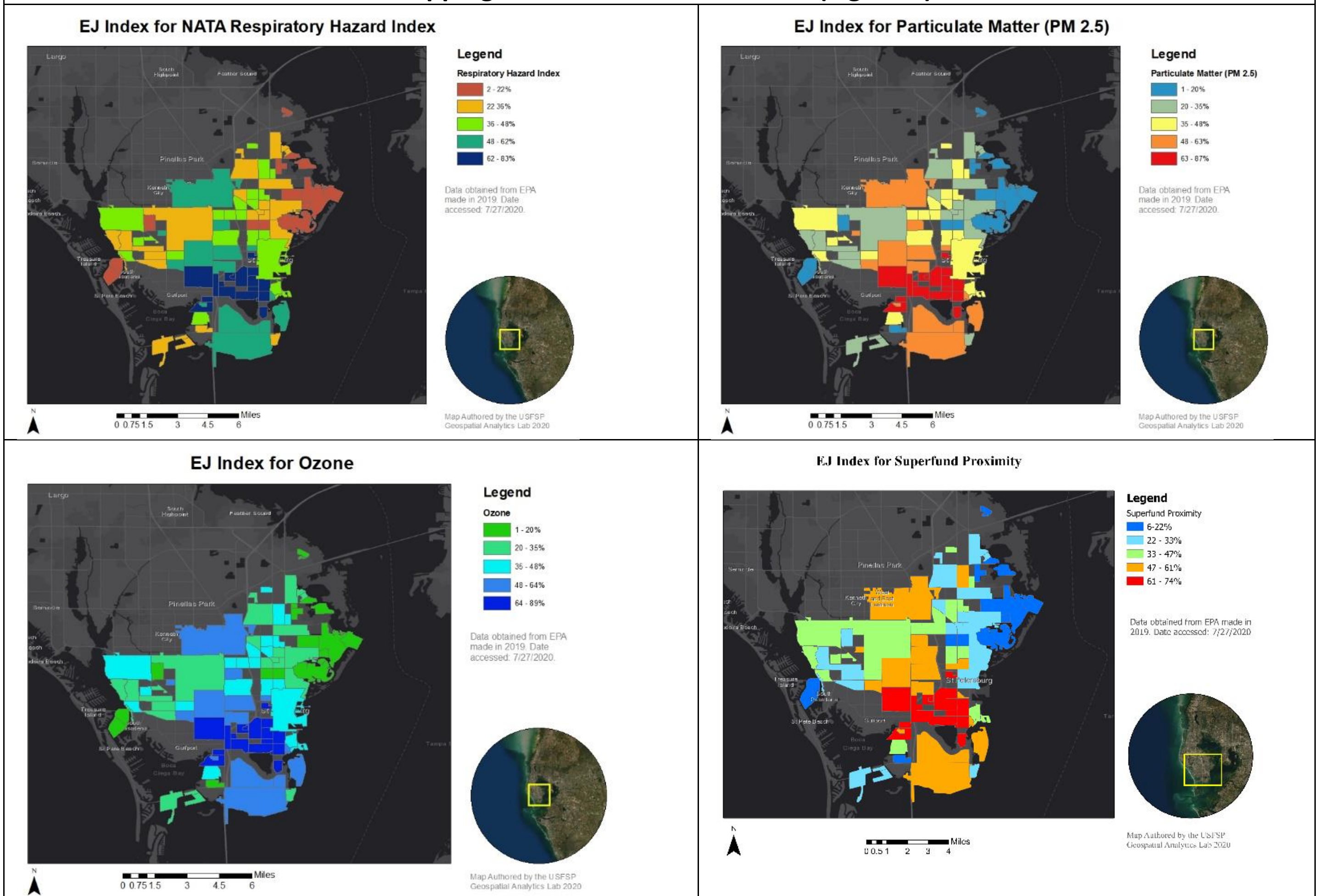


Figure 9. Biophysical, socioeconomic and EJ variables

Figure 10 shows Argonne National Lab (ANL) data modeled at regional scale overlaid with neighborhood characteristics. The ANL data, when downscaled to the neighborhood level, will be helpful. Future research plans in collaboration with ANL include the use of local high-water mark to downscale and calibrate model results. We are also installing air quality and weather sensors to monitor and characterize neighborhoods' air quality and cross validate EPA EJ data via particulate matter 2.5 and ozone. Examples of sensor data are presented in Figure 11. Figure 12 shows various biophysical hazards in the context of socioeconomic vulnerabilities by neighborhood. For example, flood data obtained from FEMA can be augmented with ANL flood model data when downscaled at neighborhood level. Table 1 shows if a neighborhood within the study area is coastal or non-coastal.

Display of ANL Data at Neighborhood Level (Figure 10)

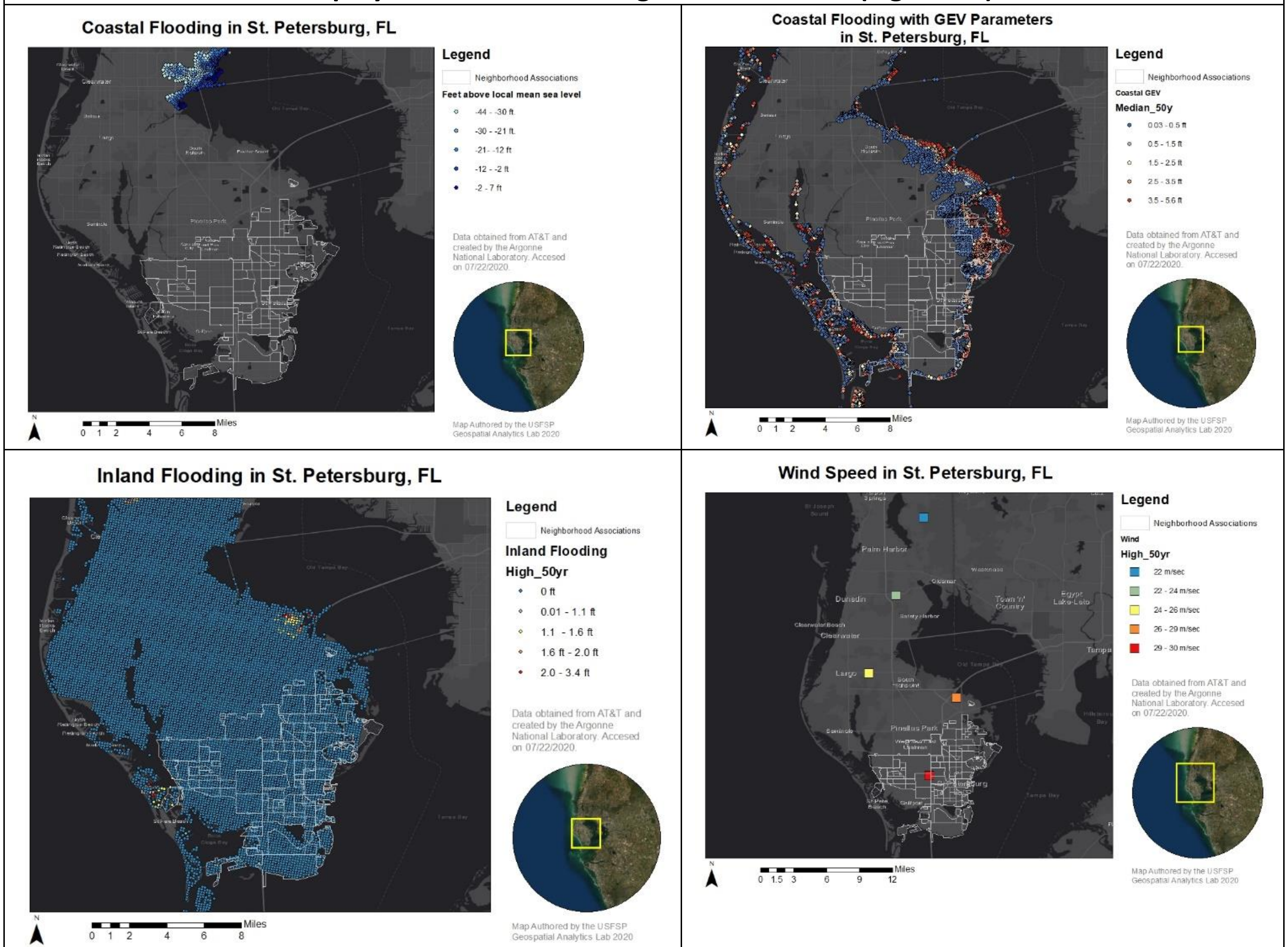
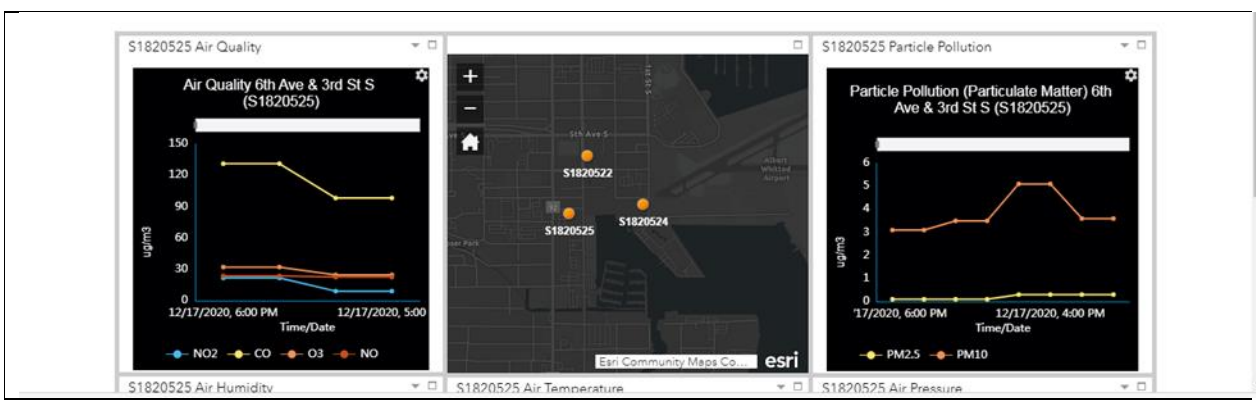


Figure 10. Display of ANL data against study area and neighborhoods.

The sensor data (Figure 11) are linked via CRIS and will help us characterize air quality at neighborhood level and cross validate EPA's EJ maps.



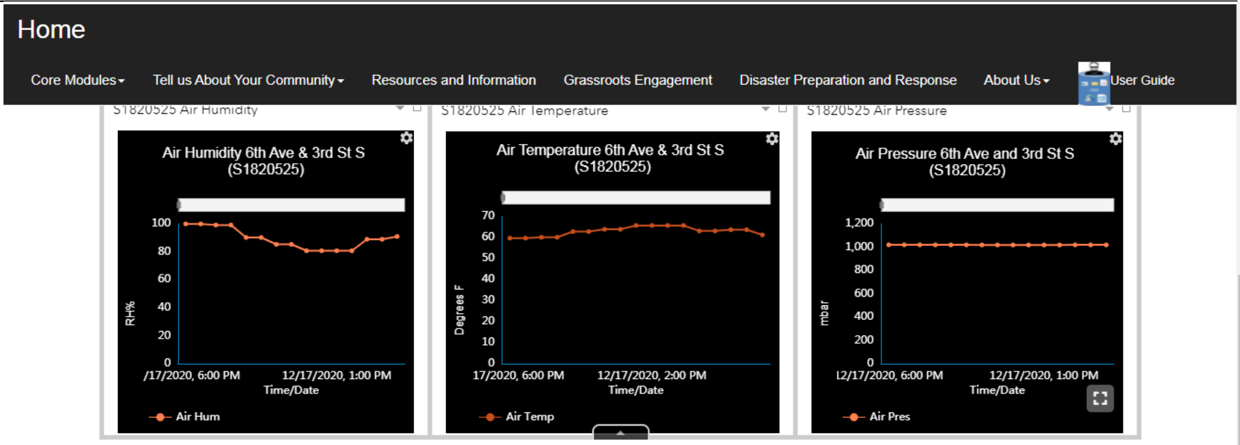


Figure 11. air quality and weather sensor data

Table 1. Summary of All Neighborhoods within the Study Area and Proximity to Coasts

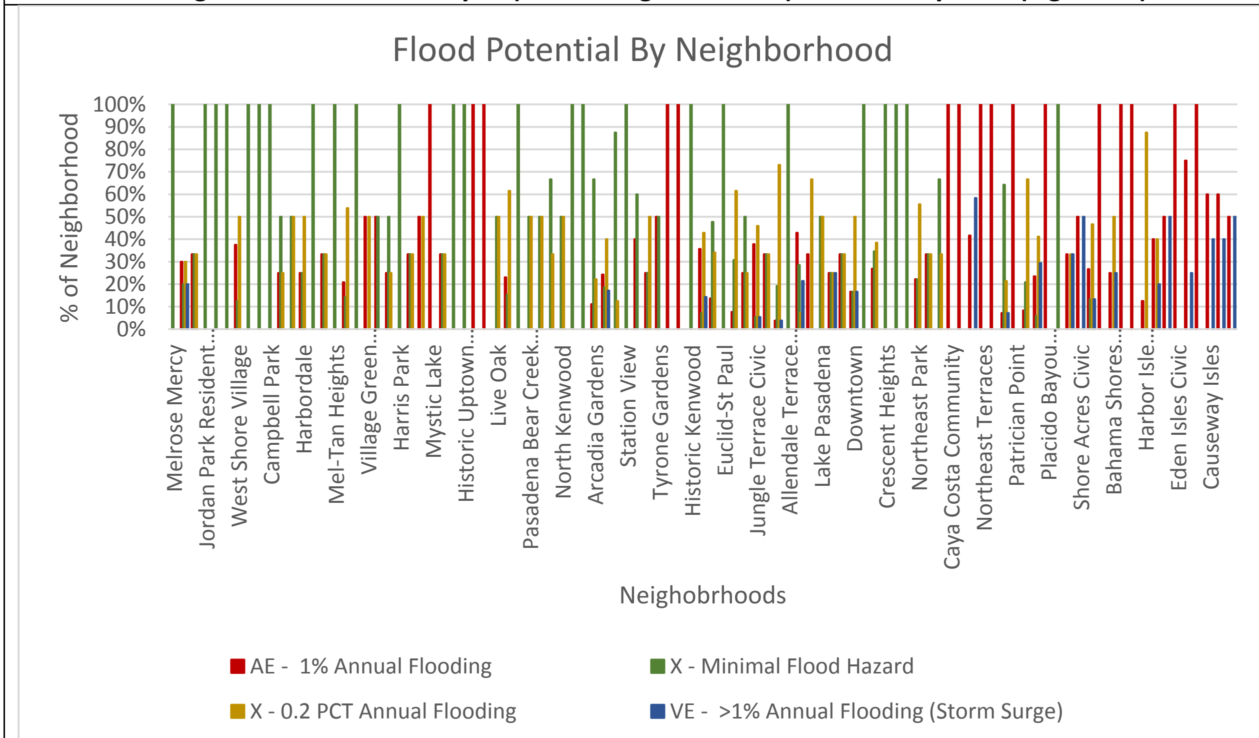
ID	Neighborhood	Coastal	Dominant Race	% master's degree	Average Household Income
1	Melrose Mercy	Noncoastal	African American	6%	$115,888
2	Bartlett Park	Noncoastal	African American	5%	$80,913
3	Jordan Park Resident	Noncoastal	African American	12%	$103,555
4	Wildwood Heights	Noncoastal	African American	4%	$67,625
5	West Shore Village	Noncoastal	African American	14%	$126,683
6	Thirteenth St Heights	Noncoastal	African American	12%	$61,197
7	Palmetto Park	Noncoastal	African American	2%	$34,889
8	Campbell Park	Noncoastal	African American	3%	$80,066
9	Thirty-First St	Noncoastal	African American	10%	$192,240
10	Cromwell Heights	Noncoastal	African American	6%	$55,987
11	Childs Park	Noncoastal	African American	7%	$112,289
12	Highland Oaks	Noncoastal	African American	0%	$42,437
13	Mel-Tan Heights	Noncoastal	African American	13%	$176,583

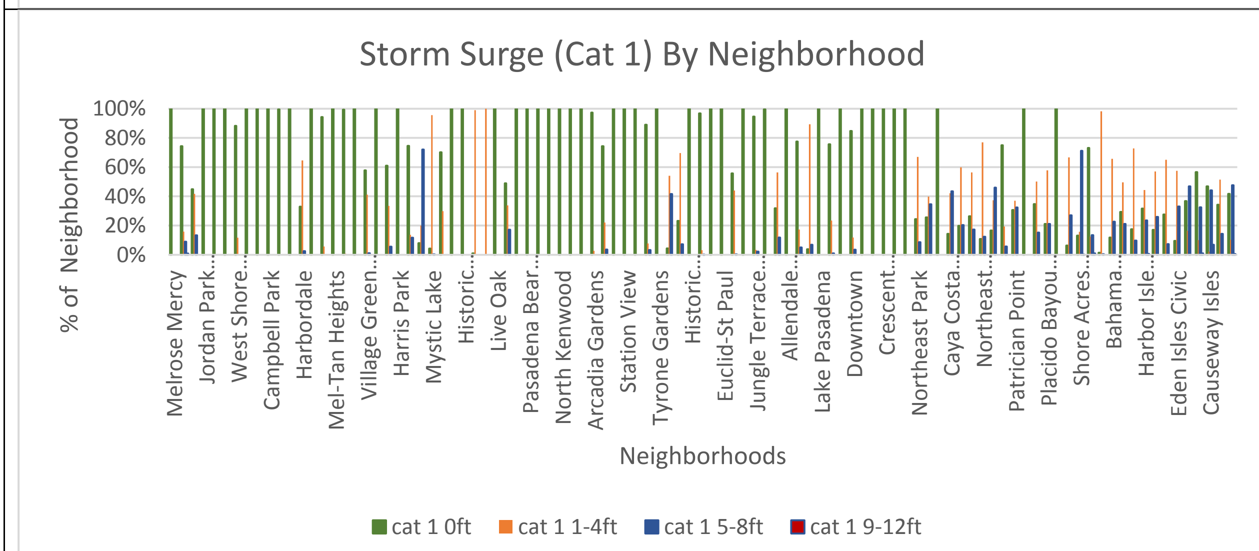
ID	Neighborhood	Coastal	Dominant Race	% master's degree	Average Household Income
14	Lake Maggiore Shores	Noncoastal	African American	4%	$74,094
15	Westminster Heights	Noncoastal	African American	10%	$74,768
16	Bayou Highlands	Noncoastal	African American	5%	$83,749
17	Lakewood Estates Civic	Noncoastal	African American	1%	$49,489
18	Clam Bayou	Coastal	African American	9%	$69,278
19	Harbordale	Coastal	African American	6%	$73,093
20	Lakewood Terrace	Coastal	African American	7%	$80,341
21	Perry Bayview	Coastal	African American	5%	$65,374
22	Greater Pinellas Point	Coastal	African American	12%	$150,867
23	Coquina Key Property Owners	Coastal	Mixed	10%	$88,087
24	Methodist Town	Noncoastal	White	4%	$73,846
25	Lealman	Noncoastal	White	12%	$103,503
26	Ponce De Leon	Noncoastal	White	4%	$65,317
27	Village Green Homeowners	Noncoastal	White	2%	$44,525
28	Crossroads Area Homeowners	Noncoastal	White	6%	$34,584
29	Harris Park	Noncoastal	White	9%	$89,221
30	Mystic Lake	Noncoastal	White	4%	$55,374
31	Oakwood Gardens	Noncoastal	White	13%	$86,984
32	Historic Uptown	Noncoastal	White	12%	$93,742
33	Fossil Park	Noncoastal	White	5%	$86,448
34	Barcley Estates Homeowners	Noncoastal	White	14%	$154,941
35	Live Oak	Noncoastal	White	4%	$83,391
36	Pasadena Bear Creek Estates	Noncoastal	White	4%	$97,600
37	Central Oak Park	Noncoastal	White	5%	$59,413
38	Euclid Heights	Noncoastal	White	5%	$71,895
39	North Kenwood	Noncoastal	White	2%	$77,814
40	Greater Grovemont	Noncoastal	White	3%	$65,914
41	St Pete Heights	Noncoastal	White	6%	$68,384

ID	Neighborhood	Coastal	Dominant Race	% master's degree	Average Household Income
42	Arcadia Gardens	Noncoastal	White	9%	$87,003
43	Allendale Oaks	Noncoastal	White	5%	$44,383
44	Station View	Noncoastal	White	2%	$55,782
45	Garden Manor	Noncoastal	White	4%	$47,299
46	Historic Roser Park	Noncoastal	White	8%	$73,177
47	Tyrone Gardens	Noncoastal	White	14%	$106,036
48	Brighton Bay	Noncoastal	White	11%	$81,715
49	Wyngate Homes Homeowners	Noncoastal	White	2%	$72,458
50	Historic Kenwood	Noncoastal	White	7%	$59,325
51	Azalea Homes Community	Noncoastal	White	7%	$108,717
52	Disston Heights Civic	Noncoastal	White	11%	$103,619
53	Euclid-St Paul	Noncoastal	White	1%	$36,255
54	Meadowlawn	Noncoastal	White	13%	$120,849
55	Garden Manor Lake Estates	Noncoastal	White	4%	$79,664
56	Holiday Park Homeowners	Noncoastal	White	2%	$52,339
57	Allendale Terrace Neighbors United	Noncoastal	White	4%	$55,761
58	Edgemoor	Noncoastal	White	6%	$56,726
59	Lake Pasadena	Noncoastal	White	4%	$61,751
60	Eagle Crest Homeowners	Noncoastal	White	9%	$125,394
61	Greater Woodlawn	Noncoastal	White	2%	$30,964
62	Crescent Heights	Noncoastal	White	4%	$36,302
63	Crescent Lake	Noncoastal	White	14%	$58,613
64	Magnolia Heights	Noncoastal	White	2%	$65,826
65	Placido Bayou Community	Noncoastal	White	6%	$104,249
66	Allendale Crime Watch	Noncoastal	White	14%	$149,037
67	Five Points	Noncoastal	White	2%	$59,095
68	Eden Isles Civic	Noncoastal	White	22%	$52,356
69	Historic Park Street	Coastal	White	1%	$49,907
70	Jungle Terrace Civic	Coastal	White	7%	$58,942
71	Caya Costa Community	Coastal	White	10%	$86,434
72	Americana Cove Residents	Coastal	White	1%	$37,553

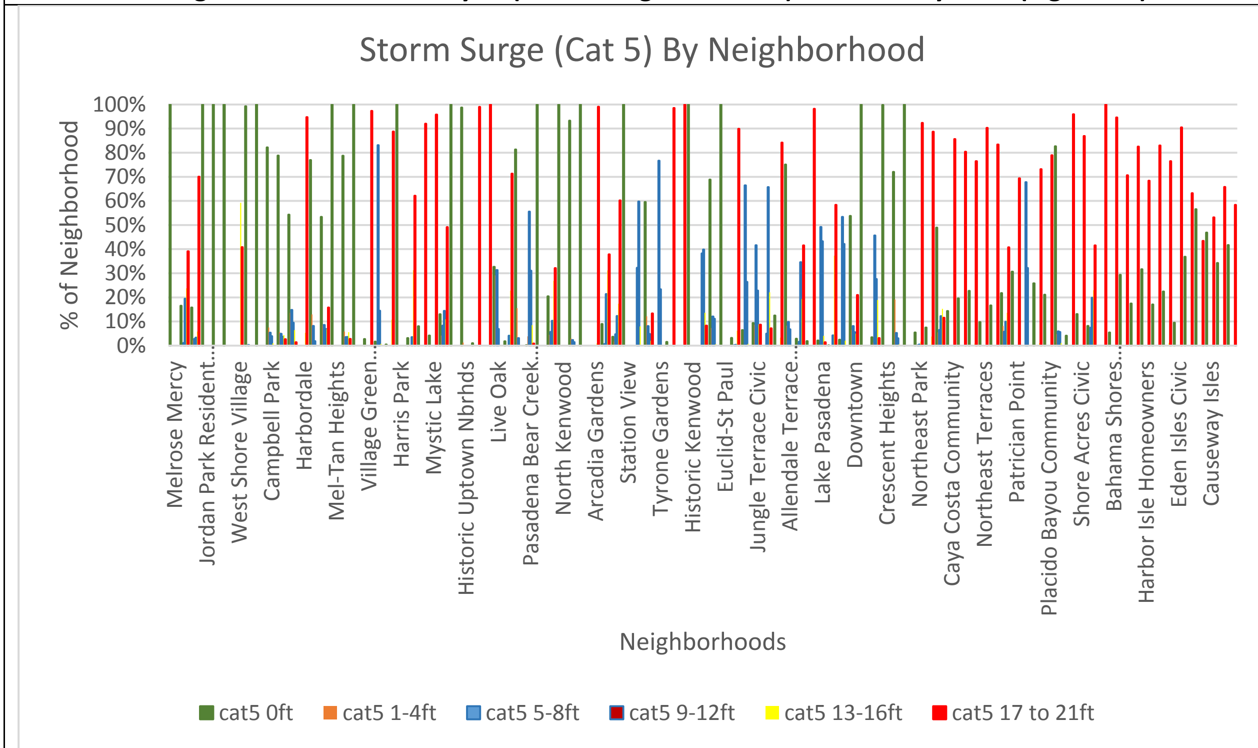
ID	Neighborhood	Coastal	Dominant Race	% master's degree	Average Household Income
73	Isla Del Sol Owners	Coastal	White	2%	$64,423
74	Northeast Terraces	Coastal	White	9%	$107,688
75	Riviera Bay Civic	Coastal	White	2%	$61,894
76	Historic Old Northeast	Coastal	White	10%	$113,841
77	Patrician Point	Coastal	White	12%	$153,525
78	Old Southeast	Coastal	White	11%	$89,816
79	Downtown	Coastal	White	4%	$75,351
80	Broadwater Civic	Coastal	White	NA	$147,774
81	Big Bayou	Coastal	White	12%	$89,261
82	Ling-A-Mor Estate	Coastal	White	2%	$43,611
83	Big Bayou	Coastal	White	12%	$89,261
84	Ling-A-Mor Estate	Coastal	White	2%	$43,611
85	Tropical Shores	Coastal	White	10%	$117,930
86	Shore Acres Civic	Coastal	White	18%	$152,066
87	Jungle Prada	Coastal	White	1%	$66,596
88	Maximo Civic	Coastal	White	2%	$69,335
89	Bahama Shores Homeowners	Coastal	White	11%	$161,333
90	Renaissance	Coastal	N/A	5%	$37,035
91	Riviera Bay Subdv Home Owners	Coastal	White	2%	$43,455
92	Harbor Isle Homeowners	Coastal	White	9%	$117,194
93	Snell Isle Property Owners	Coastal	White	5%	$72,586
94	Sunset Drive South	Coastal	White	5%	$36,710
95	Yacht Club Estates Civic	Coastal	White	2%	$64,374
96	Causeway Isles	Coastal	White	1%	$36,283
97	Bayway Isles Homeowners Club Inc	Coastal	White	6%	$73,093
98	Northeast Park	Coastal	White	6%	$92,487
99	Driftwood Property Owners	Coastal	White	12%	$104,069
100	Venetian Isles Homeowners	Coastal	White	13%	$176,358
101	Point Brittany Community	Coastal	White	22%	$208,471

Neighborhood Level Analysis (for all Neighborhoods) in the Study Area (Figure 12)





Neighborhood Level Analysis (for all Neighborhoods) in the Study Area (Figure 12)



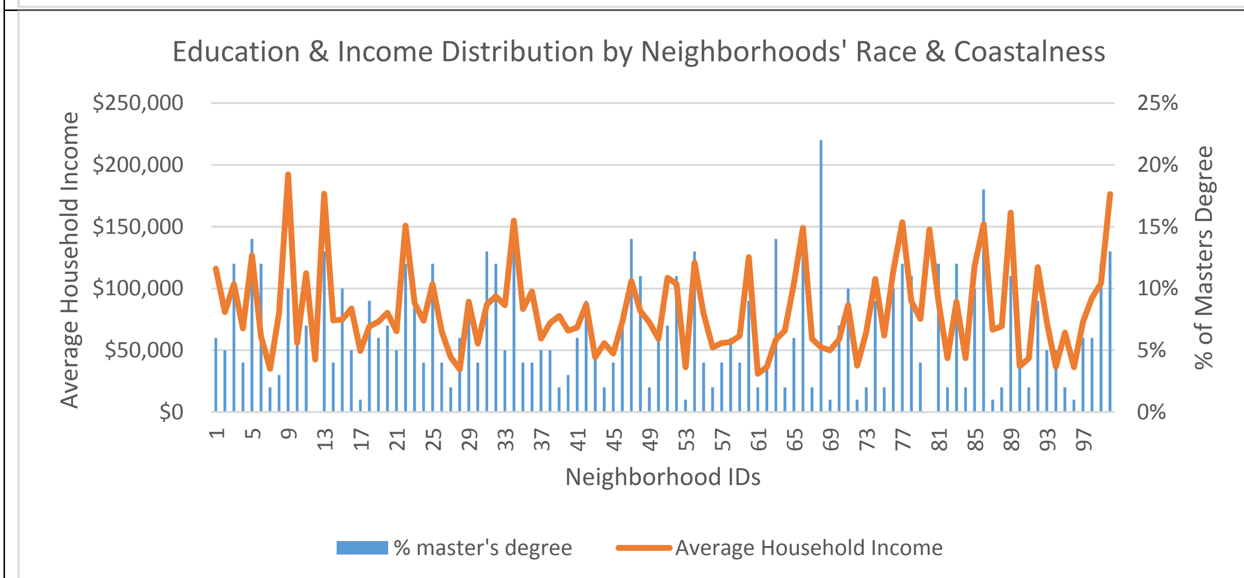


Figure 12. Characteristics of neighborhoods within entire study area. (Note: Please refer to Table 1 for neighborhood names and coastal or noncoastal classifications)

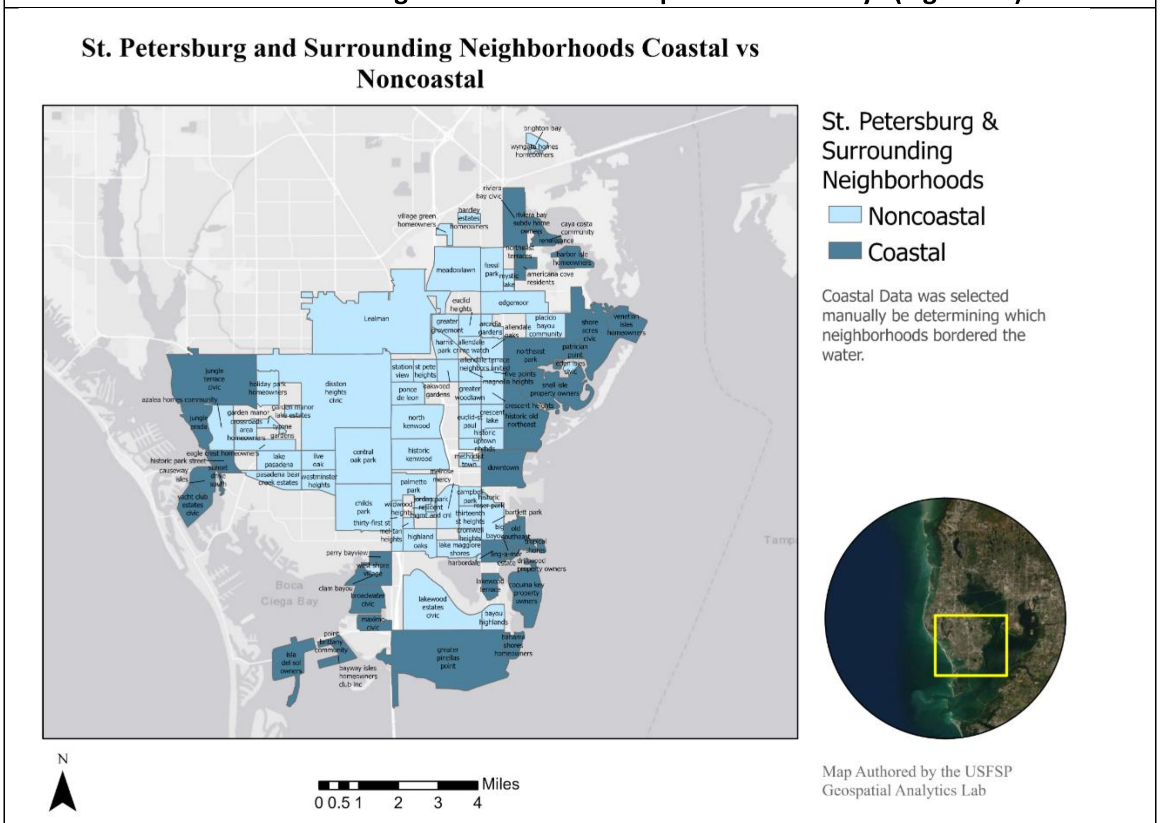
4.2 Survey Response Analysis

This section is divided into 3 subsections that will discuss characteristic of respondents, overall percentage analysis of responses and a detailed analysis of responses for relevant questions at the neighborhood level. This survey analysis included a small pilot sample of n=78. We are seeking funding to reach marginalized communities, and we expect this database to grow over time. The following section describes the data that has come in thus far.

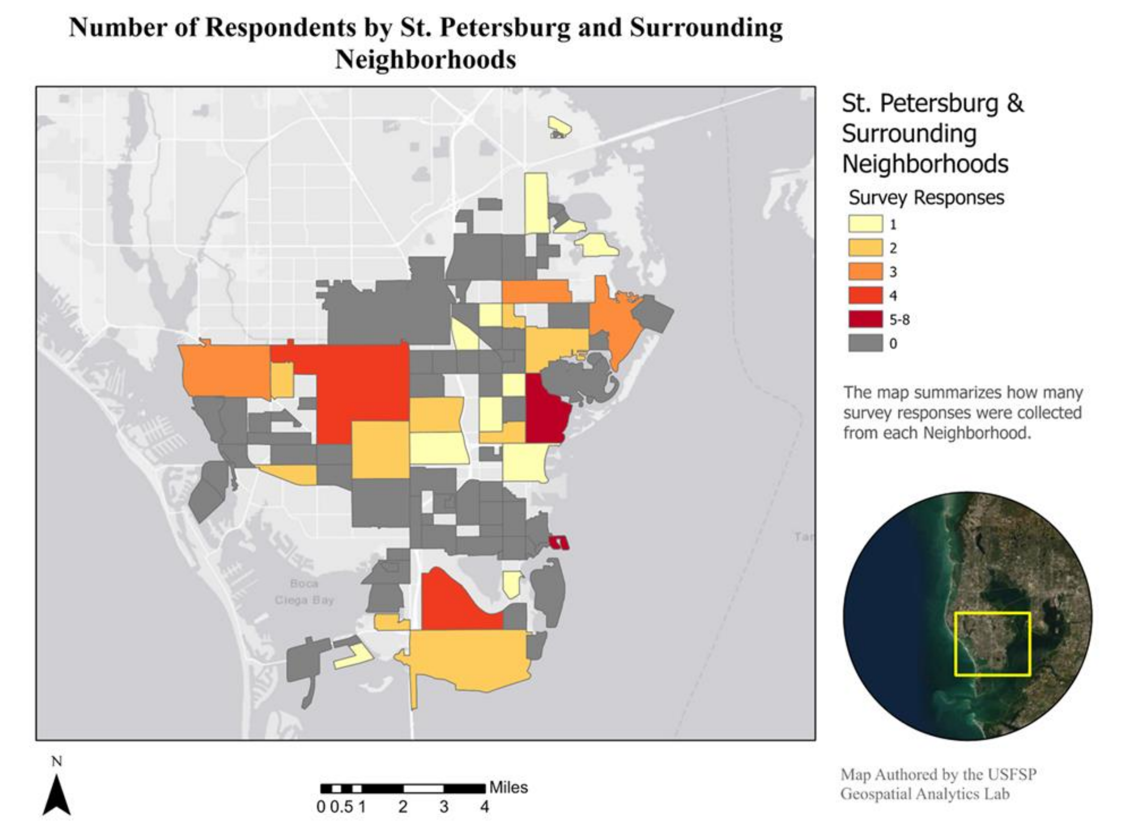
4.2.1 Characteristics of Survey Respondents

Figure 13 shows survey response distributions by neighborhood types (i.e., coastal or noncoastal). The highest number of responses received is from wealthy coastal neighborhoods like old northeast and tropical shores with over $100,000 average household income. About 56% of survey responses came from neighborhoods with low storm surge potential whereas 44% came from lowest flood risk (zone X with minimal flood hazard).

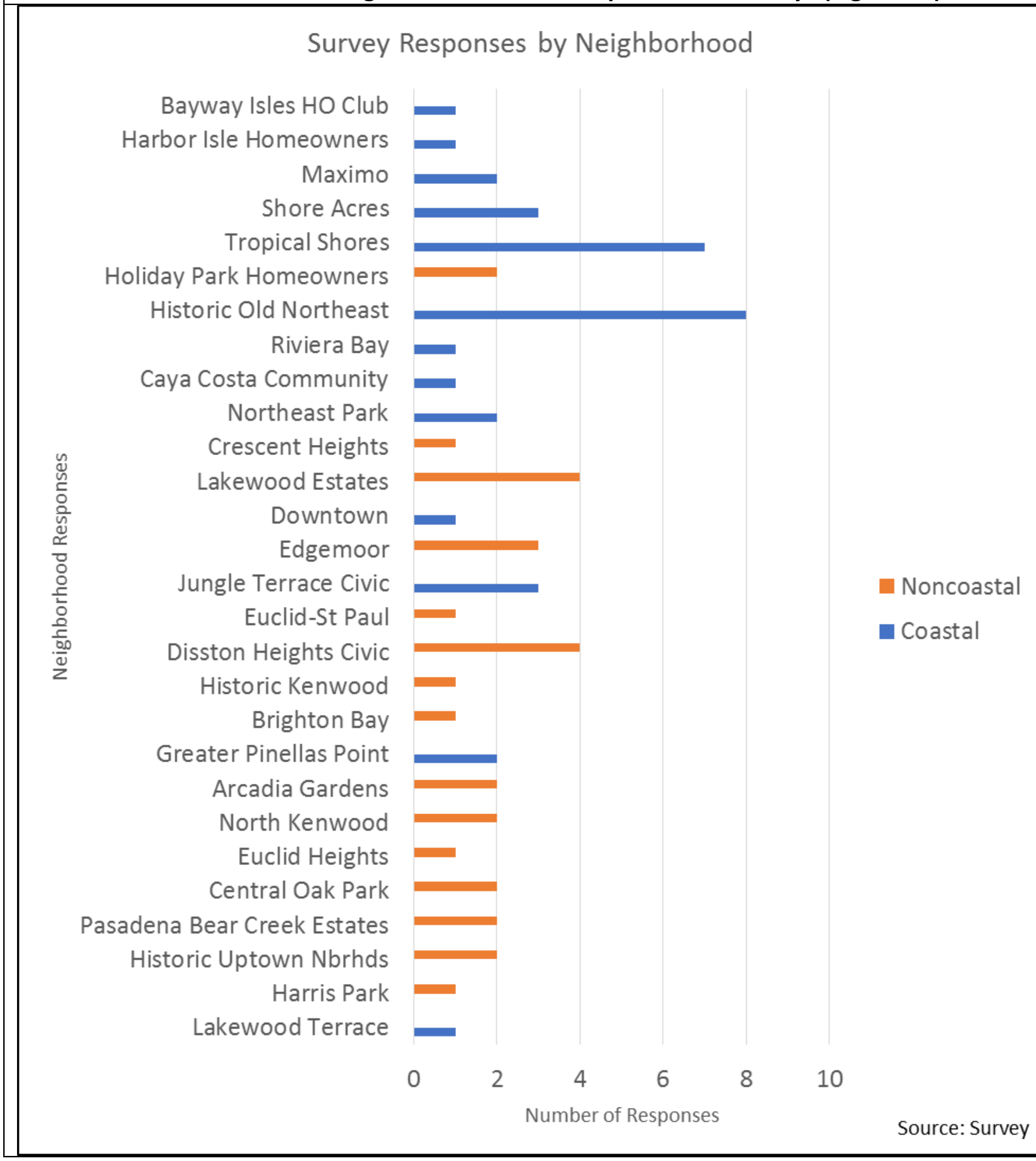
Characteristics of Neighborhoods that Completed the Surveys (Figure 13)



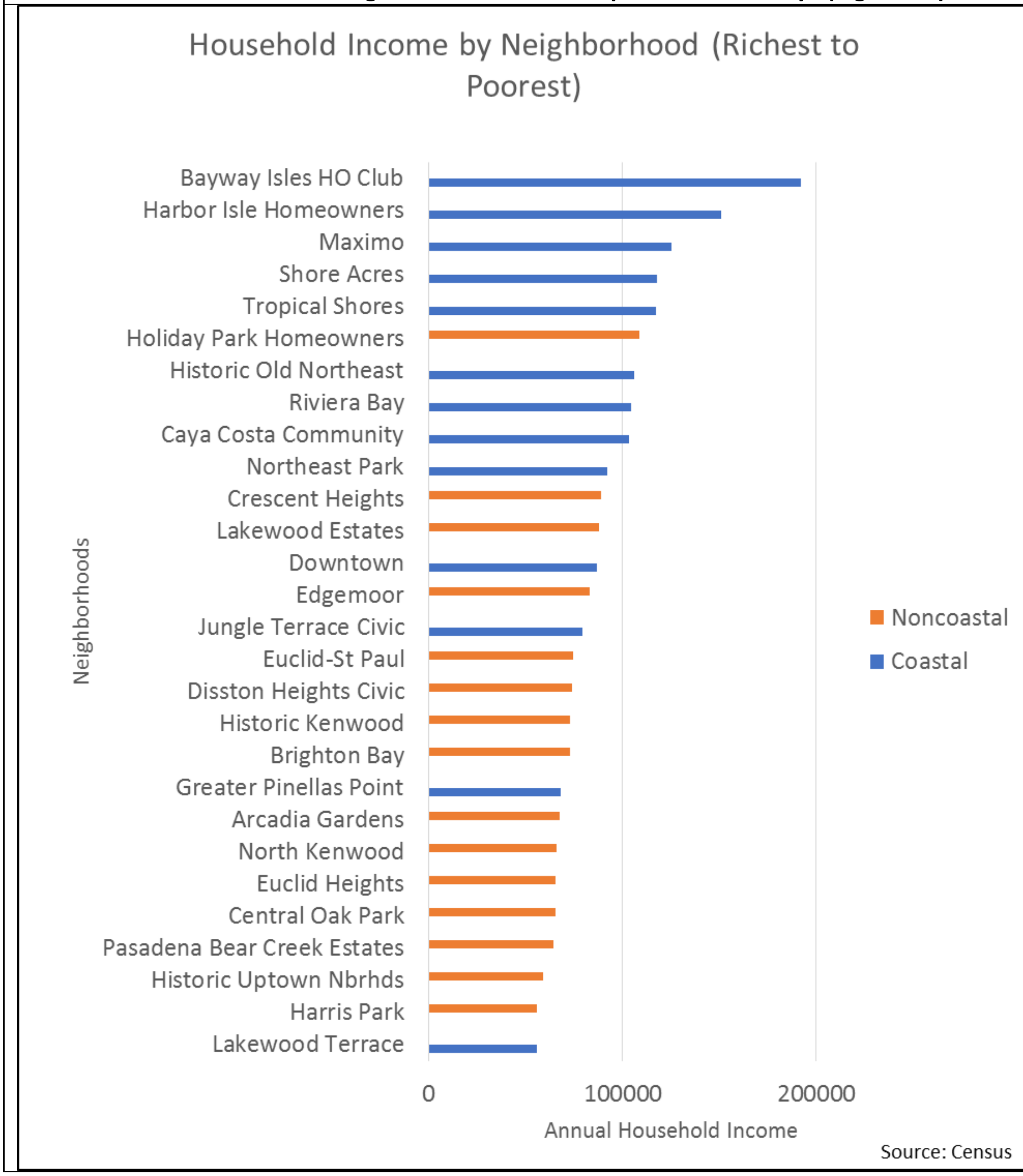
Characteristics of Neighborhoods that Completed the Surveys (Figure 13)



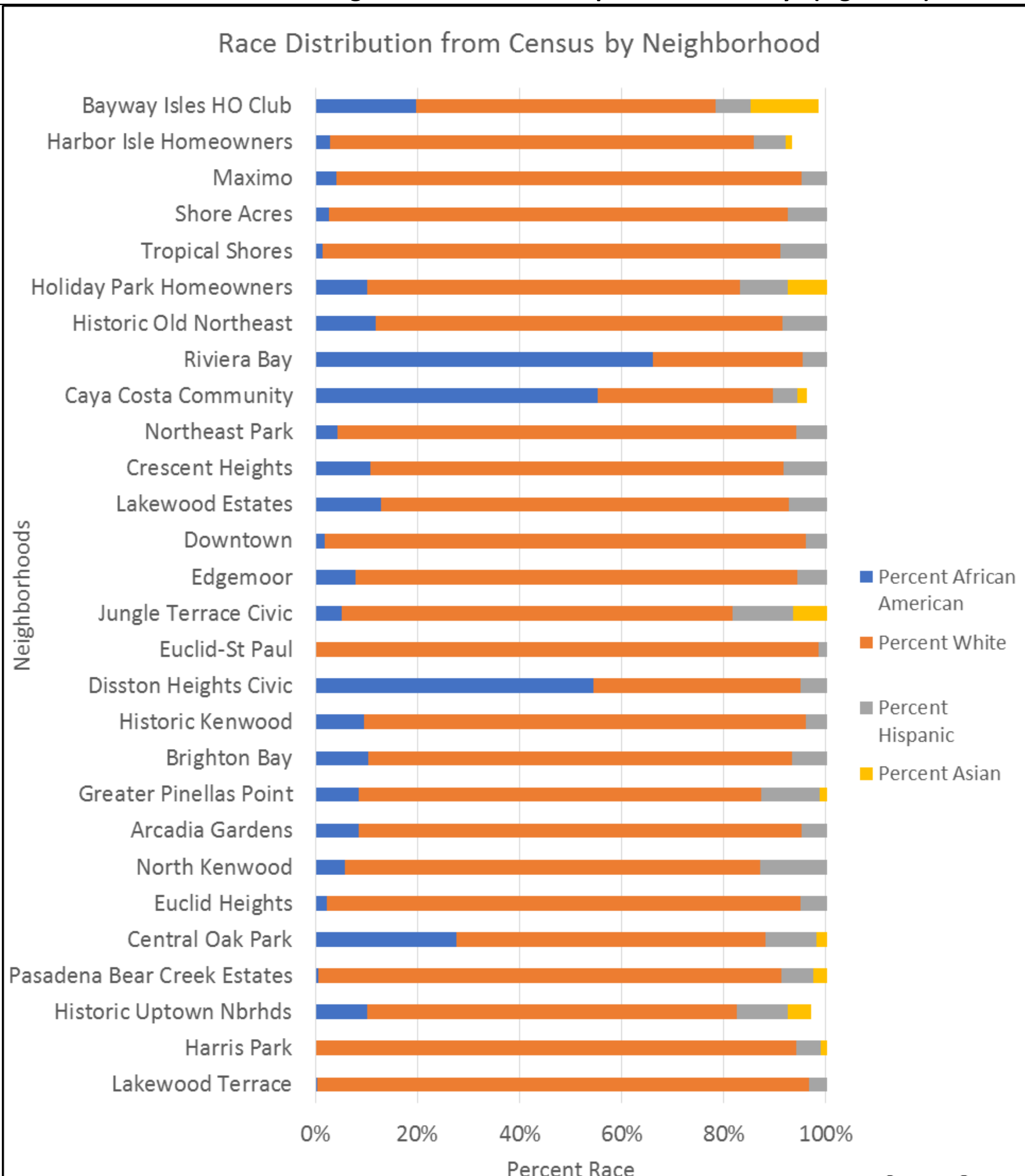
Characteristics of Neighborhoods that Completed the Surveys (Figure 13)



Characteristics of Neighborhoods that Completed the Surveys (Figure 13)

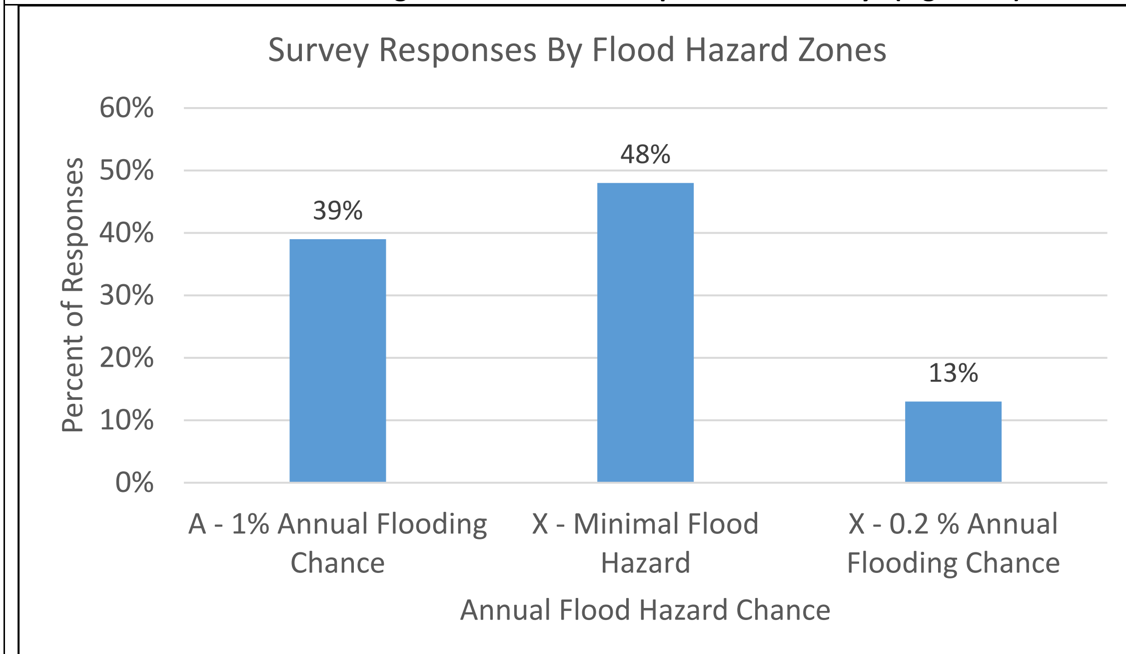


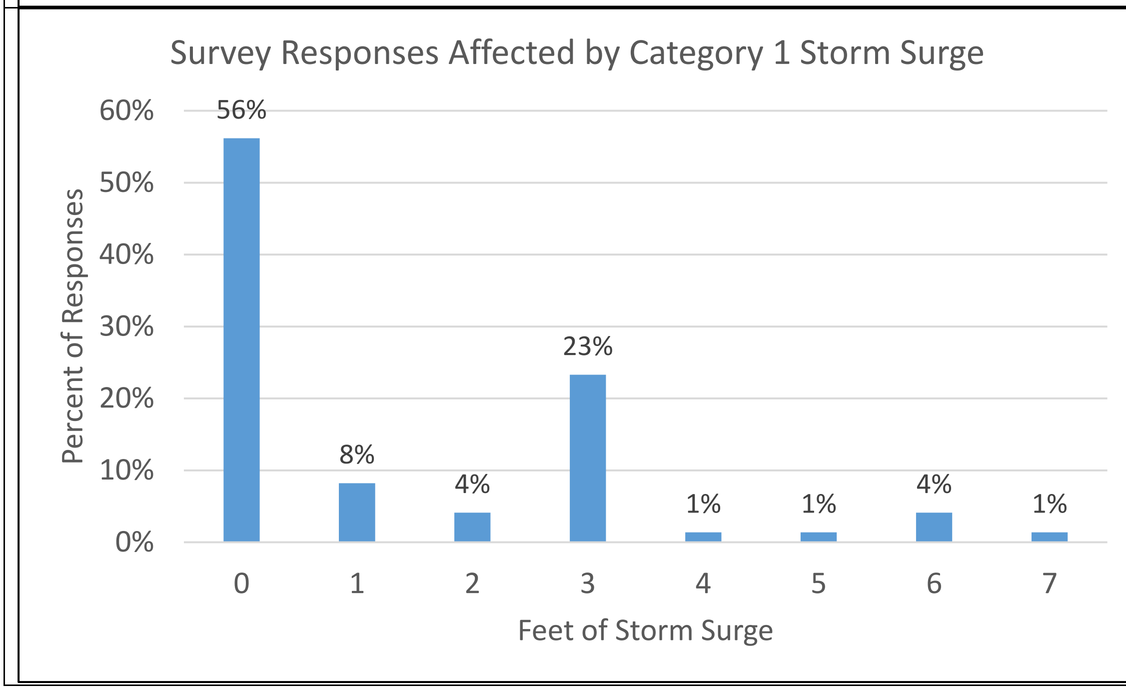
Characteristics of Neighborhoods that Completed the Surveys (Figure 13)



Source: Census

Characteristics of Neighborhoods that Completed the Surveys (Figure 13)





Characteristics of Neighborhoods that Completed the Surveys (Figure 13)

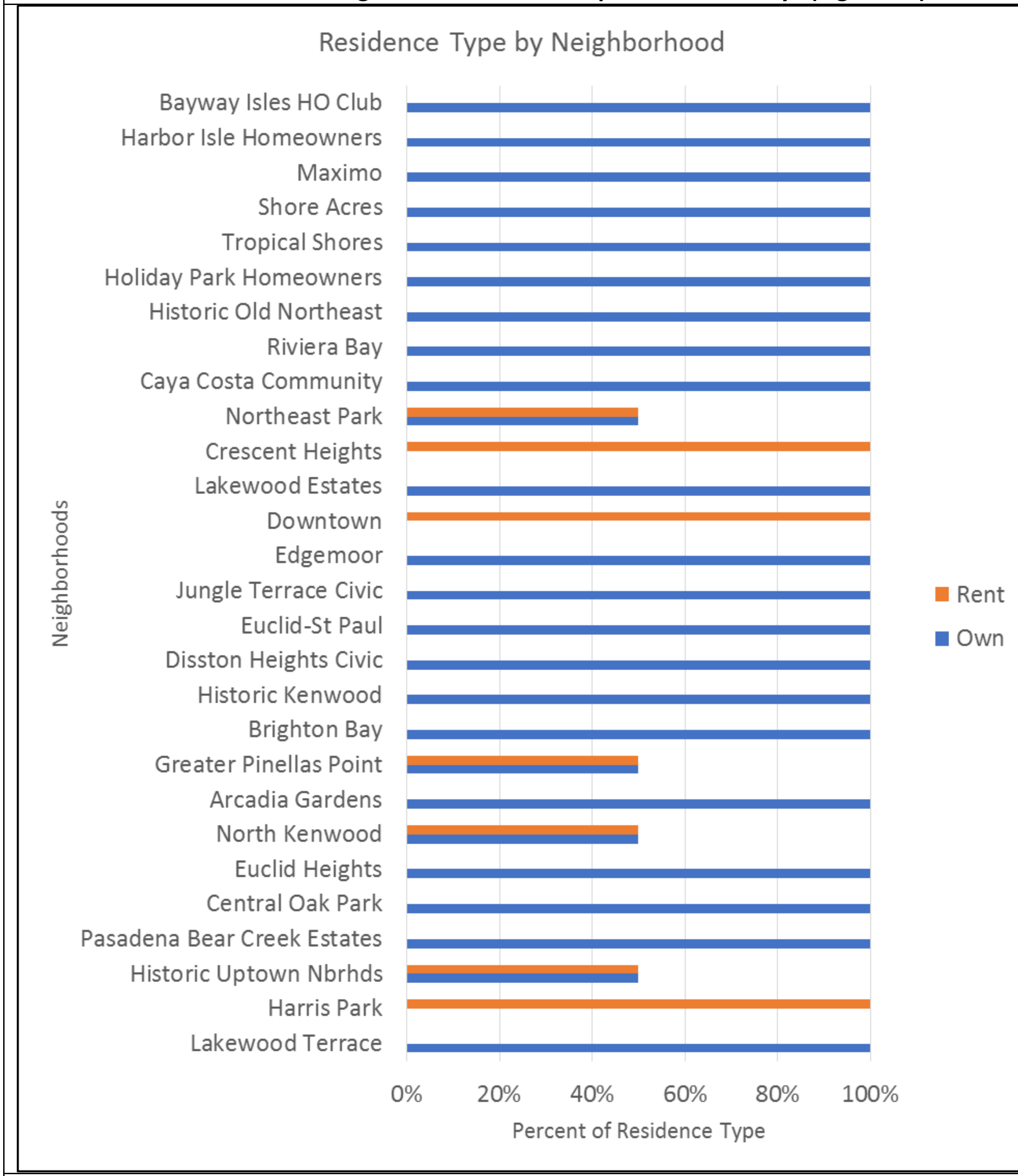


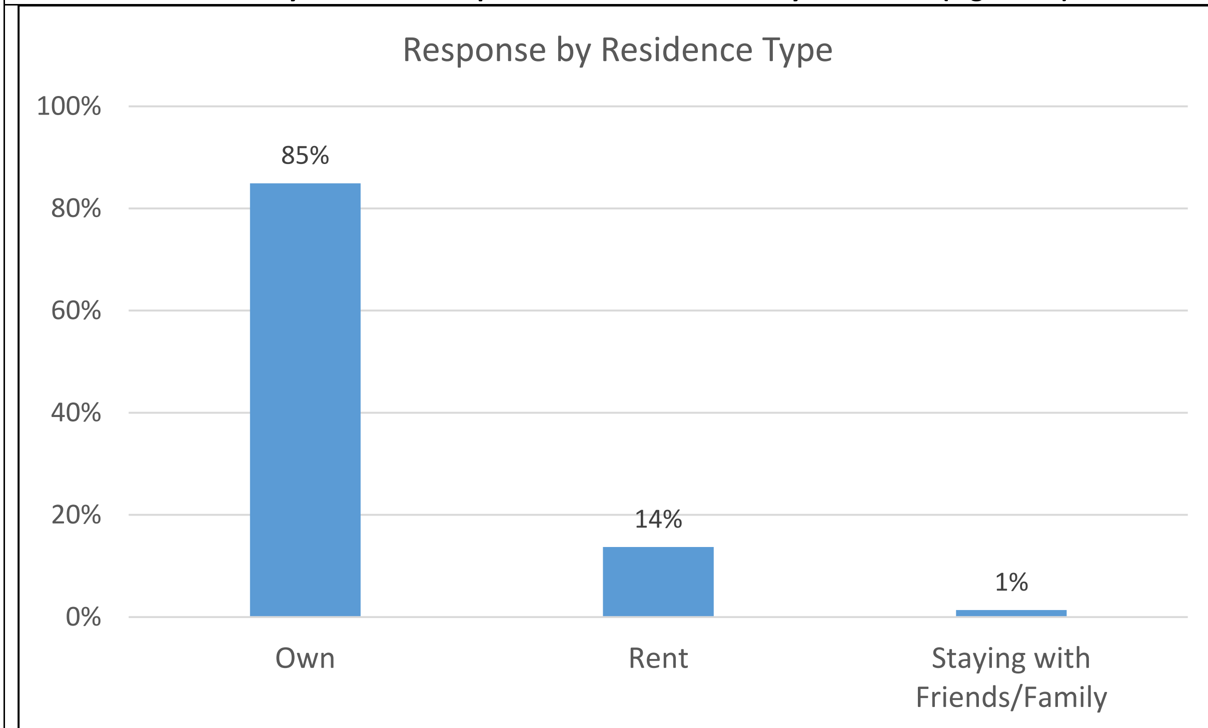
Figure 13. Characteristics of neighborhoods that completed the surveys

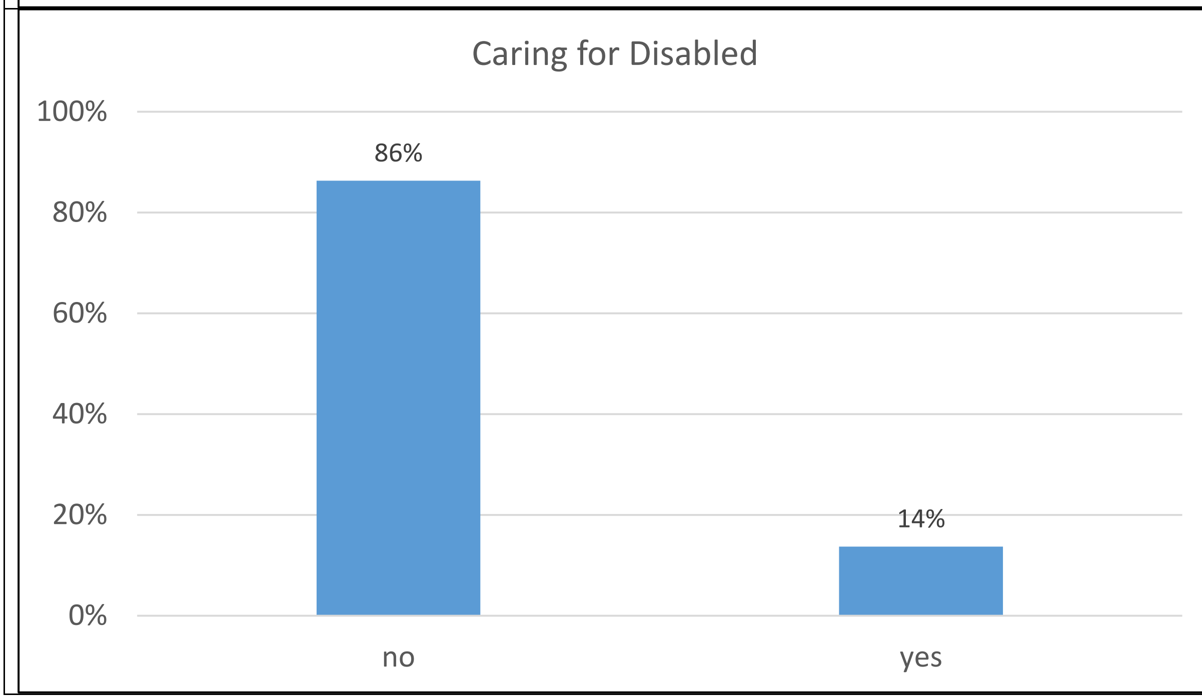
4.2.2 Overall Analysis

Figure 14 shows examples of survey response gathered through in-built survey with CRIS. Overall 85% of respondents identified themselves as homeowners while 14% of respondents are renters. About 86% of the respondents had no family member identified as disabled while

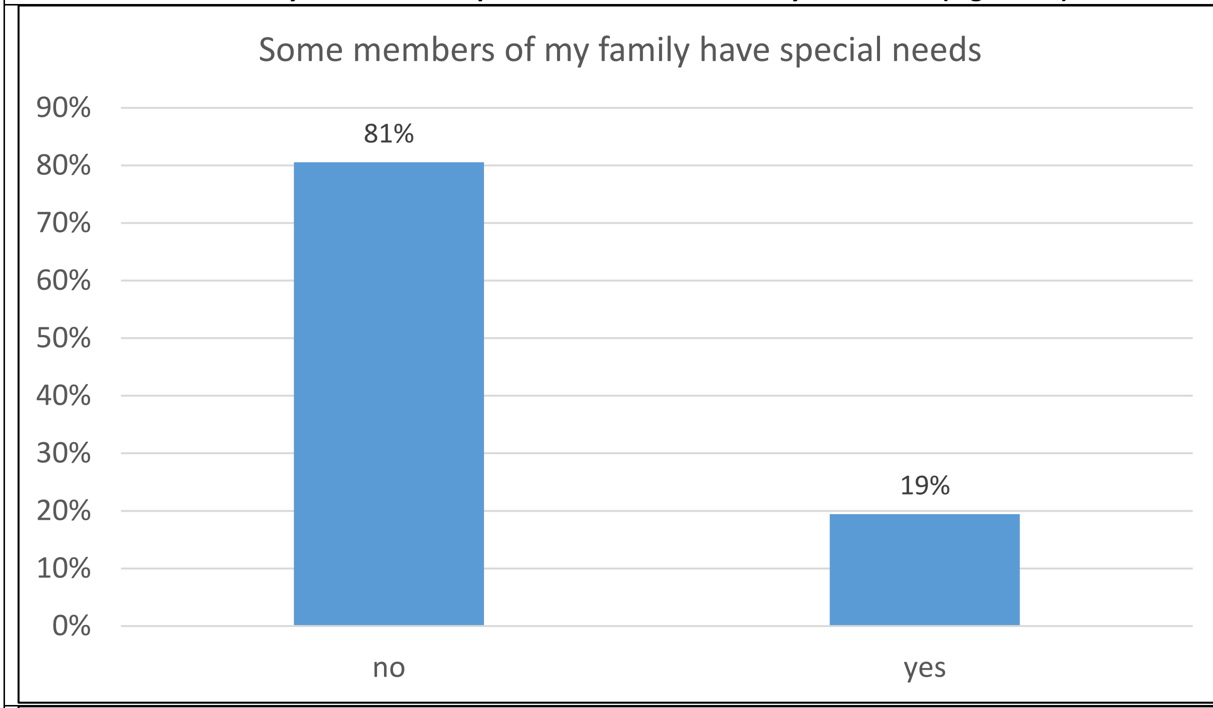
14% replied that they had a family member who was disabled. While 20% of respondents indicated that a family member has special needs, about 32% reported that they had experienced flooding and 68% reported experiencing a hurricane or major tropical storm. About 67% stated that they have flood insurance and 56% believed they have resources to recover from a flood. Approximately 34% of respondents identified excessive rain as the primary cause of flooding; this was the most frequent response. About 56% and 58% of respondents were concerned about being impacted by flooding and hurricane, respectively. It should be noted that 38% identified power outage as the major concern during and after hurricane followed by 31% concerned about water damage. This concern about power outage was also noted in our previous studies when we comparted only 2 neighborhoods (Johns et al, 2020). When asked if the respondent thinks that the chances of a hurricane strike will increase, 44% agreed and 22% strongly agreed while 28% remain neutral and 6% strongly disagreed and 3% disagreed. About 63% of the respondents stated that they have resources to recover from a hurricane (agreed, 53%) or strongly agreed (14%). About 21% disagreed with the statement and 14% were neutral (i.e. unsure – if they have adequate resources or not). About 57% percent of respondents were either unsure (14%) or did not know (43%) which government agency to reach out to for assistance after a disaster. This indicates about 57% did not know with certainty who to contact to get help about hurricane damage related issues. The city and the county needs to do more outreach. Resources available through CRIS will be helpful to citizens. CRIS is also sending custom emails to survey respondents with key information and resources based on their responses.

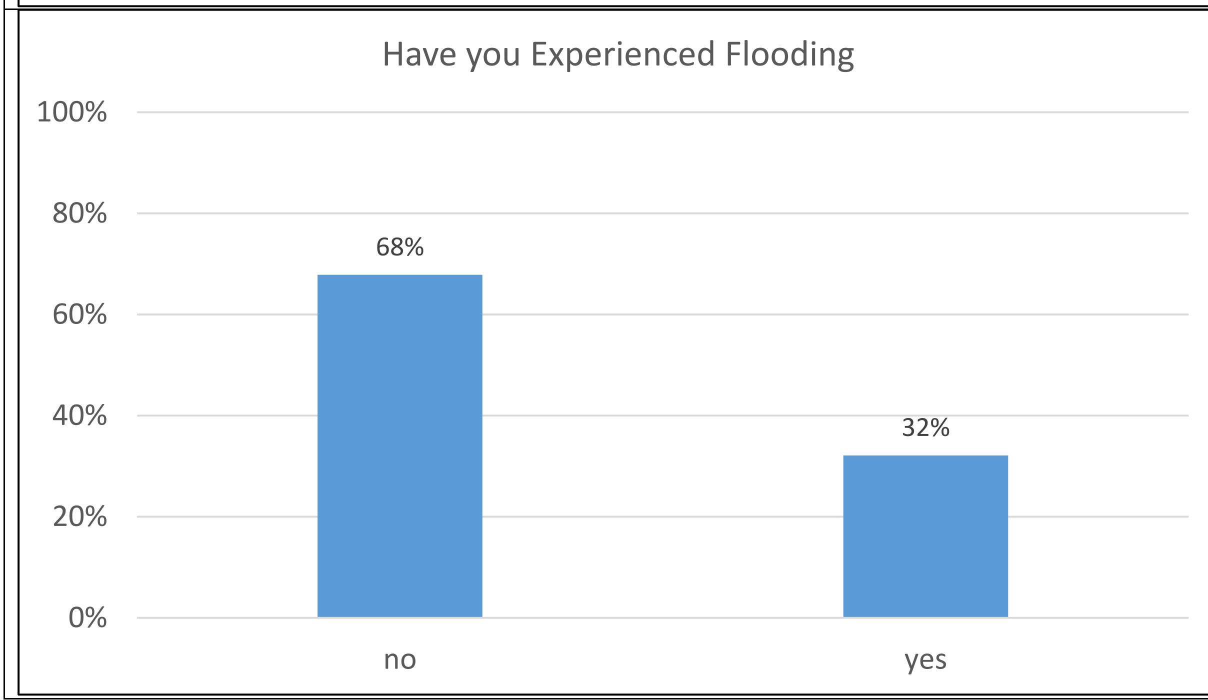
Summary of Overall Responses for Selected Survey Questions (Figure 14)



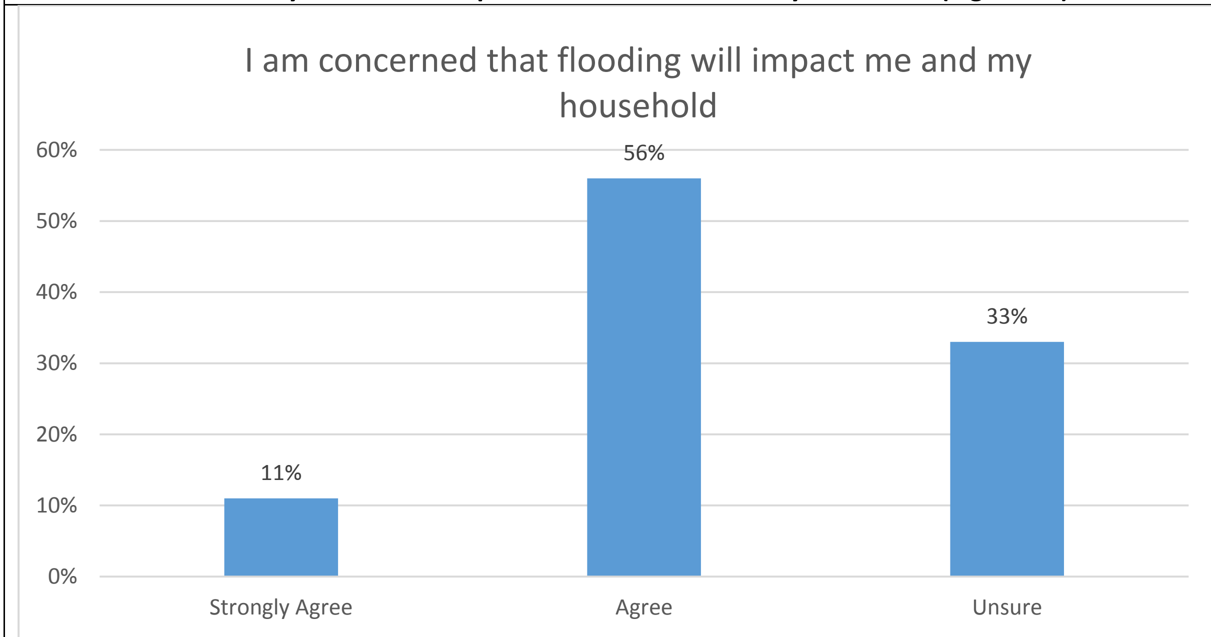


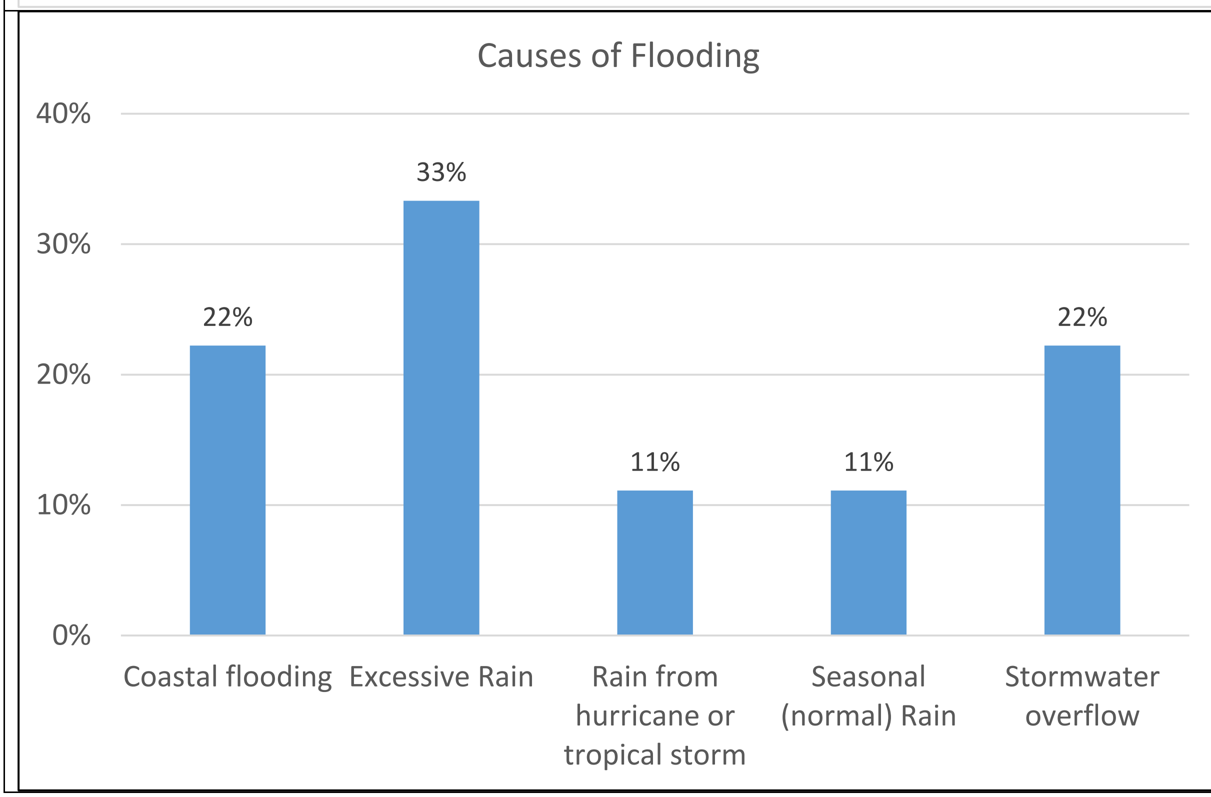
Summary of Overall Responses for Selected Survey Questions (Figure 14)



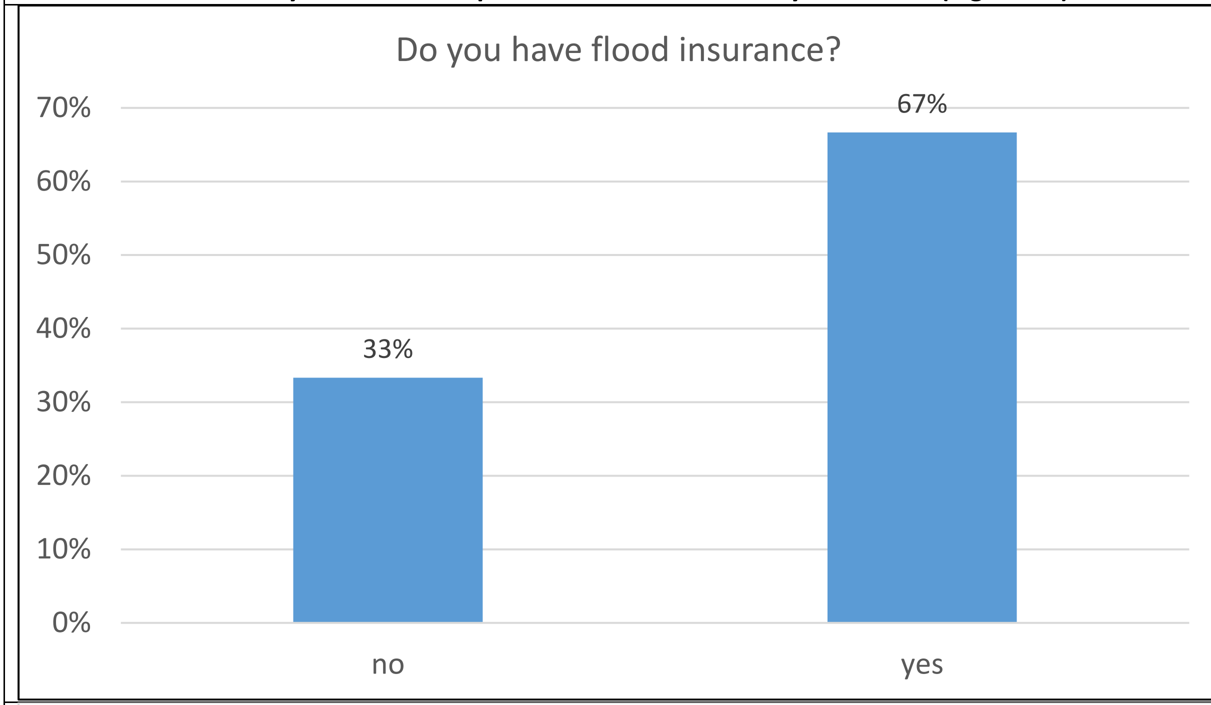


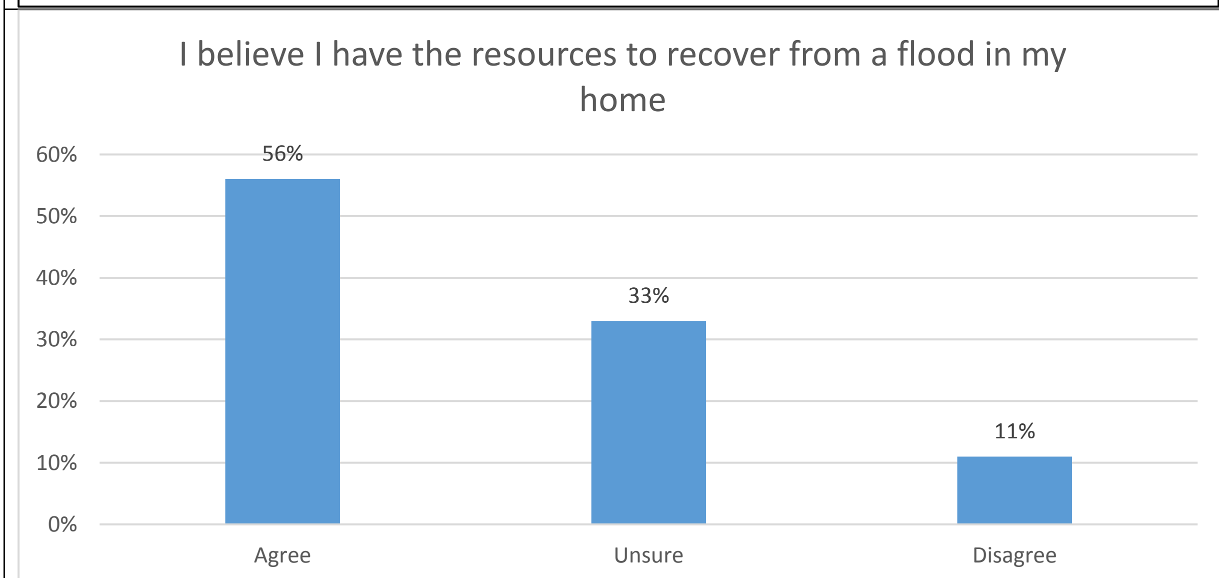
Summary of Overall Responses for Selected Survey Questions (Figure 14)





Summary of Overall Responses for Selected Survey Questions (Figure 14)





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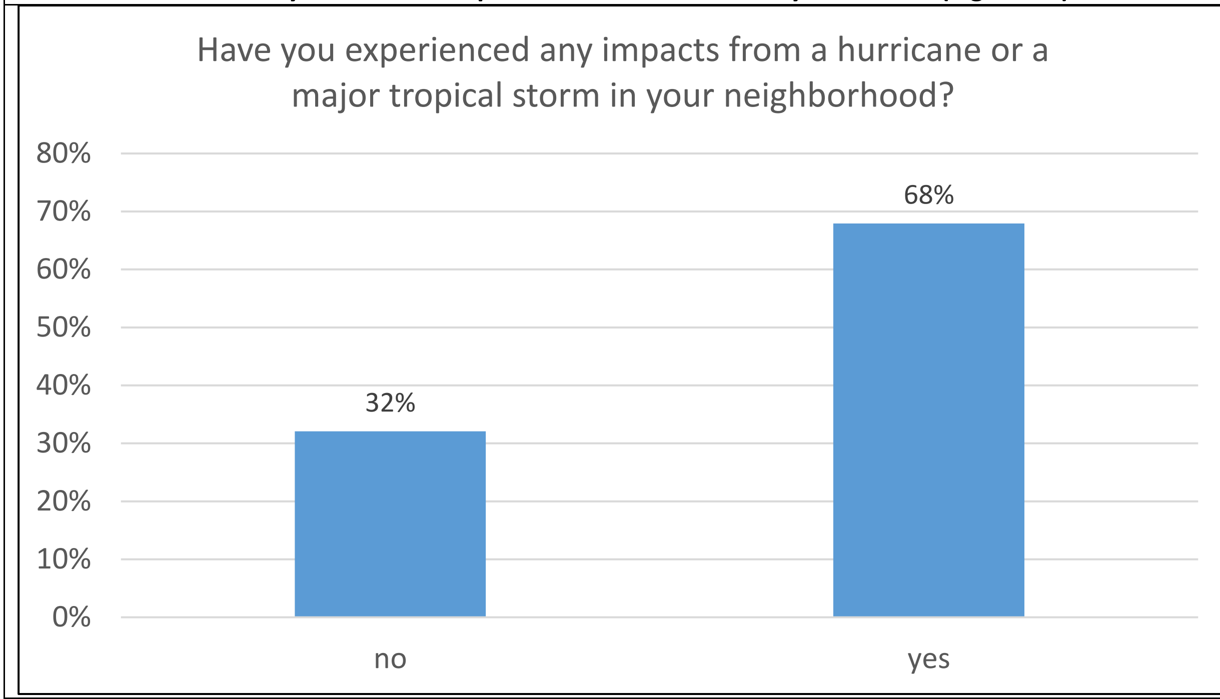

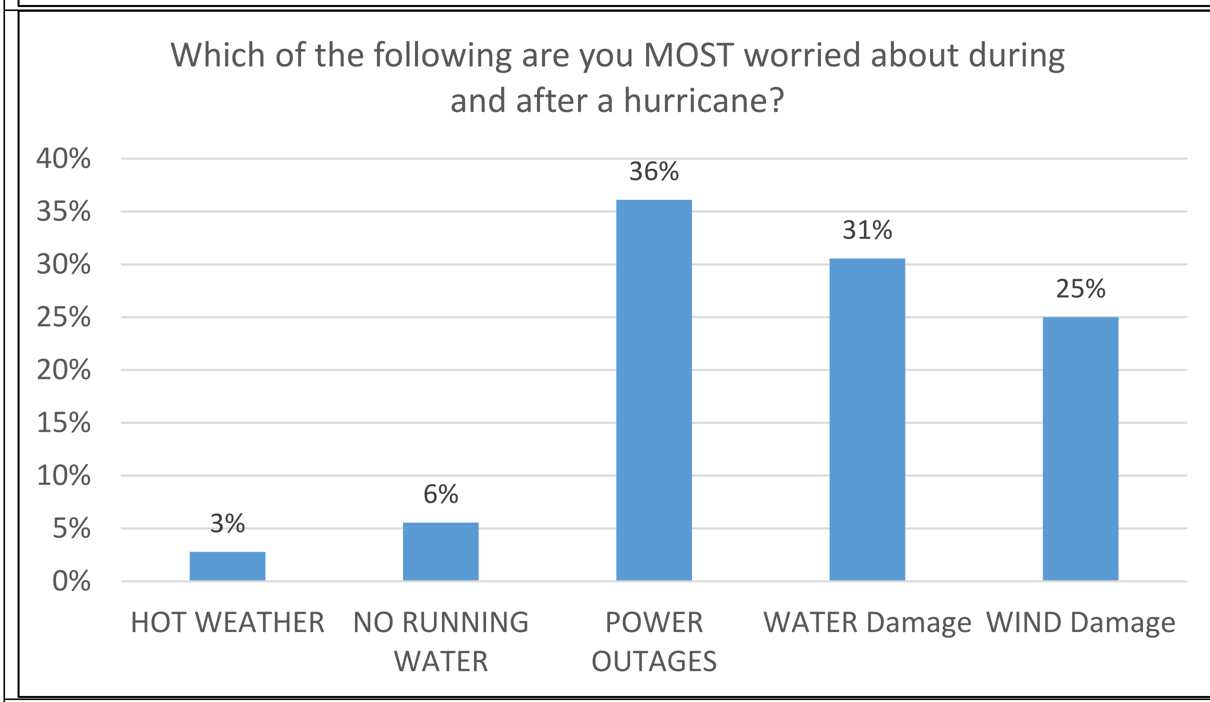

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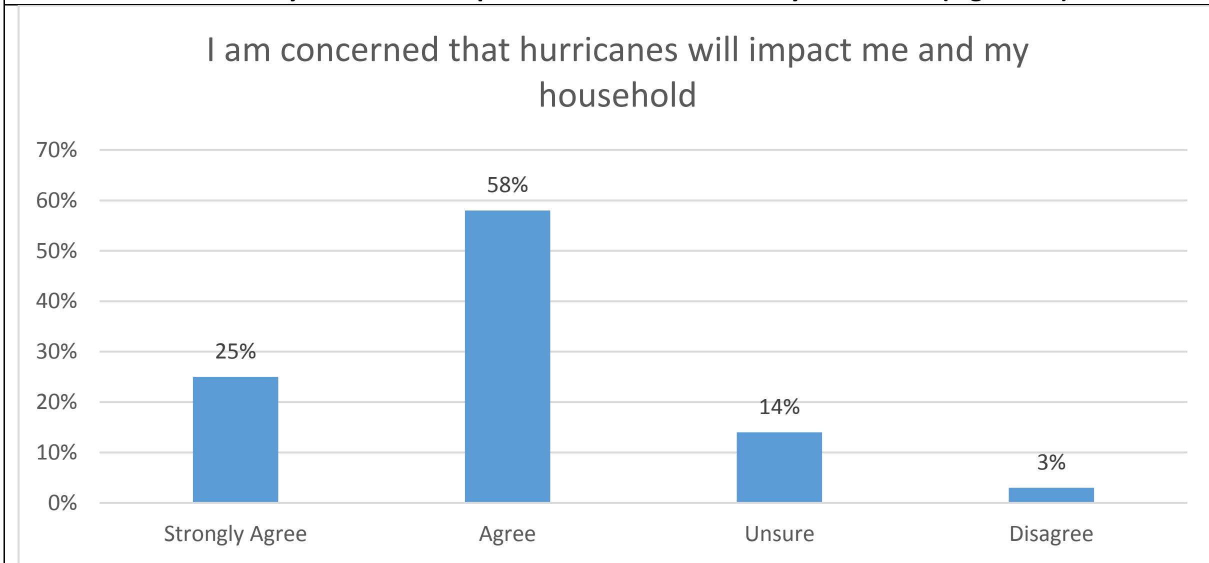

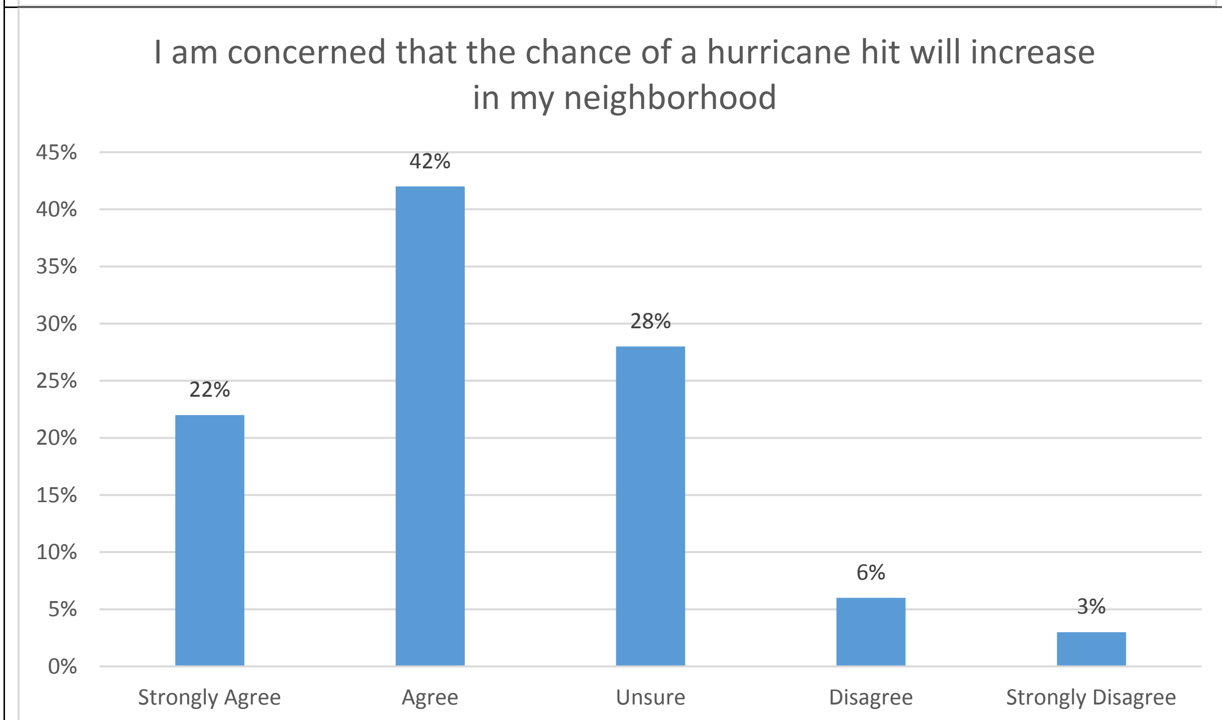

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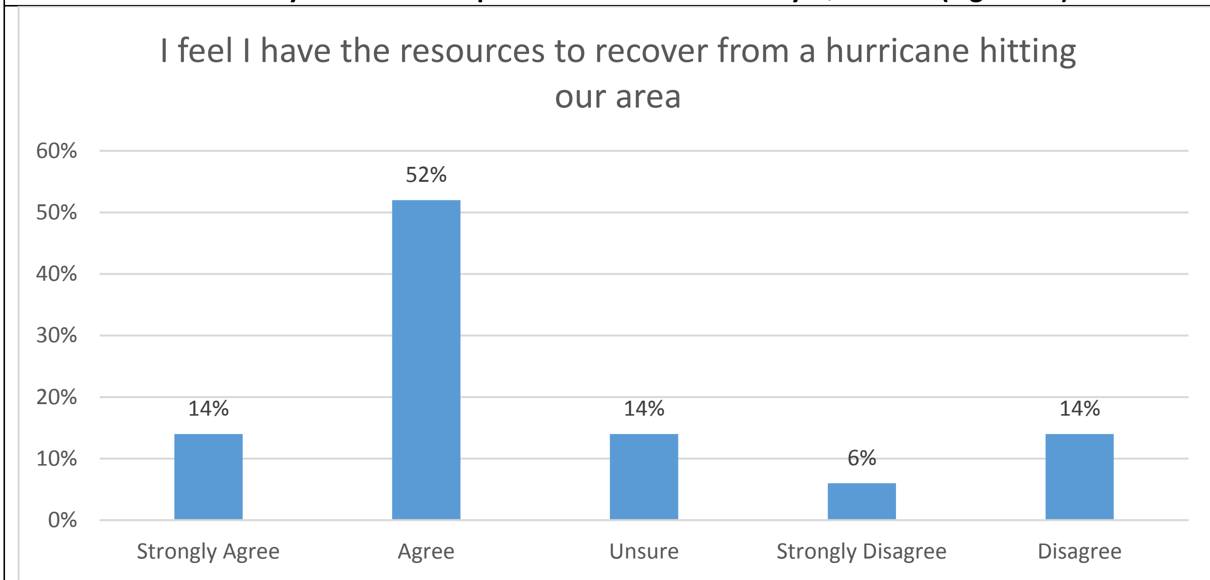


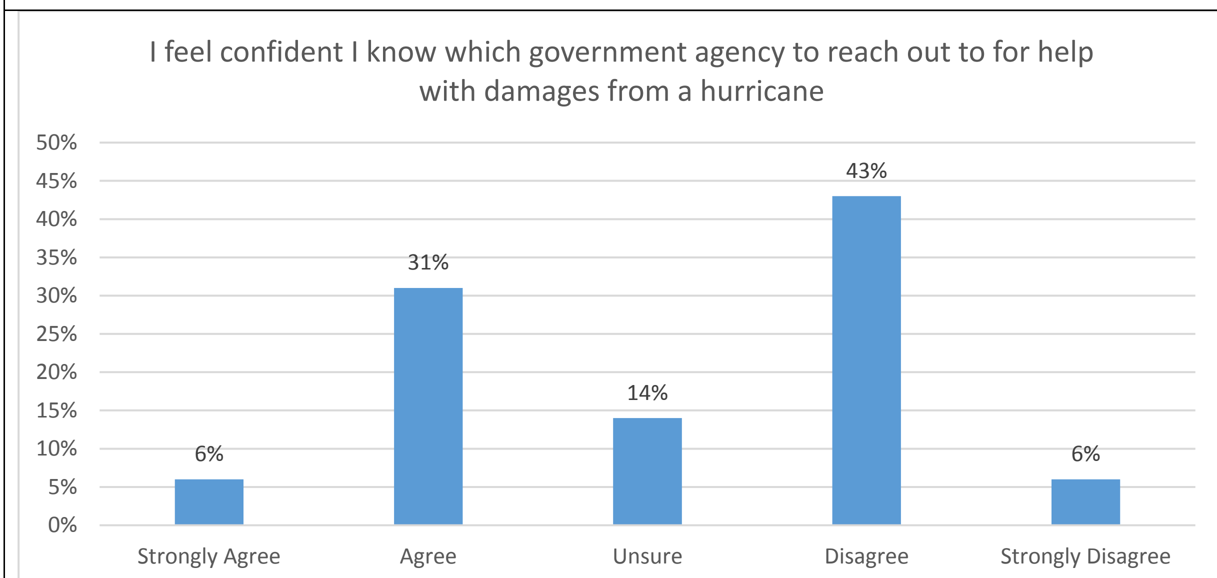


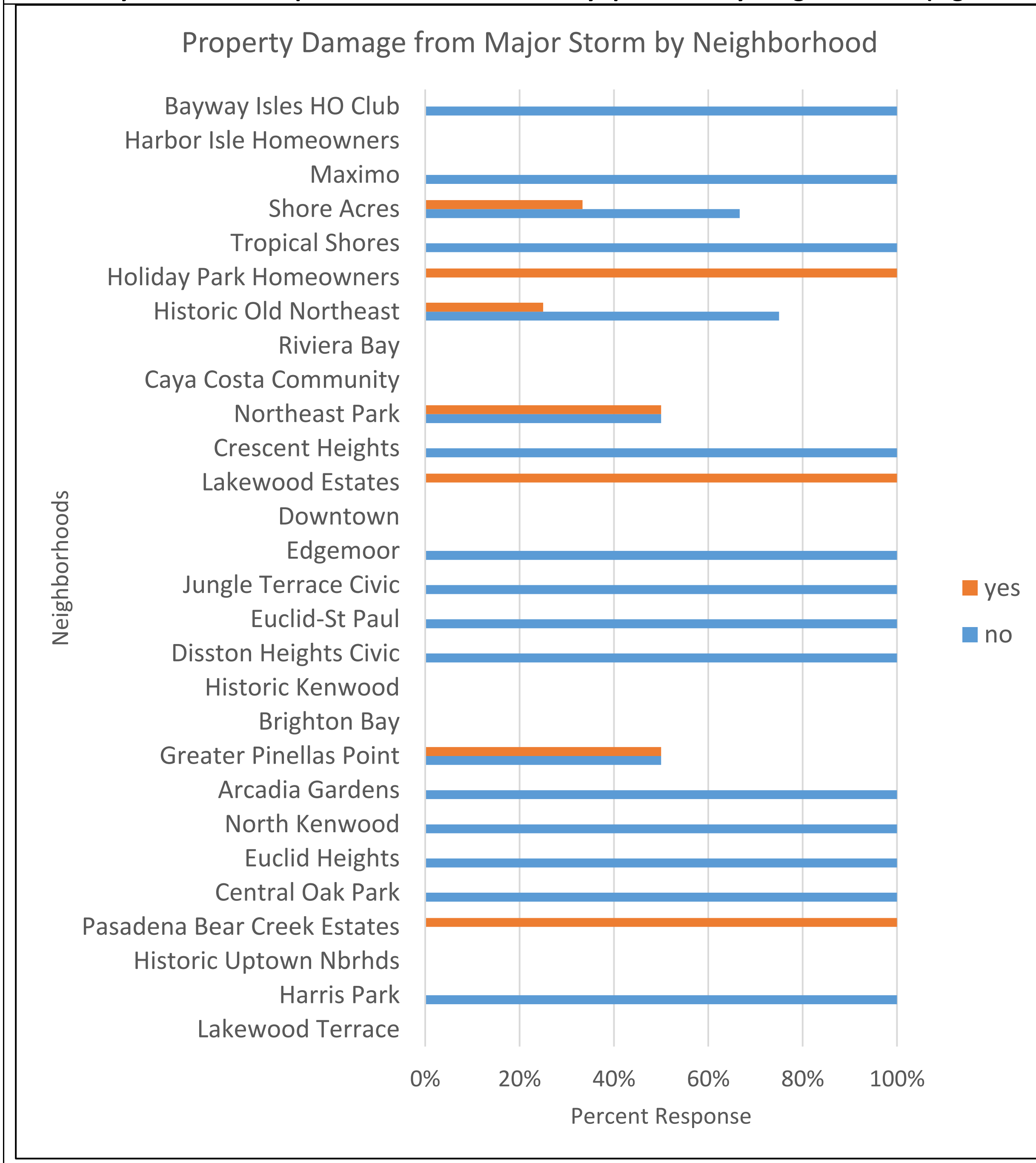
Figure 14. Summary of overall responses for selected survey questions n=78

4.2.3 Neighborhood Level Analysis

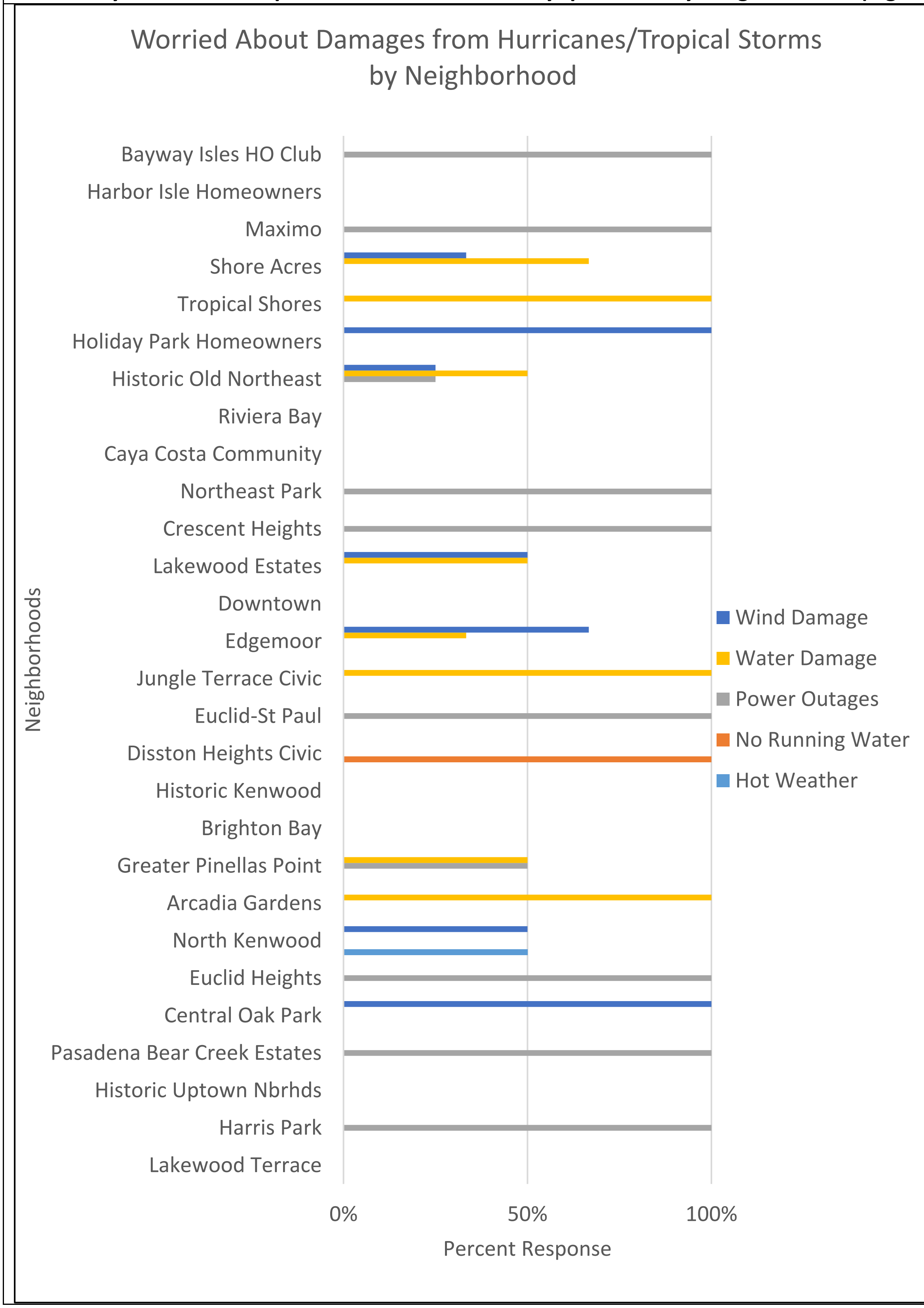
Survey responses were mapped at the neighborhood level (not exact street address for privacy reasons as we are interested in aggregated response and neighborhood level and not from a specific household). Figure 15 shows examples of responses mapped at neighborhood level. We received responses from 29 neighborhoods. As noted earlier we need to do in-person outreach to increase participation from marginalized communities – we could not do this due to COVID19 but we are looking for other funding to promote community engagement using CRIS in marginalized communities. This report includes preliminary data and efforts will be on-going so new data when collected may change the findings. We are reporting data collected between

Sep – November of 2020. For example Bayway Isle HO club, the wealthiest coastal neighborhood (average household income nearly 200K) in our survey database, reported less property damages than Pasadena Bear Creek Estate (a relatively less wealthy with less than 100K average income and noncoastal neighborhood). Greater Pinellas Point (a coastal neighborhood with mixed race and average income of less than 100K) reported 50% experienced property damage and 50% experienced no damage. This is also the only neighborhood that reported lack of car ownership by a respondent. Neighborhoods vary in their responses regarding their concerns about damages from hurricane and tropical storms (10 neighborhoods expressed concerns about power outages, 8 neighborhoods about water damages, 7 neighborhoods about wind damage, 6 neighborhoods expressed concerns about 2 or more issues). The neighborhood of Disston Heights, a noncoastal predominantly African American community (per census) with average household income of less than 100K reported hot weather as a concern. When analyzed for 'actions taken' noncoastal communities reported selection of 'pack up and leave' and finding alternative routes over coastal communities. Perhaps this could be attributed to the anxious and prepared nature of the residents than biophysical risk or mandatory evacuation order and this needs further investigation. Noncoastal neighborhoods with income of ~75K or lower also reported more frequently that they would call upon their neighbors for assistance. This is a similar finding we noted in Johns et al. (2020).

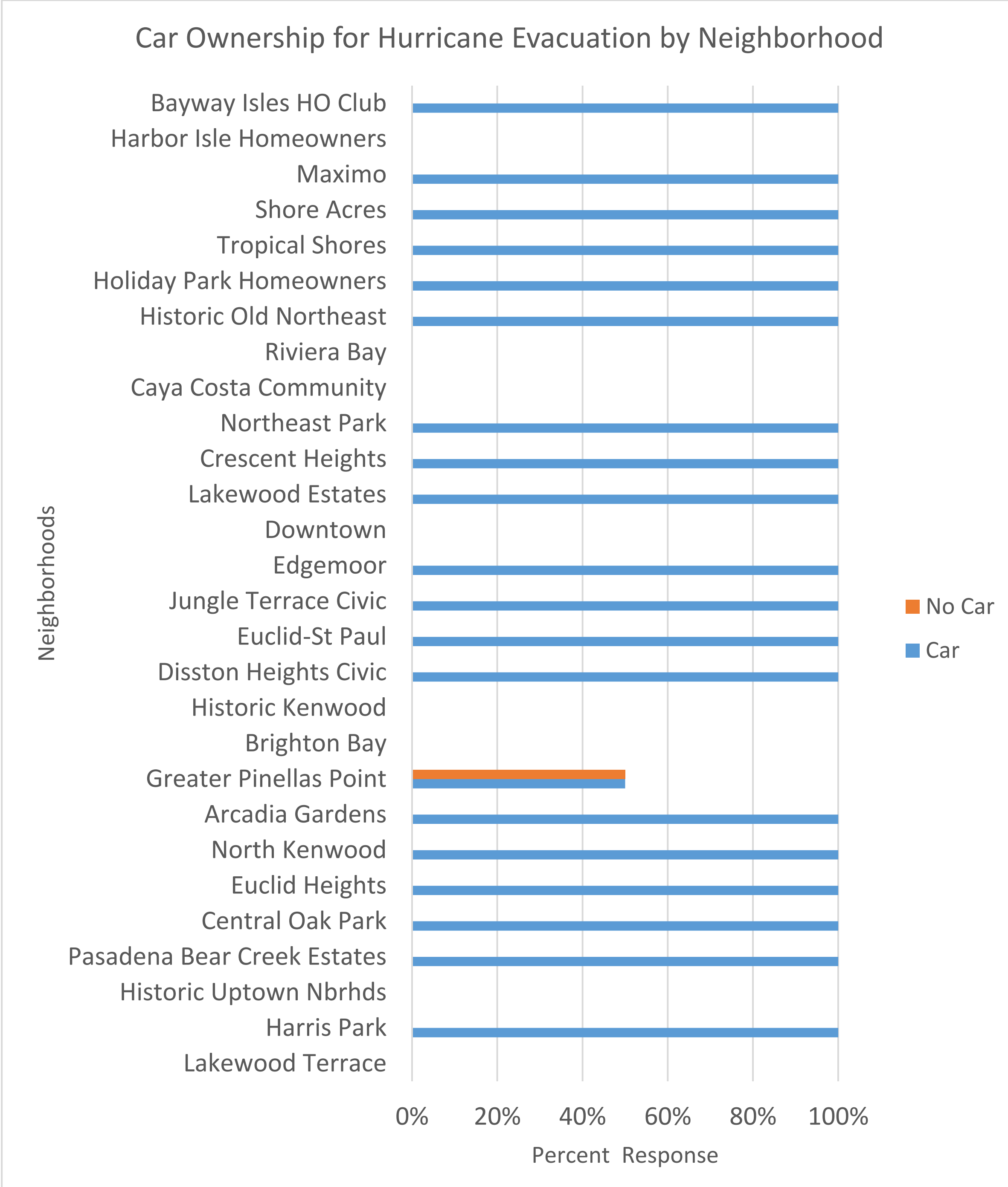
Summary of Overall Responses for Selected Survey questions by Neighborhood (Figure 15)



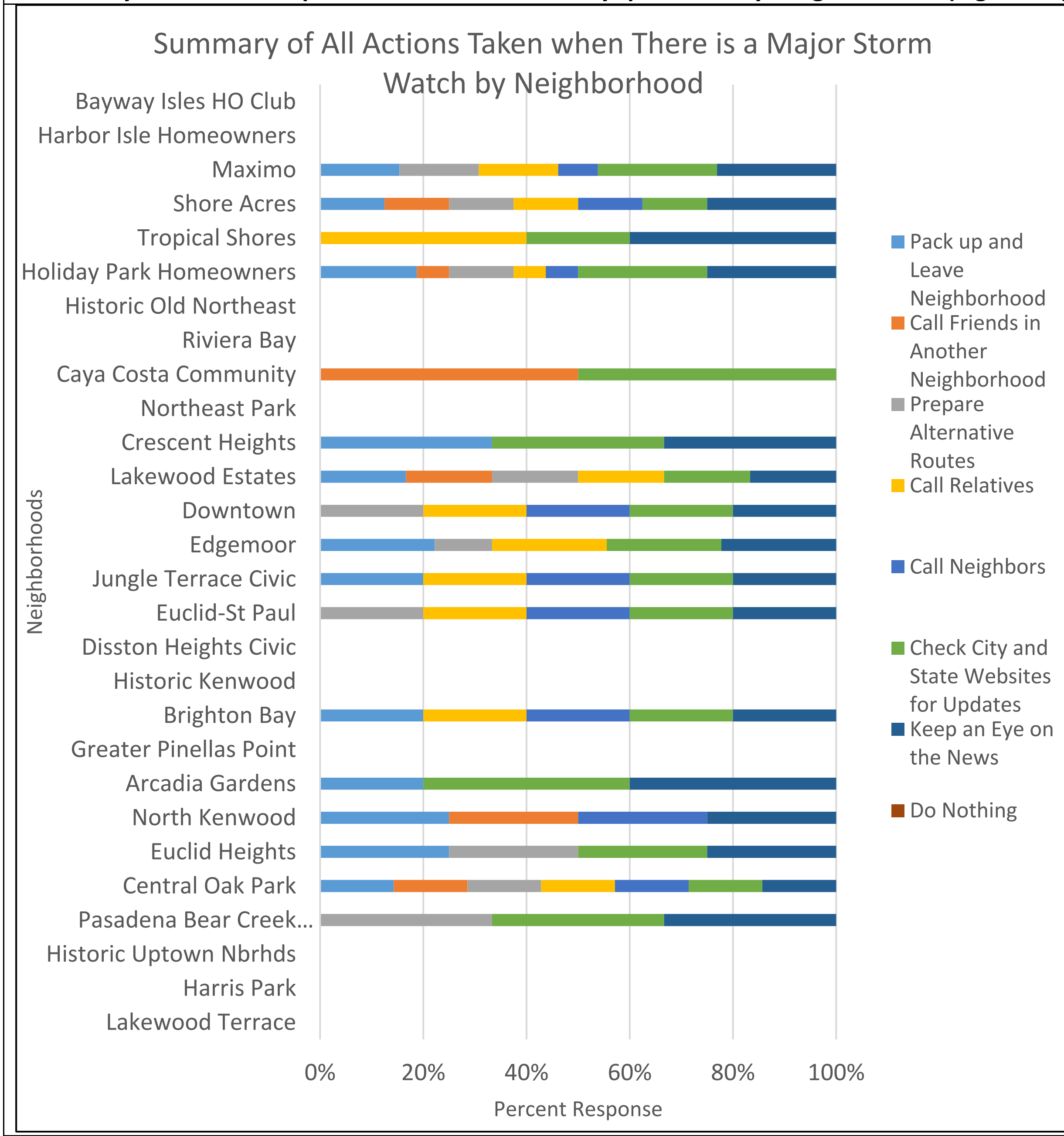
Summary of Overall Responses for Selected Survey questions by Neighborhood (Figure 15)



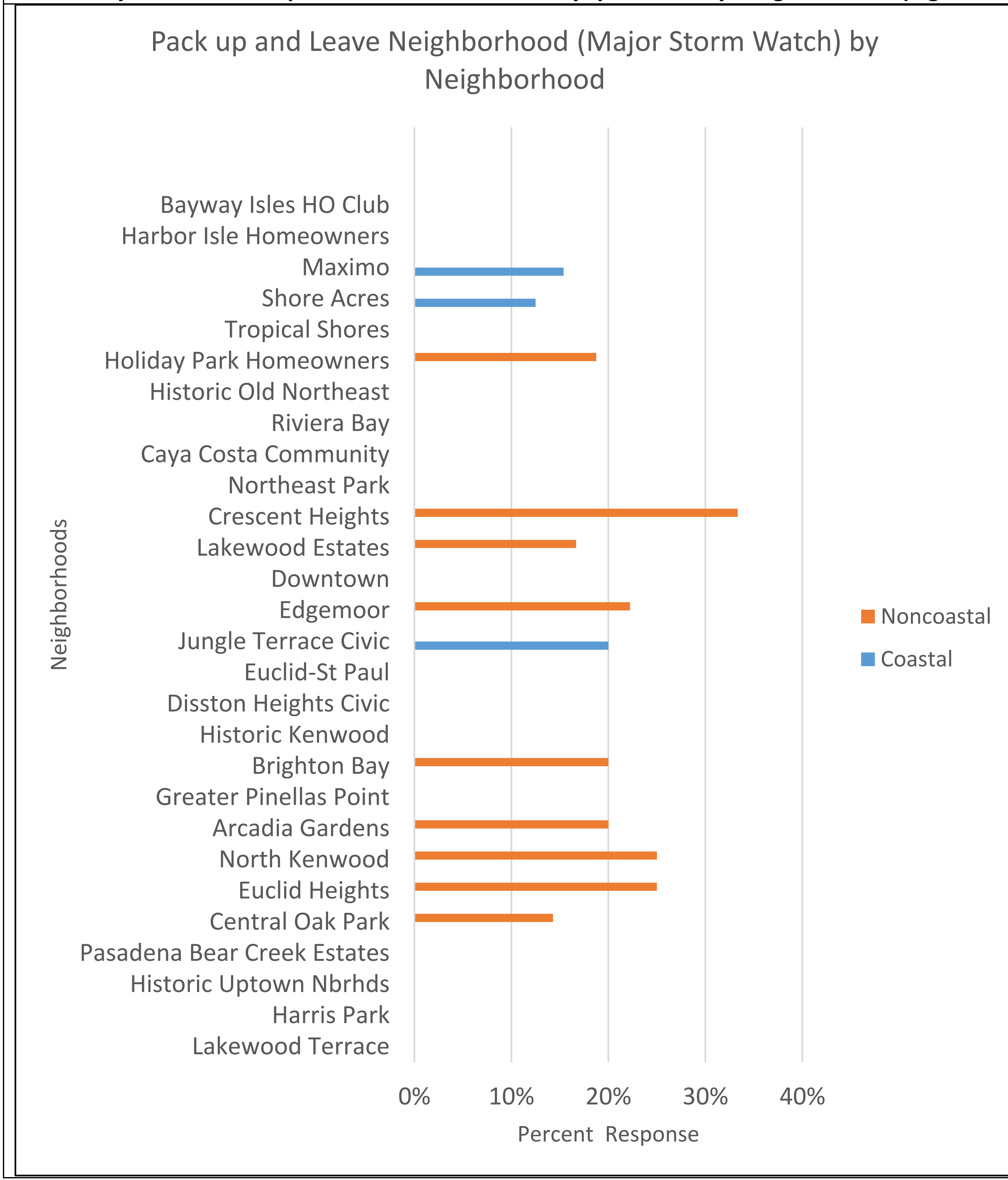
Summary of Overall Responses for Selected Survey questions by Neighborhood (Figure 15)



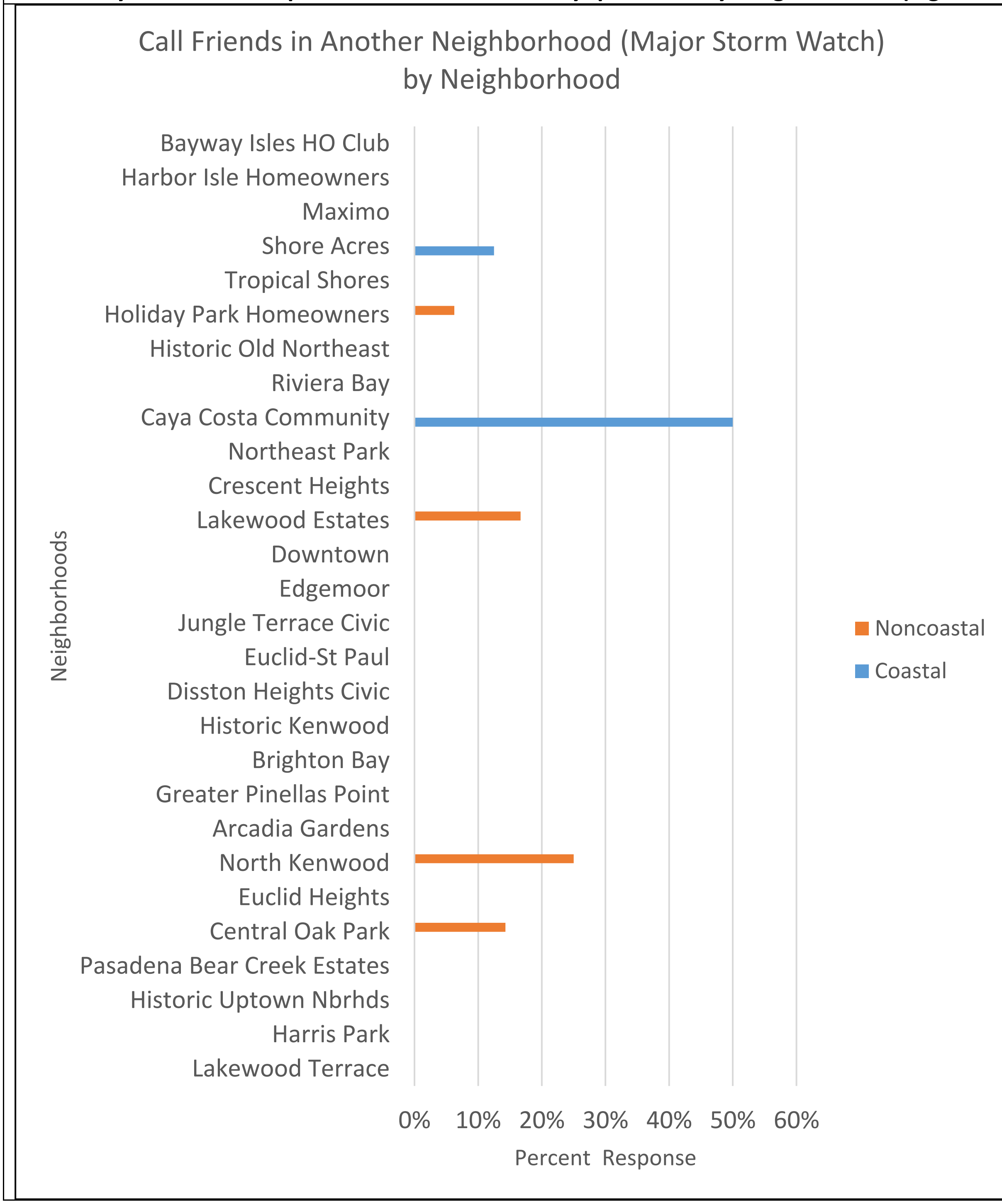
Summary of Overall Responses for Selected Survey questions by Neighborhood (Figure 15)



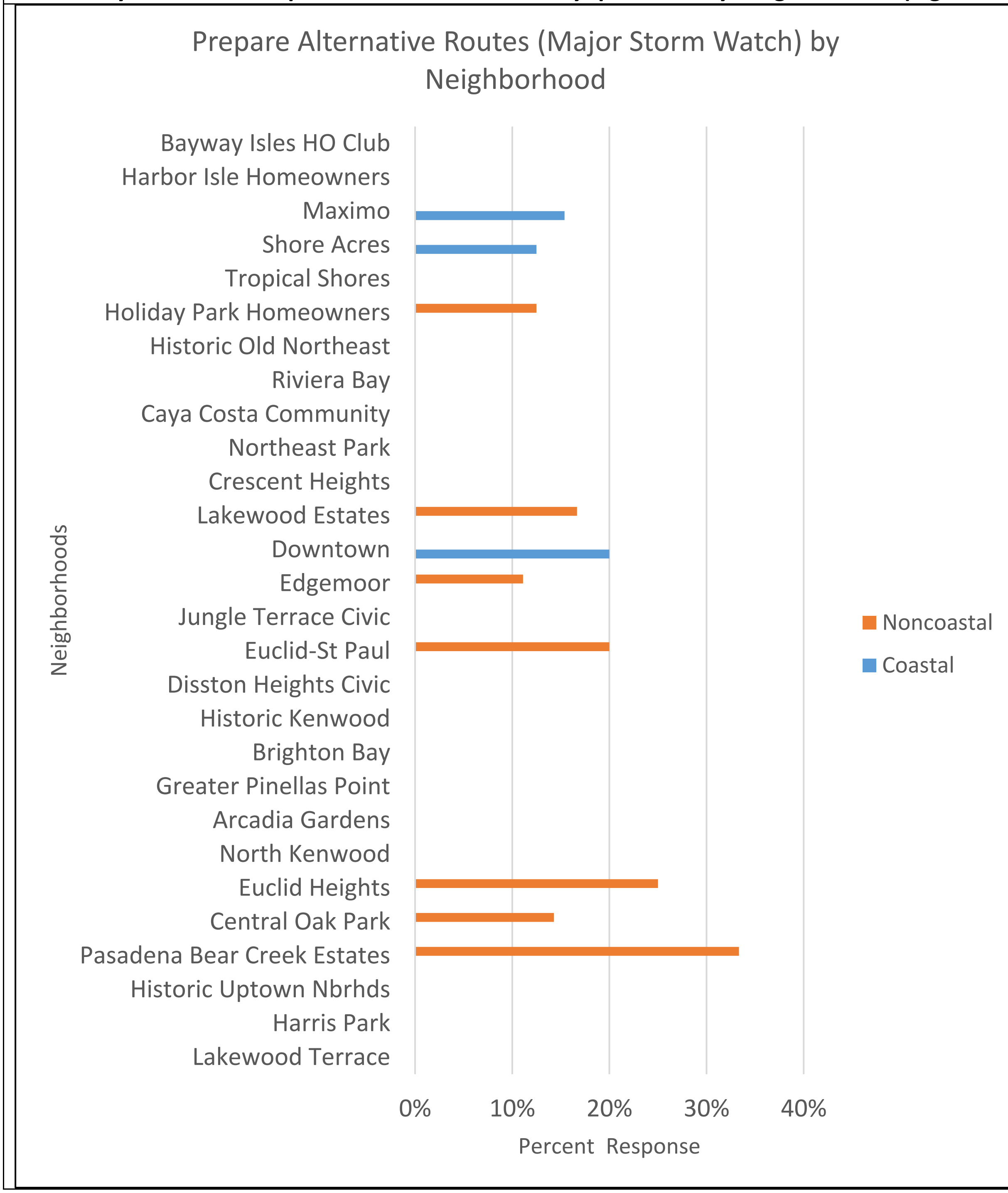
Summary of Overall Responses for Selected Survey questions by Neighborhood (Figure 15)



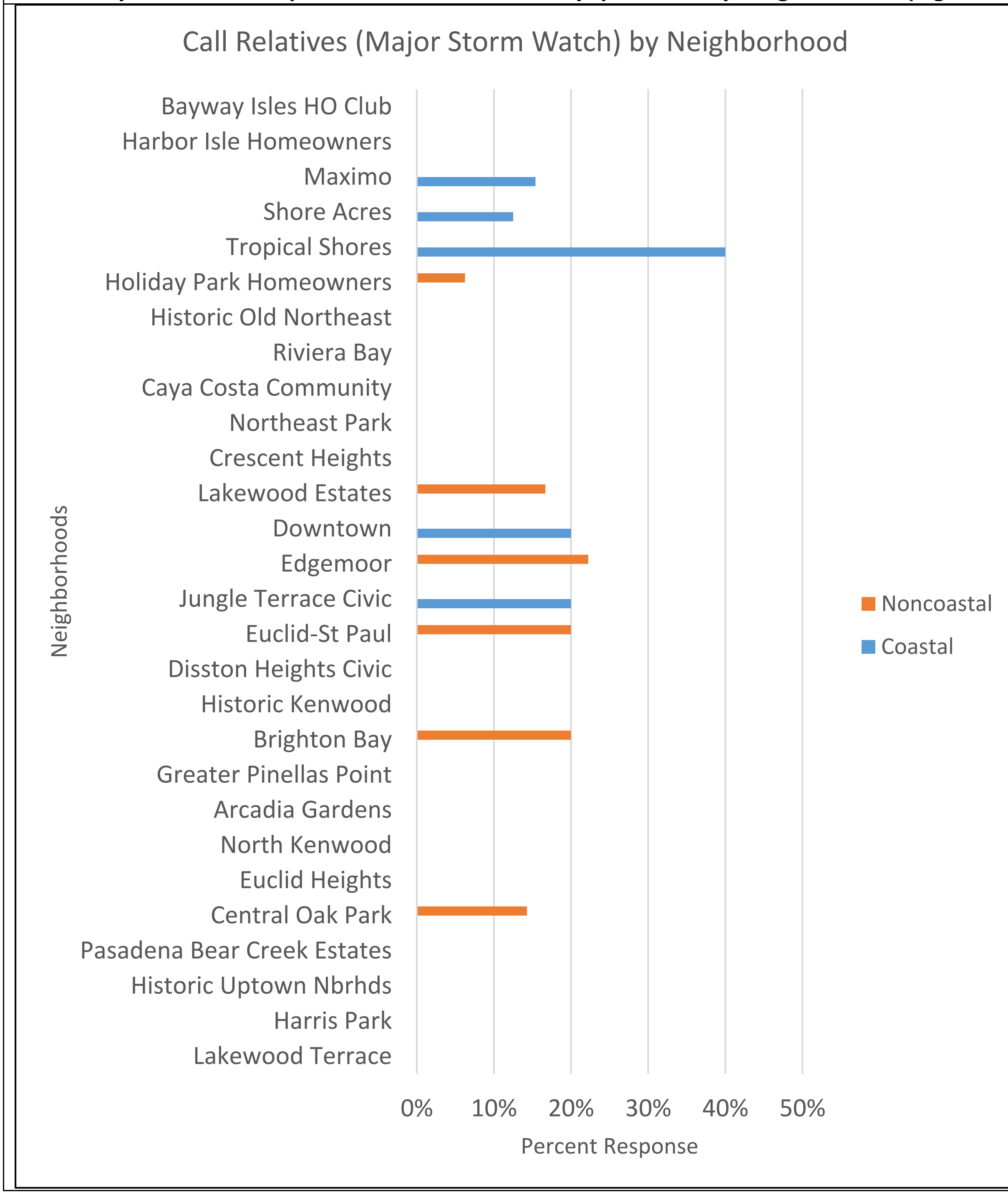
Summary of Overall Responses for Selected Survey questions by Neighborhood (Figure 15)



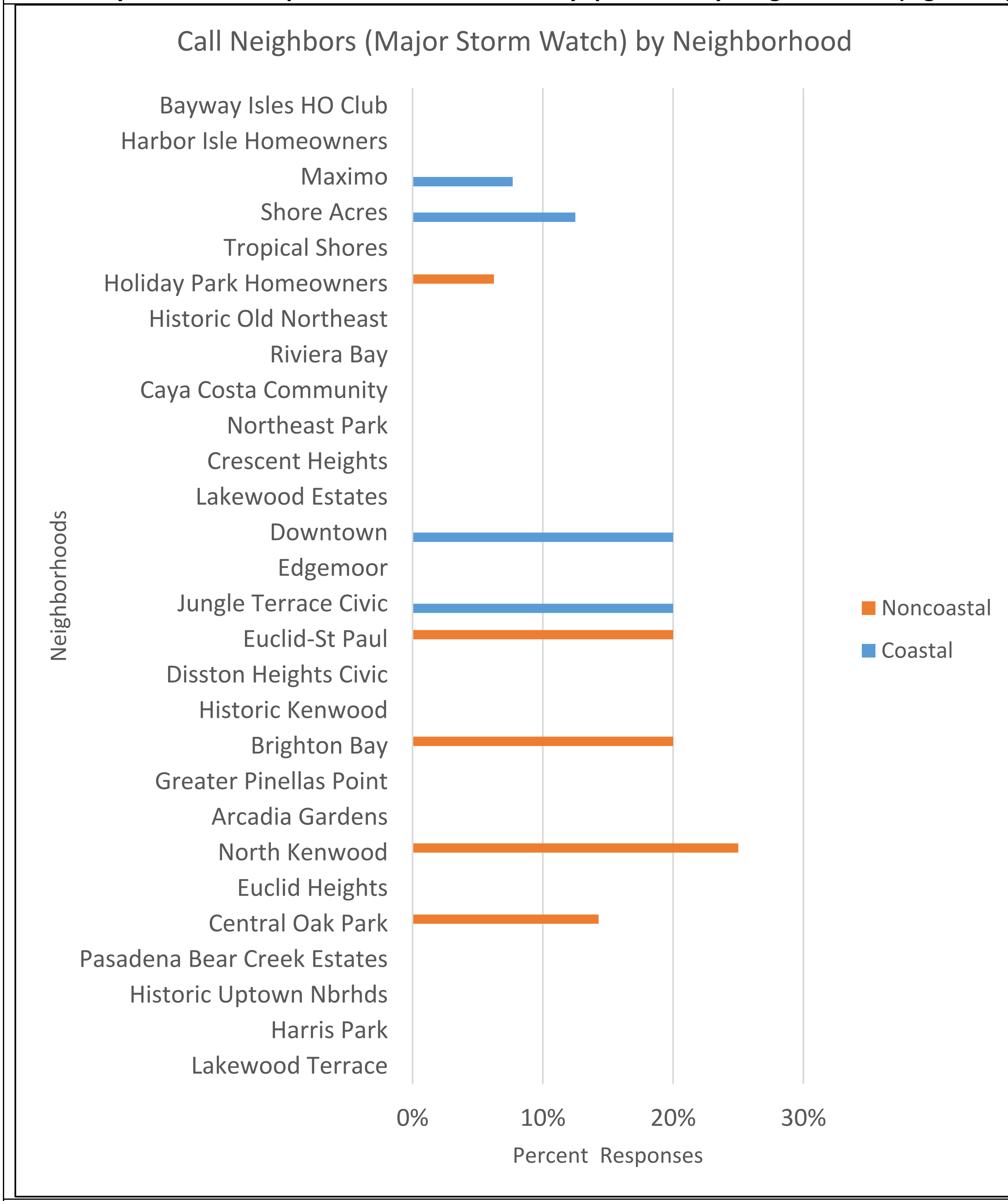
Summary of Overall Responses for Selected Survey questions by Neighborhood (Figure 15)



Summary of Overall Responses for Selected Survey questions by Neighborhood (Figure 15)



Summary of Overall Responses for Selected Survey questions by Neighborhood (Figure 15)



Summary of Overall Responses for Selected Survey questions by Neighborhood (Figure 15)

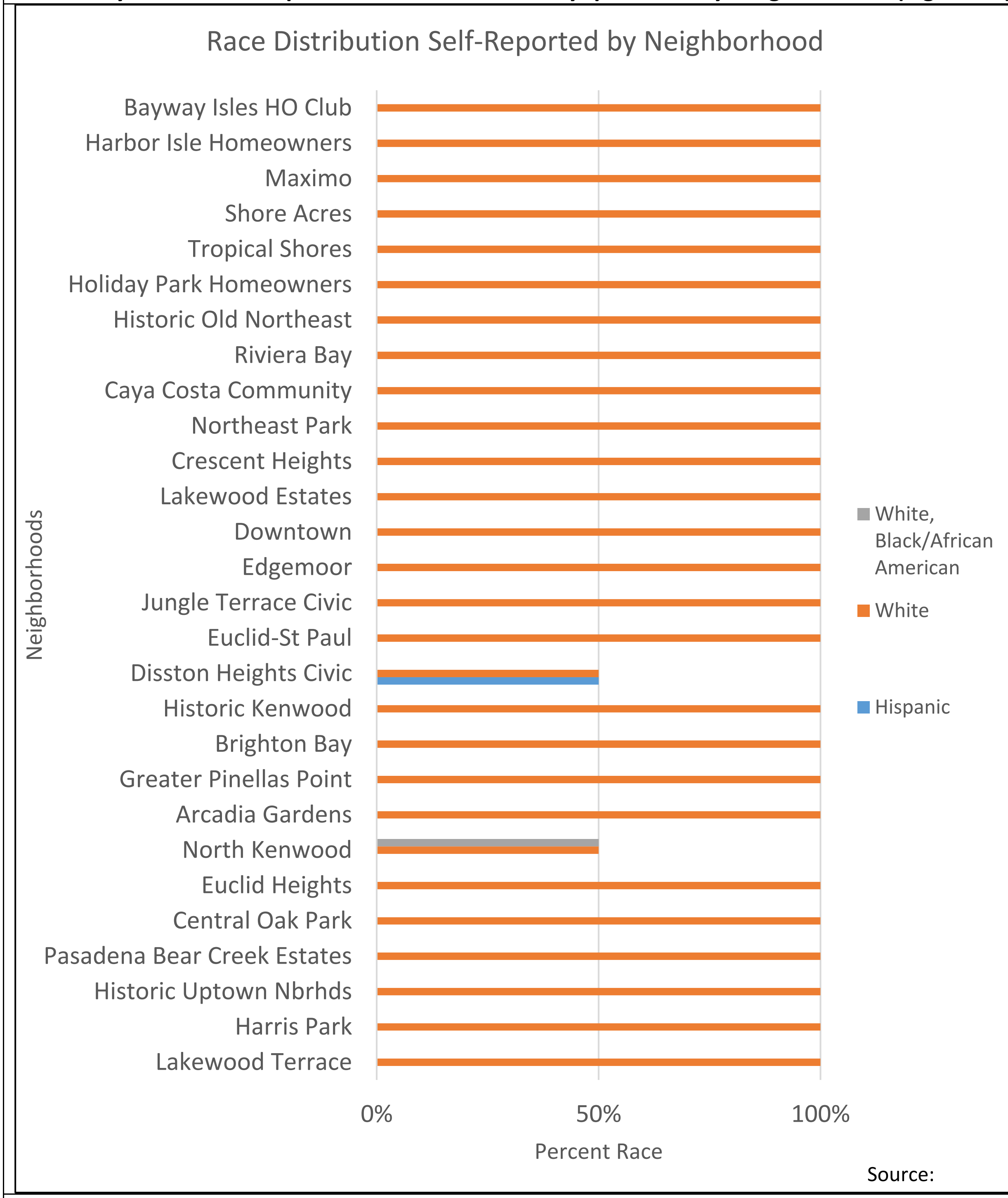


Figure 15. Summary of overall responses for selected survey questions by neighborhood n=78

5. Conclusions:

Analysis of the pilot data clearly indicates the potential usefulness of CRIS in assisting residents in conveying their unique concerns and in providing emergency planners with critical information about residents' needs. Identifying households where residents have special needs or disabilities is a key strength of CRIS. As more data is collected, researchers will be able to provide maps and ongoing reports to government officials about hot spots of special needs in the community to enhance planning for disaster preparation and response. Combining this specific neighborhood data with ANL data on flood risk and patterns of environmental justice provides planners with a detailed understanding of geographically specific risks and needs.

CRIS also helps identify the level of self-reported preparedness for disasters. Emergency planners in St. Petersburg are concerned about a false sense of security in the community; it may be the case that some residents are overestimating their ability to respond and recover from a hurricane – particularly a direct hit. This concern is amplified by the high percentage of people who do not know which government office to reach out to for assistance. CRIS data thus indicates a need to improve communication between residents and local officials about the avenues for assistance following a disaster.

The bias in the data toward coastal and more affluent neighborhoods was expected but needs to be addressed through alternative outreach tactics. The best approach for gaining trust and increasing the use of this digital tool will be through partnerships with leaders and community organizers in the Black community. Funds to train local leaders and work with respected individuals in the Black community to promote the use of CRIS are needed and will be actively pursued by the research team.

Analysis of the pilot data clearly indicates the usefulness of CRIS in combining geographically specific data about household needs with larger scale flood and environmental risk patterns. Aggregation of the data, with continual updates from residents, provides government officials with a detailed portrait of hot spots of concern around specific characteristics, such as disability, health threats from potential power loss, preparedness and community response to evacuation orders. As CRIS becomes more widely used, residents will see the fulfillment of a feedback loop as emergency responders and government planners are aware of the specific needs of neighborhoods and better able to provide required resources.

6. References:

Dixon B. and R. Johns. 2019. Vision for a Holistic Smart City (HSC)- Integrating Resiliency Framework via Crowdsourced Community Resiliency Information System (CRIS). ACM ISBN 978-1-4503-6954-1/19/11 https://doi.org/10.1145/3356395.3365541

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Johns, R. A. Dixon, B and R. Pontes. 2020. Tale of Two Neighborhoods: Biophysical and Socio-Economic Vulnerability to Climate Change in Pinellas County, Florida. Local Environment: the International Journal of Justice and Sustainability. 25(9): 697-924. https://doi.org/10.1080/13549839.2020.1825356

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Appendix A: Data Sources for CRIS

Summary of data sources using in biophysical (Table A1), socioeconomic (Table A2) and environmental (Table A3) modules of CRIS.

Table A1-. Sources of Data used for Mapping Biophysical vulnerability within CRIS

Storm Surge Data	Storm surge (SLOSH Model results) Inundation Data for Storms (Cat 1- 5).	https://www.nhc.noaa.gov/nationalsurge/
Sea Level Rise	Sea level rise and inundation	https://coast.noaa.gov/slrdata
Flood Potential Map	FEMA's National Flood Hazard Layer	https://hazards.fema.gov/gis/nfhl/services

Table A2: Census Data Sources for socioeconomic module[1]

Feature Layer/Shape file	Name	TableID	Survey	Product	Census level	URL
Percent under 18	Sex by age	B01001	American Community Survey	2018: ACS 5-Year Estmates Data	Block-Group	https://data.census.gov/cedsci/map?q=B01001&g=0500000US12103.150000 &tid=ACSDT5Y2019.B01001 &vintage=2019 &layer=VT_2019_150_00_PY_D1 &cid=B01001_001E&mode=thematic
Percent over 65	Sex by age	B01001	American Community Survey	2018: ACS 5-Year Estmates Data	Block-Group	https://data.census.gov/cedsci/map?q=B01001&g=0500000US12103.150000 &tid=ACSDT5Y2019.B01001 &vintage=2019 &layer=VT_2019_150_00_PY_D1 &cid=B01001_001E&mode=thematic
Percent renter	Household type by tenure	B11012	American Community Survey	2014: ACS 5-Year Estmates Data	Block-Group	https://data.census.gov/cedsci/map?q=B11012&g=0500000US12103.150000&tid=ACSDT5Y2019.B11012&vintage=2019&layer=VT_2019_150_00_PY_D1&cid=B11012_001E&mode=thematic

[1] American Community Survey Data (census.gov)

Percent owner	Household type by tenure	B11012	American Community Survey	2014: ACS 5-Year Estmates Data	Block-Group	https://data.census.gov/cedsci/map?q=B11012&g=0500000US12103.150000&tid=ACSDT5Y2019.B11012&vintage=2019&layer=VT_2019_150_00_PY_D1&cid=B11012_001E&mode=thematic
ACS 2018 SNAP w food stamps	From ESRI	From ESRI	From ESRI	From ESRI	From ESRI	https://livingatlas.arcgis.com/en/browse/#d=2&q=current%20year%20American%20Community%20Survey%20owner%3Aesri_demographics&type=layers
Hispanic	Race	B02001	American Community Survey	2018: ACS 5-Year Estmates Data	Block-Group	https://data.census.gov/cedsci/map?q=B02001&g=0500000US12103.150000&tid=ACSDT5Y2019.B02001&vintage=2019&layer=VT_2019_150_00_PY_D1&cid=B02001_001E&mode=thematic
Native Hawaiian and other Pacific Islander	Race	B02001	American Community Survey	2018: ACS 5-Year Estmates Data	Block-Group	https://data.census.gov/cedsci/map?q=B02001&g=0500000US12103.150000&tid=ACSDT5Y2019.B02001&vintage=2019&layer=VT_2019_150_00_PY_D1&cid=B02001_001E&mode=thematic
Asian	Race	B02001	American Community Survey	2018: ACS 5-Year Estmates Data	Block-Group	https://data.census.gov/cedsci/map?q=B02001&g=0500000US12103.150000&tid=ACSDT5Y2019.B02001&vintage=2019&layer=V

						T_2019_150_00_PY_D1&cid=B02001_001E&mode=thematic
American Indian and Alaska Native	Race	B02001	American Community Survey	2018: ACS 5-Year Estmates Data	Block-Group	https://data.census.gov/cedsci/map?q=B02001&g=0500000US12103.150000&tid=ACSDT5Y2019.B02001&vintage=2019&layer=VT_2019_150_00_PY_D1&cid=B02001_001E&mode=thematic
White	Race	B02001	American Community Survey	2018: ACS 5-Year Estmates Data	Block-Group	https://data.census.gov/cedsci/map?q=B02001&g=0500000US12103.150000&tid=ACSDT5Y2019.B02001&vintage=2019&layer=VT_2019_150_00_PY_D1&cid=B02001_001E&mode=thematic
African American	Race	B02001	American Community Survey	2018: ACS 5-Year Estmates Data	Block-Group	https://data.census.gov/cedsci/map?q=B02001&g=0500000US12103.150000&tid=ACSDT5Y2019.B02001&vintage=2019&layer=VT_2019_150_00_PY_D1&cid=B02001_001E&mode=thematic
Below poverty with disability	Poverty status in the past 12 months by disability status by employment status for the population 20 to 64 years	B23024	American Community Survey	2018: ACS 5-Year Estmates Data	Block-Group	https://data.census.gov/cedsci/map?q=B23024&g=0500000US12103.150000&tid=ACSDT5Y2019.B23024&vintage=2019&layer=VT_2019_150_00_PY_D1&cid=B23024_001E&mode=thematic

Below poverty	Poverty status in the past 12 months by household type by age of householder	B17017	American Community Survey	2018: ACS 5-Year Estmates Data	Block-Group	https://data.census.gov/cedsci/map?q=B17017&g=0500000US12103.150000&tid=ACSDT5Y2019.B17017&vintage=2019&layer=VT_2019_150_00_PY_D1&cid=B17017_001E&mode=thematic
Not in labor force	Employment status for the population 16 years and over	B23025	American Community Survey	2018: ACS 5-Year Estmates Data	Block-Group	https://data.census.gov/cedsci/map?q=B23025&g=0500000US12103.150000&tid=ACSDT5Y2019.B23025&vintage=2019&layer=VT_2019_150_00_PY_D1&cid=B23025_001E&mode=thematic
Unemployed	Employment status for the population 16 years and over	B23025	American Community Survey	2018: ACS 5-Year Estmates Data	Block-Group	https://data.census.gov/cedsci/map?q=B23025&g=0500000US12103.150000&tid=ACSDT5Y2019.B23025&vintage=2019&layer=VT_2019_150_00_PY_D1&cid=B23025_001E&mode=thematic
Employed	Employment status for the population 16 years and over	B23025	American Community Survey	2018: ACS 5-Year Estmates Data	Block-Group	https://data.census.gov/cedsci/map?q=B23025&g=0500000US12103.150000&tid=ACSDT5Y2019.B23025&vintage=2019&layer=VT_2019_150_00_PY_D1&cid=B23025_001E&mode=thematic
ESRI no high school	From ESRI	From ESRI	From ESRI	From ESRI	From ESRI	https://livingatlas.arcgis.com/en/browse/#d=2&q=current%20year%20American%20Community

diploma 2020						%20Survey%20owner%3Aesri_demographics&type=layers
Avg number vehicle per household ACS 2018	From ESRI	From ESRI	From ESRI	From ESRI	From ESRI	https://livingatlas.arcgis.com/en/browse/#d=2&q=current%20year%20American%20Community%20Survey%20owner%3Aesri_demographics&type=layers
Avg household income 2020	Household income in the past 12 months (in 2018 inflation-adjusted dollars)	B19001	American Community Survey	2018: ACS 5-Year Estmates Data	Block-Group	https://data.census.gov/cedsci/map?q=B19001&g=0500000US12103.150000&tid=ACSDT5Y2019.B19001&vintage=2019&layer=VT_2019_150_00_PY_D1&cid=B19001_001E&mode=thematic
neighborhood with population	ACS demographic and housing estimates	B01003	American Community Survey	2018: ACS 5-Year Estmates Data	Block-Group	https://data.census.gov/cedsci/map?q=B19001&g=0500000US12103.150000&tid=ACSDT5Y2019.B19001&vintage=2019&layer=VT_2019_150_00_PY_D1&cid=B19001_001E&mode=thematic

Table A3. Description of EJ Indicator variables obtained from EPA[2]

The description of each environmental indicator description can be found below.
• Air Toxics Cancer Risk (NATA Cancer Risk) – The risk of cancer from inhalation of air toxics if calculated by per lifetime per one million people by the EPA.
• Air Toxics Respiratory Hazard Index (NATA Respiratory HI) – This is the sum of hazardous air toxics with respiratory endpoints. The Index is then a ratio of exposure to toxics in air and to the EPA's reference of healthy air.
• Diesel Particulate Matter level in air (NATA Diesel PM) – this calculated by measuring the amount of diesel matter in the air by micrograms per cubic meter (µg/m3) by the EPA.
• Ozone level in air – this is the summer seasonal average of daily maximums 8 hour concentrations of ozone in the air by parts per billion.
• PM2.5 level in air – PM2.5 is particular matter in the air that a diameter of 2.5 micrometers or smaller. The levels in the air are measured annually at micrograms per cubic meters (µg/m3).
• Traffic Proximity and Volume – this is calculated by the count of vehicles per day at major roads within 500 meters and divided by distance in meters by the U.S. department of transportation
• Lead Paint Indicator (% pre-1960 housing) – this is the percent of housing units built before 1960 for a potential estimate. Calculated by the U.S. Census Bureau.
• Proximity National Priority List Sites (NPL) – National priority list sites are areas where there are known or threatened releases of hazardous materials. This is calculated by number of sites within 5 km divided by distance in km.
• Proximity to Risk Management Plan (RMP) Facilities – these are facilities that have risk management plans because they work with certain hazardous materials. This is calculated by areas within 5 km and divided by distance in km.
• Proximity to Treatment Storage and Disposal Facilities (TSDF) (Hazardous Waste Proximity) – this is calculated by TSDF's within 5 km and divided by distance in km.
• Wastewater Dischargers Indicator (Stream Proximity and Toxic Concentration) – using the EPA's Risk-Screening Environmental Indicators model to measure concentrations of toxics in stream segments within 500 meters and divided by distance in meters.

[2] EPA (2020). Glossary of EJSCREEN terms. Retrieved from https://www.epa.gov/ejscreen/glossary-ejscreen-terms

Appendix B: CRIS System Architecture

CRIS runs on three virtual servers are running in a VMware vSphere 6.7.0 environment consisting of three ESXi hosts and a NetApp SAN system. Servers are being replicated via SAN replication and vSphere replication to two locations. Table B1 Summarizes System Architecture.

Table B1. Summary of System Architecture used with CRIS

Virtual machine 1
• crisae.stpt.usf.edu
• 2 CPU
• 12GB Ram
• 60GB System Drive
• 100GB Data
• Windows 2019 Server
• ArcGIS Enterprise 10.8 Portal and Server
Virtual machine 2
• crisds.stpt.usf.edu
• 2 CPU
• 8GB Ram
• 40GB System Drive
• 100GB Data
• Windows 2019 Server
• ArcGIS Enterprise 10.8 Data Store
Virtual machine 3
• crismdb.stpt.usf.edu
• 2 CPU
• 8GB Ram
• 500GB Data
• CentOS Linux 8.2.2004
• MongoDB 4.2.8 Community
• Python 3.7.6
ArcGIS cloud based services
• Survey 123 Connect - 3.9.120