Equity-Centered Emergency Management Dashboard

Research Findings & Recommendations for BakerRipley

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July 2025

Introduction

Harris County faces compounding disaster risks - not only from the physical impacts of hurricanes and riverine flooding, which the National Risk Index identifies as having “very high expected asset loss rates,” but also from the unequal recovery trajectories that follow such events (FEMA, 2021). Households in historically marginalized communities are often displaced longer, receive less financial assistance, and experience greater long-term wealth loss, reflecting how recovery processes can reproduce and deepen existing social inequities (Howell and Elliot, 2019). BakerRipley, a nonprofit organization that serves all of Houston, wants to improve their efforts to properly allocate resources before, during, and after disasters for socially vulnerable populations in the Houston area. The goal is to lessen the impact of disasters to continue a cycle that deepens existing social inequities. This report supports BakerRipley’s goals by defining key criteria for disaster resource allocation and offering recommendations for an equity-centered data dashboard.

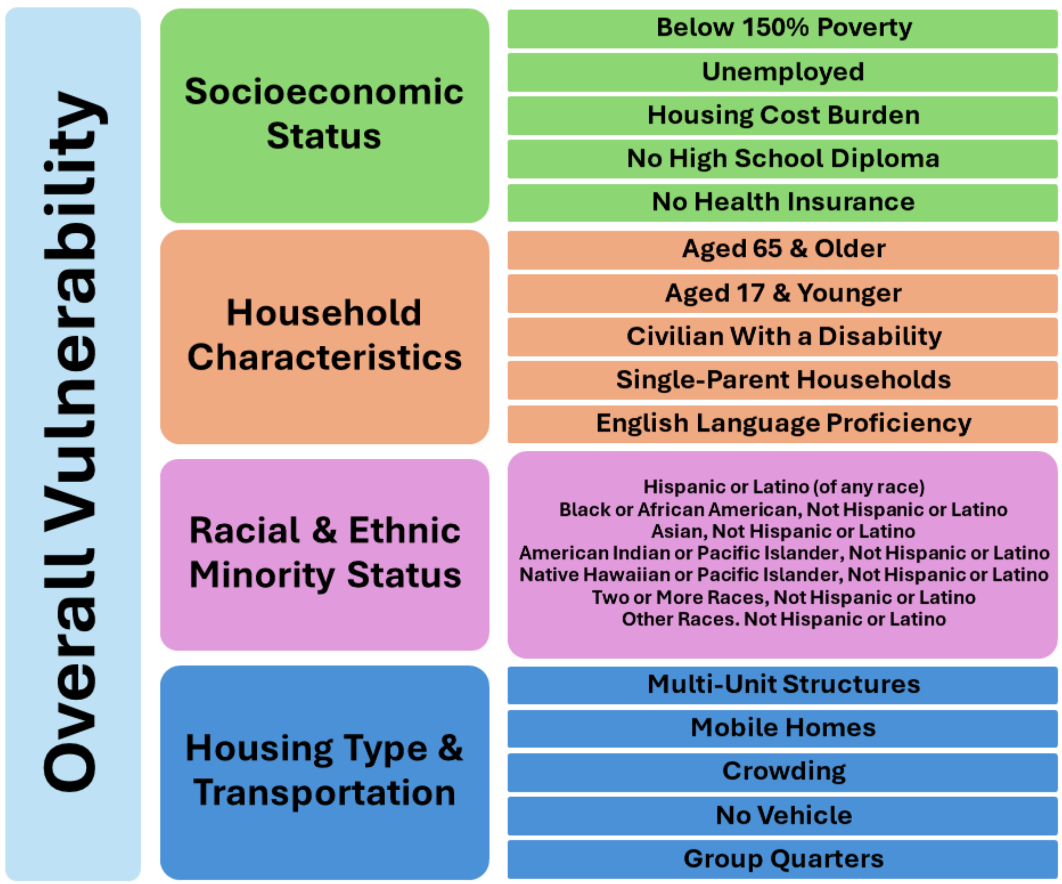
Defining and Measuring Risk, Vulnerability, and Preparedness

“Risk” refers to the potential for loss or damage resulting from natural hazards, typically measured by the Expected Annual Loss (EAL), which incorporates hazard frequency, exposure, and property value, as demonstrated in FEMA’s National Risk Index (FEMA, 2025). “Vulnerability” describes the social and economic conditions that make certain populations more susceptible to harm, most often measured using indices like the CDC’s Social Vulnerability Index (SVI) (CDC/ATSDR, 2023). “Preparedness” reflects the ability of individuals and communities to anticipate, respond to, and recover from disasters, assessed through factors like household readiness, mitigation behaviors, and institutional support systems (Shubandrio et al., 2022). For BakerRipley, understanding these dimensions allows for the identification of neighborhoods facing overlapping hazards (risk) and social stressors (vulnerability), while also measuring gaps in disaster readiness (preparedness). This integrated perspective supports more equitable resource allocation and outreach strategies in the Houston area.

Social Vulnerability Index

With definitions for risk, vulnerability, and preparedness in place BakerRipley requires measures to assess each. Multiple frameworks assess risk and vulnerability at varying scales. The social vulnerability index is built from socioeconomic and demographic data to measure vulnerability to environmental hazards (Cutter, 2003). Built following the work of Cutter et al, the CDC’s Social Vulnerability Index (SVI) provides tract-level insight into social disadvantage, or vulnerability (CDC/ATSDR, 2023). While Cutter’s index is a conceptual foundation, we recommend the CDC/ ATSDR Social Vulnerability Index for its interoperability with federal tools and ongoing institutional support. This makes it more practical for coordination and funding alignment in BakerRipley’s work. The current index has changed over the last few years but as of now it considers 16 US Census variables from the 5-year American Community Survey grouped into socioeconomic, household composition, minority status, and housing themes to identify communities that may need support before, during, and after disasters. The variables are grouped by theme to cover the four major areas of social vulnerability and combined into a single measure of overall vulnerability (Social Vulnerability) as shown in Figure 1 below. These four themes directly address BakerRipley's population prioritization requirements.

Figure 1: Social Vulnerability Index Variable Composition by Theme



Household composition variables (age, disability status, single-parent households) reveal populations requiring specialized assistance during emergencies. Minority status and language variables identify communities potentially excluded by language barriers in emergency communications. Housing and transportation variables indicate physical vulnerability to displacement and evacuation challenges. While this measure is robust for seeing who is vulnerable to disasters it does not incorporate hazard exposure or infrastructure resilience–key components to understanding risk.

FEMA National Disaster Risk Index

To address the gap in vulnerability and hazard exposure, we incorporated the Federal Emergency Management Agency's (FEMA) National Disaster Risk Index (NRI), which accounts for both hazard likelihood and community resilience. This risk index is created by taking into account a measure of Expected Annual Loss, or EAL, and multiplying it by a community risk factor as shown below. Expected Annual Loss (EAL), estimates the average dollar loss from 18 types of natural hazards by factoring in hazard frequency, community exposure (e.g., population, buildings, agriculture), and asset value. To contextualize EAL, FEMA's National Risk Index (NRI) multiplies this loss estimate by a Community Risk Factor, the ratio of a community's social vulnerability score to its community resilience. The risk index score is then calculated as:

Risk = EAL × (Social Vulnerability / Community Resilience)

This formulation reflects that two communities with similar hazard exposure may have different outcomes depending on social and institutional capacity. Tracking EAL in high risk zones would allow BakerRipley to monitor tracts with high loss rates that have received aid or preparedness materials and distinguish from those that have not received aid.

Preparedness Indicators

While measures of vulnerability and risk help identify communities likely to be hit hardest by disasters they do not reflect how prepared said communities are. Preparedness reflects the capacity to anticipate, respond to, and recover from disasters. While not directly measured by FEMA or the CDC, BRIC scores (Baseline Resilience Indicators for Communities) estimate community resilience across six domains: social, economic, institutional, infrastructure, community capital, and environmental. Developed by the Hazards and Vulnerability Research Institute (HVRI), BRIC scores are calculated at the county level using publicly available data sources and normalized for comparative analysis. BRIC scores enable BakerRipley's dashboard to differentiate between communities with high disaster exposure and those with additional resilience capacity limitations. This highlights where recovery capacity is limited, especially in high-exposure counties, and this differentiation is critical for resource allocation decisions, as communities with both high exposure and low resilience require more intensive and sustained intervention strategies.

To further refine preparedness insights, we also reference the Power Outage Risk Social Vulnerability Index (PO-RSVI), which links blackout frequency and duration with social vulnerability profiles. While currently limited in geographic scope, it offers valuable energy-specific insights relevant to medically vulnerable and low-income populations. By integrating SVI (vulnerability), NRI and EAL (risk), and BRIC (preparedness), BakerRipley can spatially identify neighborhoods at the tract level with both high exposure and low adaptive capacity–guiding resource prioritization and dashboard design. This multidimensional approach ensures that disaster response strategies reflect both physical hazard severity and the underlying social conditions that shape recovery outcomes.

Criteria for Resource Allocation

To operationalize BakerRipley's emergency management dashboard and ensure equitable allocation of resources, we have developed a set of core criteria based on an environmental scan of current disaster response tools, a review of available and missing data, and guidance from relevant literature. Each criterion reflects a critical aspect of disaster preparedness and vulnerability assessment, drawing upon validated metrics from sources such as FEMA, the CDC, and academic studies. These criteria were selected to help BakerRipley prioritize populations most at risk during disasters based on demographic factors, event exposure, energy dependence, and socioeconomic vulnerability. The core criteria should make up the basis for a dashboard BakerRipley can use to identify and prioritize populations in need. Table 1 below details each criterion, providing clearly defined variables or proxies, the data sources used, as well as their justification based on existing research. Additionally, the strengths and potential limitations of each measure are included to support transparency and informed decision-making.

Table 1: BakerRipley Disaster Dashboard Core Criteria

CRITERION	VARIABLE/ PROXY	DATA SOURCE	JUSTIFICATION	STRENGTHS	LIMITATIONS
Flood Risk Exposure	% of tract within 100/500-year floodplain	FEMA FIRMS; City of Houston Floodplain	Direct Measure of physical hazard aligned with Houston's disaster exposure	High spatial accuracy; FEMA-aligned	May not capture future climate-adjusted risk
Energy Vulnerability	% of seniors in areas with low rates of income & educational attainment	ACS 2023	Proxy for electricity-dependent seniors (Ezzati et al)	Cross-validates infrastructure and social risk	May not capture all energy vulnerable seniors
Communication Capacity	% of households without internet	ACS 2023	Proxy for digital divide and early warning limitation (Ezzati et al, CDC ASTDR)	Tract-level, updated annually	Doesn't capture mobile/shared access
Socioeconomic Vulnerability	% below poverty, % unemployed, % uninsured	ACS 2023; CDC SVI	Limited Financial Resilience and access to recovery resources (Cutter et al)	Federally standardized	Excludes undocumented/ informal labor
Digital Sentiment Risk	Spikes in distress keywords on social media	Google Trends; Twitter API; Nextdoor	Real-time proxy for community distress signal (Guo et al)	Low-cost early insight	Underrepresents older populations; live data only

Drainage Infrastructure Vulnerability	Drainage complaints; drainage capacity & siltation data	311 data; City of Houston Public Works	Poor drainage increases flood severity (Liu et al)	Supported by predictive flood models; locally actionable	Data coverage varies; modeling requires map layer data rather than raw data

Equity-Centered Emergency Management: Integrating Predictive Technology, Community Action, and Social Vulnerability

Predictive technologies, social vulnerability data, and community-based approaches can be leveraged to improve disaster preparedness and response. Drawing on interdisciplinary research from environmental justice, public health, existing vulnerability and risk dashboards, and urban planning, we highlight strategies for integrating technical innovation with a critical understanding of local context. The goal is to support emergency management practices that are not only more effective, but also more just.

Disparities in Disaster Recovery and Aid Access

In Flood Recovery Outcomes and Disaster Assistance Barriers for Vulnerable Populations, it is noted that consistent disparities exist in post-disaster recovery, particularly with access to funding and the exclusion of impoverished communities from traditional assistance pipelines. Research has increasingly shown that federal recovery programs such as FEMA's Individual Assistance (IA), the National Flood Insurance Program (NFIP), Small Business Administration disaster loans, and Housing and Urban Development CDBG-DR often fail to equally serve vulnerable communities. 'Flood Recovery' showed that analyses of post-disaster funding following events like Hurricanes Katrina, Rita, and Wilma had visible disproportions; for example, 'only 18% of damaged rental units received aid compared to 62% of damaged homeowner units' (GAO, 2010). Additionally, low-income households may experience less physical damage but suffer greater relative economic loss due to limited pre-disaster financial resilience (such as flood insurance). Complex application processes, insufficient documentation, and general discouragement often prevent these populations from applying for assistance. Thus, funding programs tend to favor wealthier or more formally documented applicants, leaving vulnerable groups under-supported in recovery efforts.

The study titled "Association of U.S. Household Disaster Preparedness With Socioeconomic Characteristics, Composition, and Region" delves into how socioeconomic factors and regional contexts influence household preparedness across the United States. By utilizing three logistic regression models: 'overall,' 'resource-based,' and 'action-based' preparedness, it identifies disparities in how different groups prepare for disasters. While the study highlights the importance of 'culturally tailored messaging' and targeted outreach to improve disaster readiness in diverse communities, it is limited by potential response bias, an overrepresentation of households with children, and a lack of longitudinal data.

To localize these insights, we draw on a study of Hurricane Harvey's impact on Greater Houston households, which examines how socioeconomic disparities shape preparedness and disaster outcomes (Grineski, 2020). We found that households with higher property values and longer residency were more likely to implement structural mitigation measures such as installing drainage systems, elevating utilities, or adding hurricane shutters, regardless of their actual risk level. While the research promotes self-sufficiency by offering clear examples of mitigation strategies and detailing the survey methodology and variables used when conducting the research, its findings are limited by a modest response rate to pre and post-disaster surveys, with only 57% of contacted participants completing the survey, which may impact the generalizability of results.

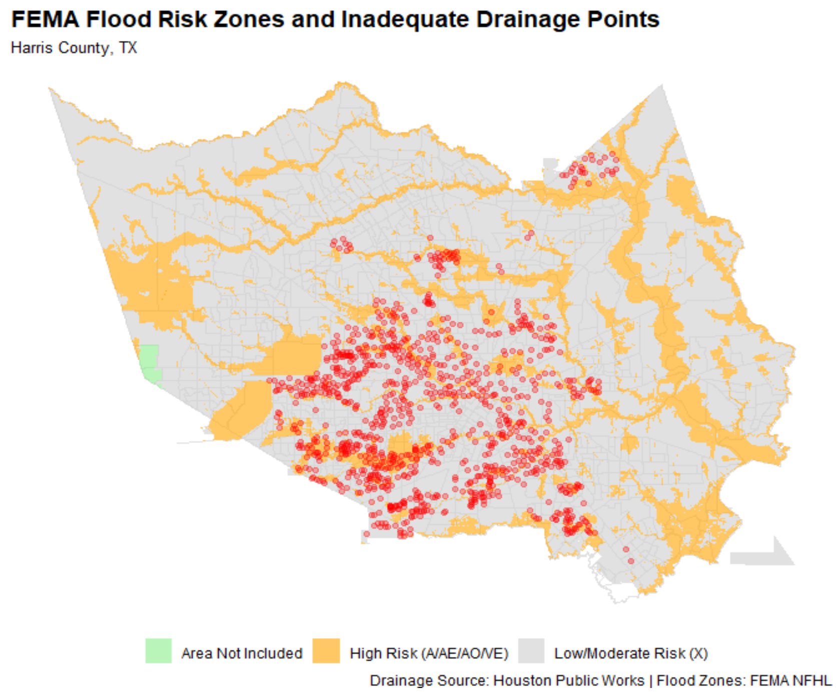
Enhancing Preparedness Through Resilience Metrics and Risk Indexes

For long-term preparedness and recovery, robust pre-disaster assessments are essential. The RESCUE project (Cardoso et al., 2020) outlines methods for measuring urban resilience but notes that much of the data used remains qualitative and fragmented. Similarly, Shubandrio et al. (2022) and Mukherjee et al. (2023) critique the limited geographic and quantitative scope of many existing resilience studies. Together, these findings point to a critical need for more comprehensive, spatially detailed datasets. For BakerRipley, this means investing in planning tools that integrate both historical flood risk data and community-level vulnerability indicators–such as age, gender, income, and health–to more effectively serve at-risk Houston neighborhoods before disaster strikes.

Advancing Predictive Modeling Through Flood Forecasting

A Comprehensive Review of Machine Learning Approaches for Flood Depth Estimation discusses the use of AI to simulate water flow and flood extent. However, its narrow focus on flooding (rather than compound risks like hurricanes) led us to prioritize models with broader scope. Liu et al. (2023) expand on these models by integrating drainage infrastructure into a hybrid deep-learning system that can adjust to urban infrastructure limitations. This has direct application in Houston, where flooding in low-income areas is often worsened by inadequate drainage. As shown in Figures 2 & 3 there are large areas of Houston in high risk flood plains that overlap with inadequate drainage as measured by the City of Houston Public Works department.

Figure 2: Map of Harris county showing High and Low/Moderate Risk flood plains, along with inadequate drainage points shown in red



We developed a spatial overlay of FEMA-designated high risk flood zones in Harris County and drainage infrastructure classified as "Inadequate" by the City of Houston Public Works Department. It must be noted that the drainage data used was limited to Houston's municipal boundary, which limits overall coverage of Harris County, but still captures a significant portion of the county. **Figure 2** highlights areas where structural risk is compounded by the likelihood of flooding and by the failure of infrastructure. The drainage structure data originally consisted of line features, which we converted each segment into point geometries and applied a dot overlay. This created a heat map visual to identify clusters of inadequate drainage infrastructure.

Figure 3: Precise map of census tracts in high risk zones that overlap with inadequate drainage falling in FEMA designated high risk flood zones

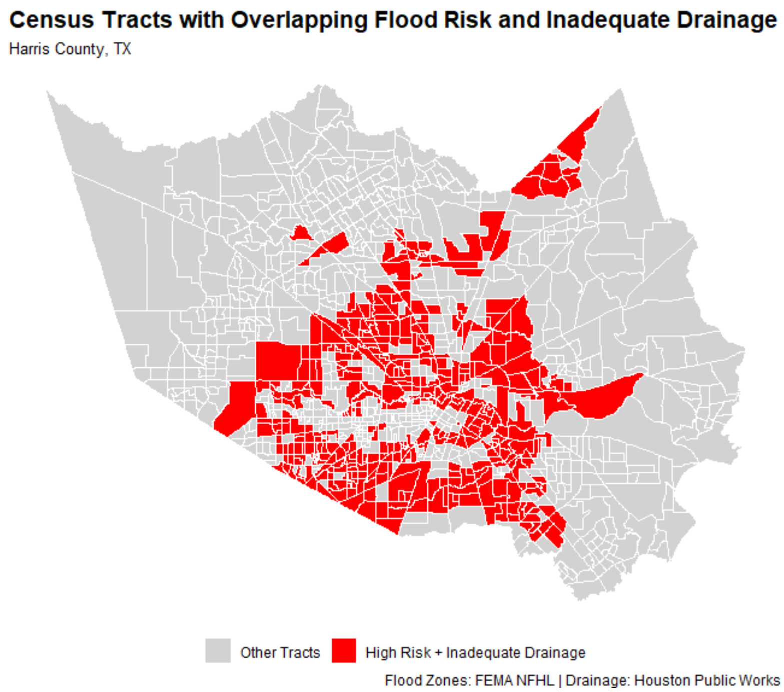


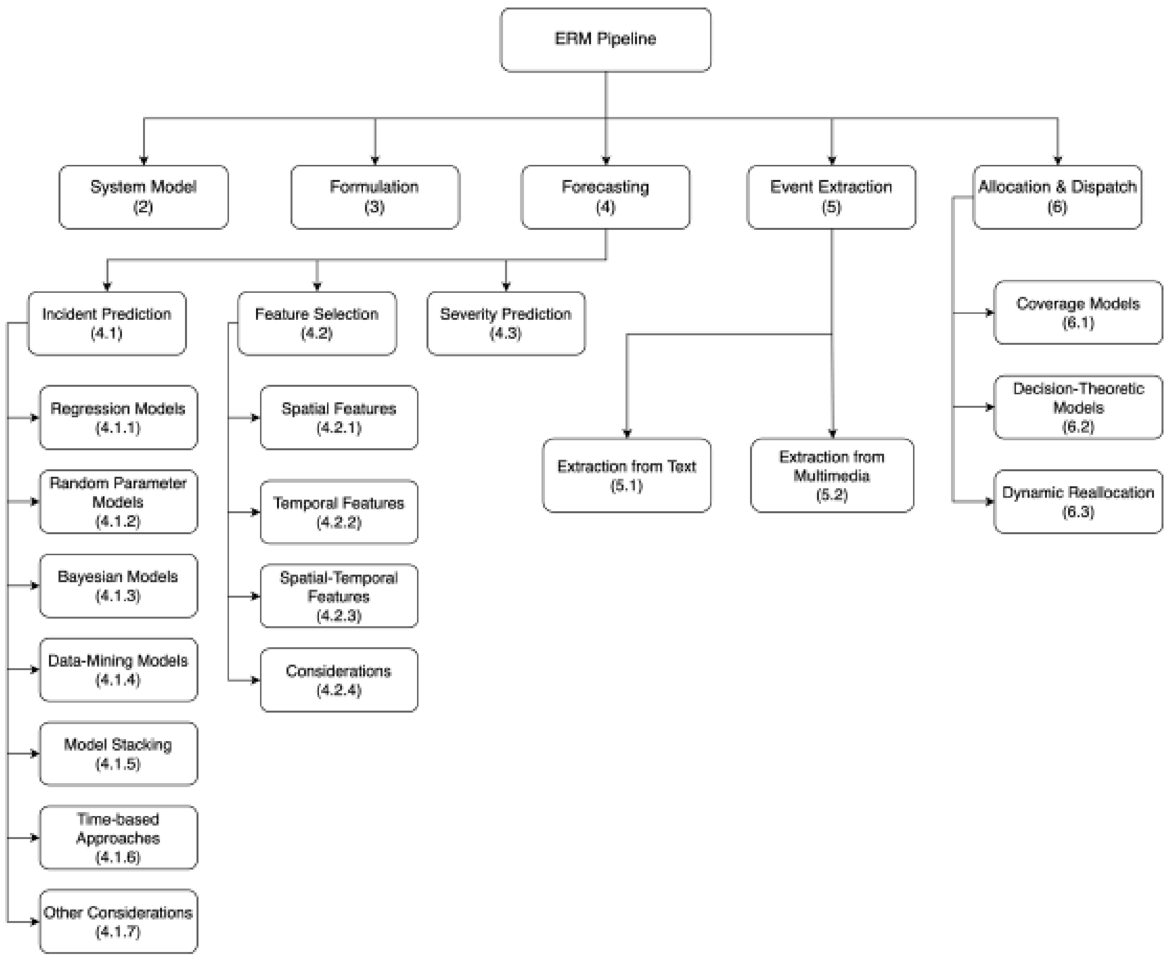
Figure 3 flags all census tracts that intersect both a FEMA high-risk flood zone and at least one instance of inadequate drainage infrastructure. These flagged tracts offer a more complete picture of localized vulnerability. By mapping the convergence of environmental hazard and infrastructural neglect, these visuals directly support BakerRipley's mission to prioritize communities facing systemic disinvestment. This approach also aligns with broader literature on compound risk modeling in flood-prone cities, illustrating how spatial overlays can serve as actionable diagnostic tools for resilience investment and public health risk mitigation.

Ge and Qin (2022) take this further with their Urban Flooding Digital Twin (UFDT) framework, which integrates real-time simulation, infrastructure data, and social vulnerability metrics into a single platform. It allows local officials to simulate scenarios and allocate resources based on variables such as housing density or mobility constraints. When paired with studies like Chen et al. (2023), which reveal inequities in flood response through social media and spatial data, the UFDT framework demonstrates how real-time tools can be used to identify and reduce disparities in aid delivery. This supports BakerRipley's goal of building models that do not just track water levels, but also account for human consequences and systemic disadvantage.

Equitable Emergency Planning Driven by Technical Systems

Mukhopadhyay et al. (2022) provide a visual overview of how emergency systems can work in practice, from predicting disasters to sending help, as seen in Figure 4. This structure for emergency response management, or ERM, provides a way to conceptualize how different data sources–from real-time weather inputs to keyword search trends–can be integrated into a unified model. This framework offers a conceptual base for integrating real-time data sources (e.g., weather inputs, search trends) with decision-making tools such as machine learning and optimization algorithms. It is especially relevant to BakerRipley, as it provides a lens for evaluating how proposed solutions like flood modeling or vulnerability mapping can work together in practice.

Figure 4: Potential Outline for Data Driven Emergency Planning proposed by Mukhopadhyay et al.



Specific Applications of Intelligent Systems that Support Operational Goals

Guo, Song, and Zhang (2023) examine how big data signals–such as online search trends–can be tied to measurable emergency management outcomes like faster response times. They introduce a two-phase model: technology-enabling and value-creation. The technology-enabling phase entails setting up the necessary infrastructure so that the data is usable in real-time; value-creation is the impact stage, where the processed data is actually applied to decision making. This model clarifies how real-time insights can inform resource deployment and outreach, particularly in underserved communities. Together with a letter in the Journal of Emergency Management (2023), which advocates for low-cost, keyword-tracking tools like Google Trends, this research supports BakerRipley's interest in using affordable, accessible technologies to enhance situational awareness in real time.

Modeling Adaptive Human Behavior in Flood Response

Qin et al. (2023) add a behavioral dimension through their two-way Coupled Human and Natural Systems (CHANS) model. This model integrates agent-based decision systems with High-Resolution Hydrodynamic Simulations (HiPIMS) to show how the strategic deployment of temporary flood defenses can significantly reduce flood impact. The CHANS framework aligns closely with equity-centered emergency management: it provides a data-backed rationale for investing in community-based decision support tools, especially for socially vulnerable populations who are often forced to self-organize in the absence of state intervention. The model justifies the inclusion of adaptive human behavior in emergency management design.

To complement predictive tools, we consider the importance of social communication and informal support networks. According to recent studies, social media can be key to helping neighbors act as first responders, especially when official systems are overwhelmed (Aldrich, 2017). It details how platforms like Nextdoor and Facebook Safety Check have been used in past Houston storms, demonstrating that social ties and digital platforms are crucial when formal infrastructure is delayed or inaccessible. This aligns with BakerRipley's grassroots engagement strategies and reinforces the need to integrate peer-to-peer communication into emergency planning. Using a dashboard element to monitor real time keyword spikes would allow BakerRipley to monitor the time between a distress signal, such as a spike in searches for flooding aid, and when BakerRipley takes action.

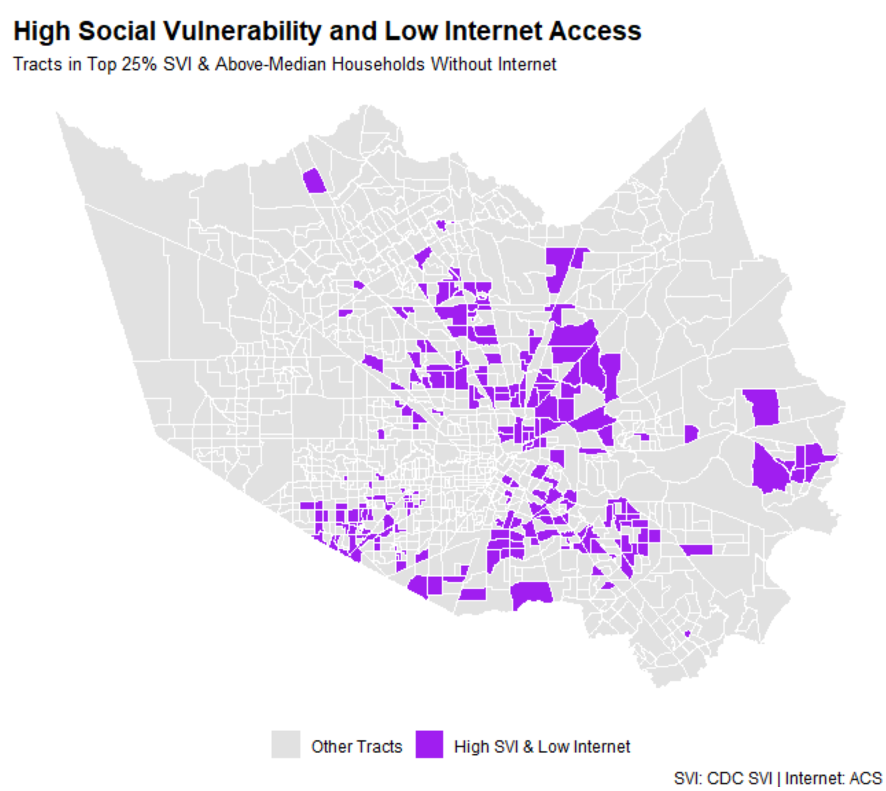
Nonprofit and Community-Based Approaches to Emergency Management

Nonprofits like BakerRipley are uniquely positioned to fill these gaps due to their community trust and multilingual outreach capacity. Community asset mapping (i.e. schools, parks), peer support groups, and trusted messengers (i.e. community leaders) are proven strategies for reaching vulnerable groups. Liu (2023) illustrates how decentralized peer-to-peer communication strategies can reduce rescue delays.

In other contexts, nonprofits have used community-based surveys, mobile chat applications, and neighborhood-based volunteer networks to disseminate information and mobilize assistance. These models empower residents to participate actively in preparedness and response efforts and are often more trusted than government alerts, especially in immigrant or linguistically diverse communities. Merdjanoff and others stress the importance of tailoring outreach to community-specific barriers, like internet access and language. Tailoring outreach based on criteria such as internet access or language barriers allows BakerRipley to become an asset to the community and engage with trusted messengers to better prepare and aid the recovery of neighborhoods that can't respond to traditional emergency or disaster warnings.

To complement these strategies, organizations also require tools for diagnosing vulnerability and targeting outreach. Figure 5 supports this effort by spatially identifying census tracts that fall in the top quartile of SVI while also exhibiting above-median rates of households without internet access, as reported by the ACS. This map was created by flagging tracts with both high vulnerability and digital exclusion, then overlaying them to identify areas where communication barriers and disaster risk converge. By visualizing this intersection, BakerRipley can better target non-digital outreach, such as door-to-door canvassing, print media, or multilingual flyers, where internet access is limited and vulnerability is high. This helps ensure that those most at risk are not bypassed by digital-only communication strategies in disaster scenarios.

Figure 5: Census tracts both in top quartile of SVI and above the median for households without internet



Limits of Current Government Tools and Gaps in the Literature

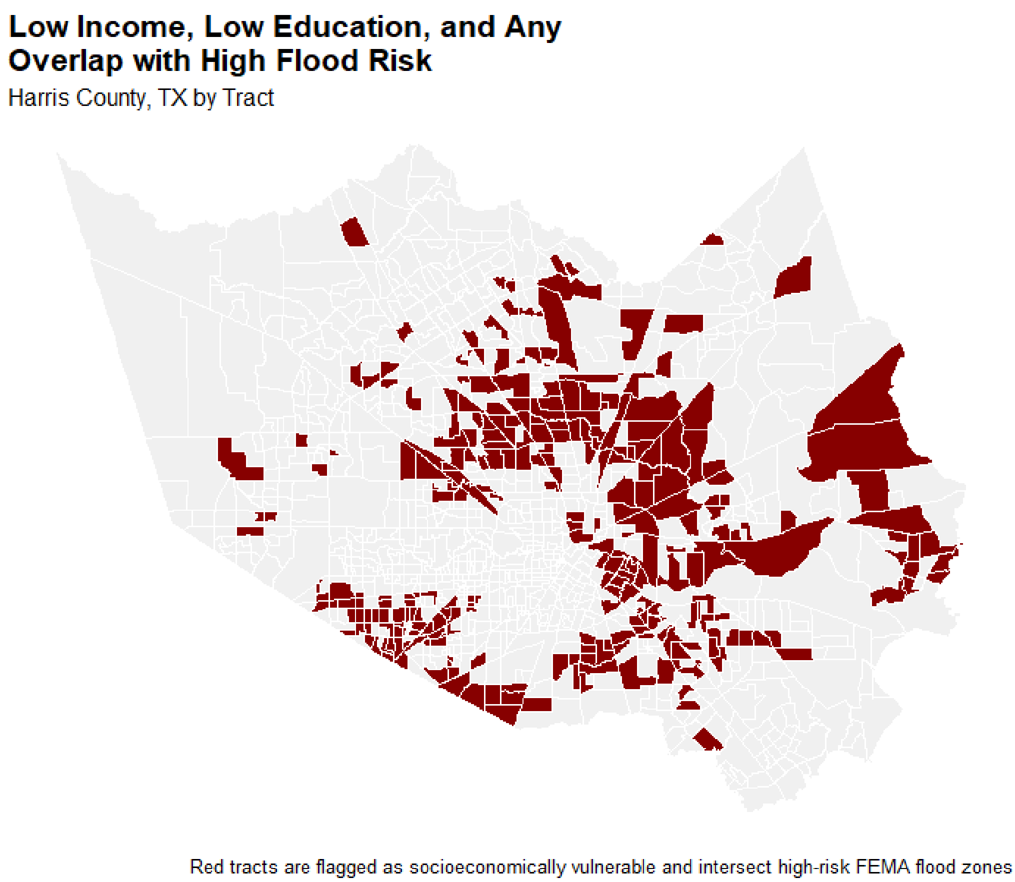
Current government tools often prioritize technical data over social data, and their decision-making frameworks tend to be top-down, with limited community engagement. Federal and state dashboards typically lack real-time adaptability, multilingual access, and community feedback mechanisms. They also tend to overlook informal networks, renters, undocumented residents, and unhoused populations - groups that are critical to equity-based planning. Cho et al. point out that tools designed without community input risk reinforcing existing inequities. The literature consistently highlights that these tools fail to translate vulnerability indices, such as the SVI or PO-RSVI, into practical, hyperlocal action. There is a significant gap between data availability and actionable insights at the neighborhood level. This section identifies key limitations in current government approaches to emergency preparedness.This is especially relevant to BakerRipley's work, which requires tools that go beyond broad metrics to support tailored, neighborhood-level decision-making for the communities it serves. These significant limitations highlight the need for emergency management systems that not only incorporate technical innovation but also actively engage communities to ensure responsiveness and equity.

Blackout Vulnerability as a Key Analytical Dimension

Blackout vulnerability has emerged as a critical analytical lens, especially in response to BakerRipley's request to identify at-risk populations such as low-income seniors. Discussed on page 6 of Ezzati et al. (2023): a higher level of education and a higher income allowed more efficient preparedness–with access and storage to non-perishable food–and evacuation measures in place of emergencies. For the highest educational attainment, high school diplomas were used as the chosen variable; and the median annual income was the level used to gauge the income level of the houses. Ezzati et al. (2023) also introduces the Power Outage-Risk integrated Social Vulnerability Index (PO-RSVI), which assesses risk by combining outage likelihood with community coping capacity and access to external support. Dugan, Byles, and Mohagheghi (2023) add a complementary perspective by mapping how demographic factors such as age, disability, and income can increase vulnerability during long-duration outages. While Ezzati's study focuses on Texas and offers insight into local demand for emergency support, Dugan et al.'s work in Colorado highlights national patterns of inequality. Together, these findings support BakerRipley's efforts to prioritize backup power for vulnerable populations and to design targeted outreach plans based on both technical risk and social need.

Building on this literature, we developed a tract-level map shown in Figure 6 to identify areas of heightened vulnerability to power outages across Harris County. The criteria used, low median household income and high percentages of residents with a high school diploma or less, align with those emphasized in Ezzati et al. (2023). Median household income was drawn from the variable median household income in the American Community Survey (ACS) and tracts were classified as “low income” if their income fell at or below the county-wide median. The percentage of residents with a high school diploma or less was calculated by aggregating the ACS estimates for individuals with less than a high school diploma, a high school diploma, or a GED/equivalent. Tracts were identified as having “low educational attainment” if their value for this combined measure was at or above the county-wide median. These median-based thresholds served as relative cutoffs for classifying vulnerability. Tracts meeting both conditions were flagged and mapped to highlight areas with reduced economic flexibility and lower likelihood of emergency preparedness–two factors that increase risk during prolonged power disruptions. FEMA-designated high-risk flood zones (Zone A, AE, and AO) were then overlaid using spatial data obtained from the FEMA Flood Map Service Center, allowing for spatial identification of communities facing both social and environmental vulnerability.

Figure 6: Spatial Distribution of Socioeconomic Vulnerability to Power Outages in Harris County as measured using PO-RSVI



While this map presents a valuable starting point, its diagnostic potential remains limited by the lack of publicly available data on historical blackout events and projected outage risks in Harris County. Without such spatial data, it is difficult to assess the extent to which these communities have already experienced compounding risks or remain disproportionately vulnerable. Once data from sources such as CenterPoint Energy, ERCOT, or local emergency management agencies becomes available, more targeted analyses could be conducted. Future visualizations could examine the overlap between outage-prone zones, high social vulnerability scores, and environmental exposure, such as flood risk, to better understand how infrastructural and social disadvantage intersect. This would support more precise and equitable prioritization of resilience investments and emergency planning efforts.

Key Findings

There is a notable gap in research linking modern, data-driven disaster tools to equitable disaster response. This highlights the need for more community informed approaches and finer grained data to better identify socially vulnerable populations disproportionately exposed to natural disaster risks. A survey will be necessary to identify which constituents will be most vulnerable to power outages based on their capacity to withstand them. Research strongly supports incorporating keyword search trends and social media monitoring as bottom-up, data-driven insight that would be invaluable to BakerRipley as it would use keyword trends to locate underserved communities before formal alerts are issued. Guo et al. (2023) provided a crucial framework for ensuring technology investments deliver equitable outcomes: arguing that data-driven systems must account and take measure of equitable outcomes, alongside being technically sophisticated.

Tools and Models that are Adaptable to BakerRipley's Mission

As discussed by Cho et al. (2021), real-time keyword monitoring and systematic searches for posts requesting help on platforms such as Facebook, Twitter, and WhatsApp (a method known as social media scraping) can reveal hyperlocal signs of emerging needs–particularly in diverse communities that are underrepresented in formal datasets. These models emphasize community involvement, adaptability, and the importance of integrating social data into emergency systems - principles that align with BakerRipley's equity-centered mission. Integrating these adaptable models with robust vulnerability indices can enhance coordination and ensure that equity remains at the core of emergency management practices.

To apply the findings and recommendations from this literature review, we constructed a localized dataset tailored to BakerRipley's needs in Harris County shown in Table 2. Drawing on sources such as the CDC's Social Vulnerability Index (SVI), the National Risk Index (NRI), and the American Community Survey (ACS), we assembled tract-level data that produces data for both environmental hazards and underlying social inequalities. Additional sources, including BRICS and Community Disaster Resilience Zone (CDRZ), were incorporated to capture community resilience and designated recovery zones. Each dataset was filtered to retain only relevant observations for Harris County. This data infrastructure combines flood risk, social vulnerability, and power outage data to build a disaster dashboard targeting Houston's most vulnerable communities in line with BakerRipley's mission.

Table 2: Dataset for use in Disaster Response dashboard including risk indices as well as demographic data

Factor	Variable	Description
Identifier	Census Tract	Unique identifier for each U.S. Census tract
Demographics	Population	Estimated total number of people residing in the census tract
	Housing Units	Housing units estimate
	Households	Households estimate
Economic Vulnerability	median income	Household median income for past 12 months
	per capita income	per capita income of individuals within the tract. Last 12 months
	poverty line	Percentage of persons below 150% poverty estimate
	unemployment rate estimate	Unemployment Rate estimate
	Unemployed	Civilian (age 16+) unemployed estimate
	Percentile unemployed	Percentile percentage of civilian (age 16+) unemployed estimate
	Percentile uninsured	Percentile percentage of uninsured estimate
Disaster Risk	Risk Score (0 -100)	National Risk Index Composite Risk Score, a percentile-based index representing overall community risk
	Coastal Flood Events	Total number of recorded coastal flooding hazard events
	Hurricane ALR - Buildings	Annualized Loss Ratio (ALR) for building exposure due to hurricane hazards
	Hurricane ALR - Population	Annualized Loss Ratio (ALR) for population exposure due to hurricane hazards
	Hurricane ALR - Agriculture	Annualized Loss Ratio (ALR) for agricultural value due to hurricane hazards
	Hurricane ALR - Percentile	National percentile rank of the total Expected Annual Loss Rate (ALR) for hurricanes
	Hurricane ALR - Total	Total expected annualized monetary loss from hurricane hazards
	Annual Loss Rate - Buildings	Composite Annualized Loss Ratio (ALR) for building value due to all included natural hazards
	Annual Loss Rate - Population	Composite Annualized Loss Ratio (ALR) for population exposure due to all included natural hazards
	Adj. EAL - National Percentile	National percentile rank of adjusted Expected Annual Loss Rate (EAL)
Asset Exposure	Building Value (USD)	Total estimated replacement value of buildings in the census tract
Health Risk	Individual older than 65	Persons aged 65 and older estimate
	Percent of individual over 65	Percentage of persons aged 65 and older estimate
	Number of individuals disabled	Civilian noninstitutionalized population with a disability estimate
	% of individuals disabled	Percentage of civilian noninstitutionalized population with a disability estimate
	persons 17 and younger	Percentage of persons aged 17 and younger estimate

Household Factors	single-parent households	Single-parent household with children under 18 estimate
	households with no vehicle	Percentage of households with no vehicle available estimate
	internet access	Households without an internet subscription estimate
Social Vulnerability	Racial and ethnic minority	Percentile ranking for Racial and Ethnic Minority Status
	Social Vulnerability Index Score	Overall Social Vulnerability Index
Resilience	Community Resilience Score	Community resilience score (BRIC)
	CDRZ Designated (Yes/No)	FEMA-designated Community Disaster Resilience Zone (binary)

Recommendations

Energy Resilience Survey

Given the absence of household-level data on blackout experiences and energy resilience in Harris County, BakerRipley could deploy a targeted survey to address these gaps. Key questions should capture outage exposure (e.g., frequency and duration of blackouts), impacts on essential services (such as heating, food storage, or communications), and coping capacity (including access to emergency supplies or backup power). The survey should also assess financial and informational barriers to preparedness, as well as awareness of flood risk–particularly whether households know they reside in a FEMA flood zone or have previously evacuated due to storm-related outages. Collecting basic demographic and locational information (such as income, education level, household age composition, and ZIP code) would allow BakerRipley to contextualize vulnerability and better prioritize outreach and resilience interventions in at-risk communities as well as communities that are unaware of their risk.

As found in Ezzati, low education and income are good proxies for disaster vulnerability, and these are key factors in the power outage social vulnerability index. While we can map which census tracts have low educational attainment and low income (two components of the energy vulnerability core criterion), we do not have historical power outage data. Additionally, we do not know how long residents could withstand prolonged power outages. We propose that the dashboard should be capable of showing census tracts with low education and low educational attainment so that BakerRipley can be targeted in survey efforts to better understand their constituents' power outage vulnerability. Doing so also allows BakerRipley to track the percentage of households in floodplains that have received surveys to track preparedness in high exposure areas.

FEMA Assistance Claims Data

To enhance the precision and equity of post-disaster resource allocation, we recommend that BakerRipley obtain an API key to access FEMA disaster assistance claims data, which is currently unavailable in our analysis due to its restricted, registration-based access. Assistance claims data shows rates of uptake for FEMA Individual and Household Assistance. It allows BakerRipley to see how many homeowners, renters, individuals, and families have made assistance claims. These claims come after FEMA designated large disasters, e.g. any natural catastrophe, fire, flood, or explosion that causes damage of sufficient severity to warrant major disaster assistance. Integrating this data into the dashboard would allow the organization to identify high-risk, high-vulnerability neighborhoods that have received little or no federal aid, revealing procedural vulnerabilities and gaps in formal recovery efforts. By mapping claims patterns against known hazard exposure, BakerRipley can better target outreach to communities that are systematically excluded from assistance pipelines and may be unaware of, or unable to access, available federal programs. Using this as a measure fits in with socioeconomic vulnerability as a core criterion.

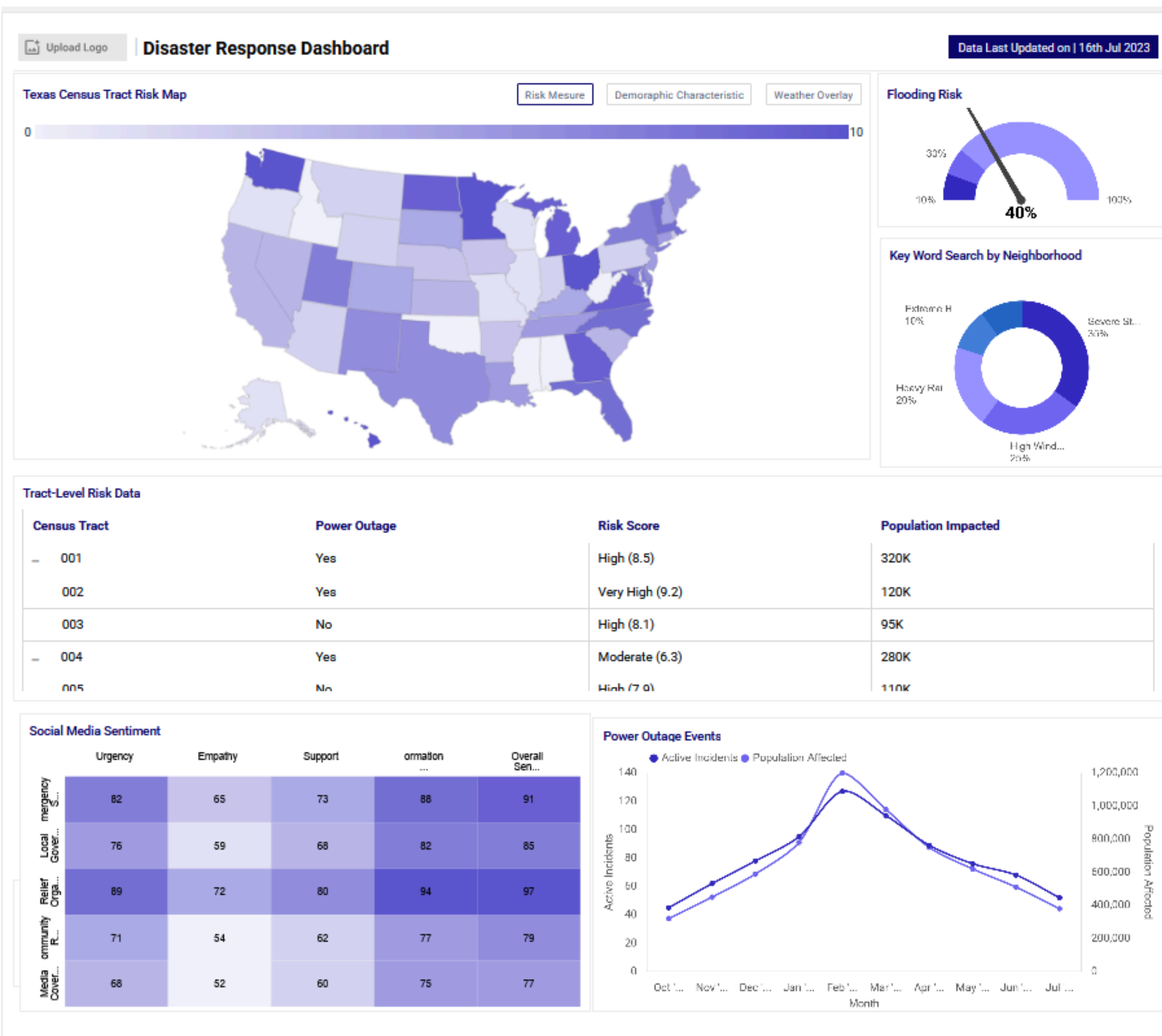
FEMA claims data also provides a more reliable and scalable proxy for recovery outcomes than traditional surveys, which often suffer from low response rates and limited generalizability (Grineski, 2020). Using this data, BakerRipley can monitor where federal support has or hasn't reached over time, enabling more responsive triage, informed survey design, and the strategic deployment of aid. BakerRipley can also use the assistance claims data to see gaps in tracts where they have intervened and there is low FEMA uptake, allowing them to monitor the impact of dashboard-informed outreach. The API connection further ensures real-time updates and supports the organization's commitment to data-driven, equity-centered emergency management.

Dashboard Design

A practical and equity-centered dashboard for BakerRipley should be structured around four key areas: hazard exposure, social vulnerability, energy dependence, and community capital (natural capital, human capital, political capital). For hazard exposure, immediate flood warnings from NOAA, rainfall projections, and historical floodplain data from FEMA should be integrated, with automatic daily and hourly updates during severe weather seasons. The social vulnerability module should incorporate the CDC's Social Vulnerability Index (SVI), updated annually, while adding locally collected data on housing insecurity, a factor highlighted in Houston-specific studies as vital to compounding disaster risk. Energy dependence should feature power outage data, sourced from ERCOT's public feeds, updated hourly, with filters for critical infrastructure like cooling centers. Community strength can be informed by locally sourced data on nonprofit locations, civic centers, and mutual aid groups, updated quarterly, providing community-based resources not shown in federal datasets.

A minimum viable product should allow users to filter by census tract, overlay dual-vulnerability zones (e.g., high flood risk and high SVI), and other demographic data to map vulnerable census tracts in real time. It should indicate flooding risk for all of Houston as well as by neighborhoods using NOAA data, and have a readout filterable by tract/neighborhood showing keyword search data for terms such as the following: shelter, flooding, EMS, medical supplies, and power outage, combined with boolean operators (and/or). A table to report granular data on selected tracts to show specific variables such as risk scores, power outage events, and weather conditions is also necessary to get real time data on desired tracts. Drawing from models like the Urban Flood Digital Twin and CHANS, but adjusted for BakerRipley's grassroots approach, the dashboard should focus on accessible, low-complexity visuals with the ability to download tract-level reports for immediate field use. The proposed modules can be seen in a dashboard wireframe below in Figure 7.

Figure 7: Proposed Wireframe for BakerRipley Disaster Dashboard



Conclusion

We have worked with BakerRipley to identify the core of a disaster preparedness and response dashboard to support equitable disaster recovery. While current emergency management frameworks often perpetuate existing inequalities, the integration of social vulnerability data with advanced technology offers significant potential for more proactive, inclusive disaster response. This finding emphasizes the critical importance of community-informed approaches to emergency management that can identify and address these systemic biases. The key to success lies in centering community needs and lived experiences while leveraging technological capabilities for real-time responsiveness. BakerRipley's community-based approach positions the organization uniquely to bridge this gap between high-tech solutions and on-the-ground equity outcomes. Moving forward, implementation should prioritize immediate data collection needs while building toward comprehensive dashboard development. Success will be measured not only by technological sophistication but by demonstrable improvements in disaster impacts for Harris County's most vulnerable residents.

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