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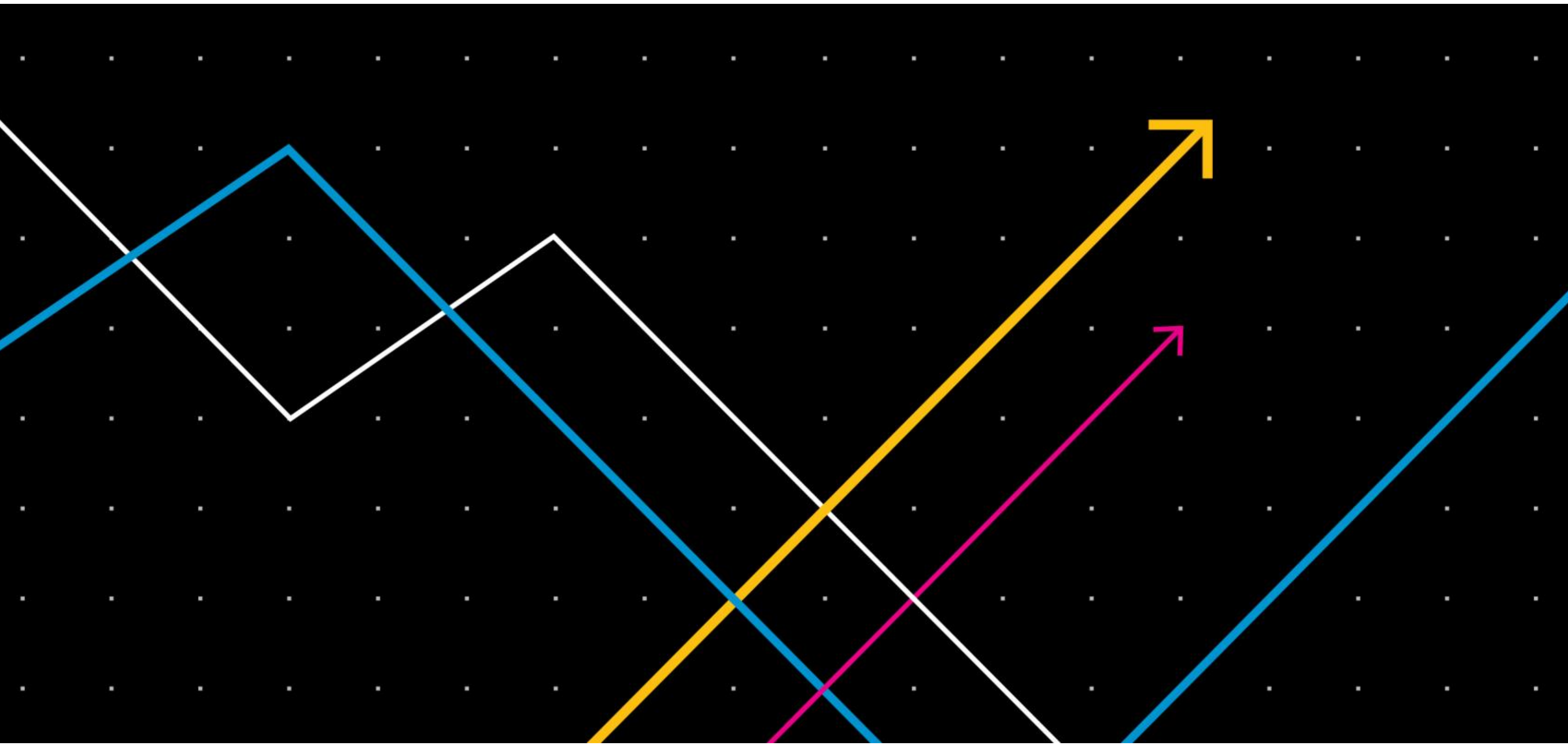

RESEARCH REPORT

Assessing Climate Risk in Marginalized Communities

The Case of Riverine Flooding

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We would also like to acknowledge Verisk for the use of data and technical assistance, as well as conversations with CoreLogic for improving our knowledge in this area. We would also like to thank RiskSpan for sharing knowledge and subject-matter expertise in climate change as it relates to the housing market. We especially appreciate RiskSpan's related analytical and data expertise in this area.

Assessing Climate Risk in Marginalized Communities

Climate Change and the Data Used to Analyze Climate Risk

On average, temperatures across the United States have been rising (Vose et al. 2017). Hotter temperatures have coincided with higher sea levels and more pronounced weather events that, combined, increase the risk of flooding. The frequency and severity of flood events have seen a marked escalation in recent decades (Ghanbari et al. 2021; Sanders et al. 2020).

Climate change, driven by increasing global temperatures and corresponding changes in precipitation patterns, has made many regions more vulnerable to riverine floods. The Congressional Budget Office projected that 9.1 percent of the properties in the United States in 2020 face at least a 1 percent annual probability of experiencing a flood at least one foot deep. The share of properties at risk is expected to rise to 10.1 percent by 2050. This illustrates the limitations of historical data and the need for measures of natural hazard risk to capture observed climate trends and possible events beyond those observed in the historical record.

As global climate change patterns evolve, flood risks have emerged as a formidable challenge for US communities. And such floods have multifaceted repercussions. For individuals, there is the immediate threat to life and property. In addition, there is the potential for long-term displacement, economic hardships, and enduring trauma. Communities as a whole grapple with infrastructure damage, disrupted economic activities, and the uphill task of recovery and resilience building. The ripple effects of these floods can challenge an entire region's socioeconomic fabric.

As the repercussions of these flood risks become increasingly pronounced, the need for deeper exploration into their sociodemographic implications within communities becomes more important. The implications of property destruction are most severe for communities considered more vulnerable and less resilient, including many communities of color. Broadly, communities of color are often more vulnerable to catastrophes and can experience a slower recovery if they experience such events. Absent an appropriate policy response, such shocks can worsen racial and ethnic disparities.

Although flood risks are pervasive, their impacts are not uniformly distributed. Previous research shows coastal floods more likely affect areas with a greater share of white households (Collins, Grineski, and Chakraborty 2018). Riverine flooding, on the other hand, is more likely to affect households that are socioeconomically disadvantaged and racially marginalized (Maantay and Maroko 2009). Wing and coauthors (2022) show that the average annual losses for flood risks combining both coastal flooding and riverine flooding are borne disproportionately by poorer communities with a proportionally larger white population, and the future projected increase in risk will disproportionately affect Black communities.

Evidence also illustrates that the recovery among communities of color may be slower as well, even when the amount of damage and loss are the same.[1] This inequitable response leads to disparate outcomes, including exacerbated wealth inequality. In addition, a study on Hurricane Harvey found that Black families had a harder time getting disaster recovery relief, which can slow their recovery (Hamel et al. 2017). Qualitative evidence on Hurricane Harvey confirms the slower recovery among communities of color owing to the racial inequities in place before the flood.[2]

For these reasons, it is critical to focus on marginalized communities in climate research to ensure policies are informed, created, and delivered equitably. This has motivated our research agenda.

Our Research Agenda

Data and flood maps from the Federal Emergency Management Agency (FEMA) are a critical tool in flood management and policymaking, but there are concerns about whether these maps are inaccurate or outdated (they are updated infrequently). Independent estimations of flood risks, which have harnessed cutting-edge technologies and updated datasets, have revealed disparities when compared with FEMA's official delineations. The discrepancy was highlighted in previous work that found that official FEMA flood maps tended to underestimate the extent of the 100-year floodplain, particularly because of systemic omissions of pluvial flood risk (Weill 2022; Wing et al. 2022). FEMA data cover rainfall that causes rivers and larger streams to overflow, but they do not cover flooding events from small creeks and tributaries or long periods of heavy rainfall that can cause flooding away from an overflowing body of water (i.e., pluvial flooding). These omissions likely underestimate and lead to inaccurate public perceptions of riverine flood risk. Moreover, there are unique challenges with data on riverine flooding, which is typically the result of prolonged heavy rainfall that causes rivers and streams to overflow their banks. This type of flooding can be forecasted to a certain extent with hydrological models, but the nature and intensity of rainfalls, especially with changing climate patterns, make prediction challenging.

Data discrepancies can lead to misguided policy decisions, insufficient investments in infrastructure, and a false sense of security for residents. These issues can be particularly critical in disadvantaged neighborhoods, where resources and advocacy may be limited. Reliance on outdated or inaccurate flood maps in these communities can compound vulnerability.

Data underlie the empirical evidence intersecting climate change and racial equity. But a review of existing literature reveals certain critical gaps in our understanding of flood risk dynamics, especially as they pertain to marginalized communities. Although floods have been a focus of extensive research, there is a noticeable dearth of studies that disentangle riverine floods from coastal floods, often treating them as homogeneous and thereby overlooking each type's unique challenges and implications.

Differentiation of flood risk type is foundational to designing equitable policies that buffer against the impact of climate change in all communities, not just the most advantaged. This differentiation is critical for several reasons. First, riverine flood risk is more closely associated with social vulnerability than coastal flood risk, as coastal landscapes are amenity-rich and desirable (Collins, Grineski, and Chakraborty 2018). Second, coastal residents are more able to socialize flood risk to US taxpayers through the National Flood Insurance Program.

When evaluating riverine or coastal flood risk, a predominant tendency has been to use expected annual loss (EAL) as a primary metric. For example, to calculate EAL, FEMA multiplies a tract's exposure value by the estimated annualized frequency and the historic loss ratio. This ratio is the representative percentage of a tract's hazard exposure that experiences loss attributable to a riverine flooding occurrence, or the average rate of loss associated with a riverine flood. Employing EAL to assess disaster impact offers a quantifiable insight into the financial risks associated with a catastrophic event. But the historic loss ratio component in EAL, when based solely on a history of climate events, can miss communities where events have not occurred, omitting a broad swath of communities that may face greater climate risk in the future. In addition, using only EAL explicitly bypasses the integral considerations of social vulnerability and community resilience, elements that can significantly alter the real-world impact of flood risks.

The literature is still equivocal on the specific burdens marginalized communities bear. The intricacies of how low- and moderate-income communities of color navigate and bear the consequences of riverine flood risk remain underexplored, pointing to a pressing need for more nuanced, community-specific investigations.

This report endeavors to bridge the critical gap in understanding the distributional impact of riverine flood risk and the data and methodologies employed to estimate them. In an era marked by increasingly unpredictable climate patterns, it becomes imperative to delve deeper into the intersection of riverine flood risks, disadvantaged neighborhoods, and the nuances of flood risk estimations. This report aims to shed light on these intricate relationships and inform policy dialogues in the following ways.

We focus on riverine flood risk, an arena that remains markedly understudied despite its pressing significance. We spotlight the specific challenges low- and moderate-income communities of color face, dissecting how they bear the brunt of riverine flood implications. These populations frequently find themselves at the front line of flood-related adversities, enduring not just the immediate physical damages but the prolonged socioeconomic repercussions. Our exploration seeks to unravel the complex layers of this vulnerability, aiming to highlight the critical need for targeted policy responses.

Diverging from traditional methodologies that often rely on limited or outdated datasets, this report introduces an innovative approach to estimating riverine flood risk. By harnessing independent data sources, we address the notable gaps in FEMA's current assessments. Our methodology is particularly noteworthy for its twofold approach to risk assessment. First, it quantifies the economic impact of potential flooding by assessing the EALs, normalized by the replacement value at the census tract level. This measurement provides a robust quantification of the potential economic repercussions involved, especially for those in marginalized communities.

Yet we recognize that mere economic metrics can sometimes fail to capture the full spectrum of flood risk implications. To this end, we formulate a composite risk metric, a risk assessment metric crafted as a function of EAL normalized by the replacement value, social vulnerability, and community resilience. This metric accentuates the traditional hazard risks and associated economic losses and incorporates geographic risk, which holds profound implications for postdisaster recovery capacity. By integrating such varied factors, inclusive of social vulnerability and community resilience—two often-neglected dimensions—we believe our approach fosters a more comprehensive assessment of the challenges marginalized communities face.

This research enhances our understanding of the disparate impacts of natural disaster shocks, particularly riverine flooding, on communities of color. Our results suggest that low- and moderate-income communities of color are disproportionately affected by riverine flooding risks. These communities are prone to greater EALs normalized by replacement value, greater social vulnerability, and weaker community resilience. Our findings highlight the need for an evolved risk assessment approach, including adopting a more inclusive definition and forward-looking assessment approach for riverine flooding risk, normalizing EALs with total replacement value, and incorporating social vulnerability and community resilience into risk assessments.

The results of this report will provide greater precision on the relative climate risk communities of color face. In the following section, we describe the data we use in this report and document how they can fill the gaps in traditional risk assessment data. We will then assess the economic impact of riverine flood risk on marginalized communities using EALs, followed by a section that combines it with measures of social vulnerability and community resilience to recalculate riverine flood risk by community-level race and ethnicity. The final section will conclude and discuss implications for policymakers and other changemakers.

Measuring Climate Risk Requires More Complete Data

Past research relied on publicly available FEMA National Risk Index (NRI) data to assess the hazard risk level at either the census tract or county level. The NRI includes a Riverine Flooding Risk Index score, a rating that represents a given census tract's relative risk for riverine flooding, compared with the rest of the country. The NRI's EAL is the average economic loss (in dollars) resulting from a given natural hazard to buildings, population, and agriculture. To calculate the EAL, FEMA multiplies a tract's exposure value by the estimated annualized frequency and the historic loss ratio, the representative percentage of a tract's hazard exposure that experiences loss attributable to a riverine flooding occurrence.

But there are several limitations in FEMA's conventional risk assessment data. First, more than one quarter of census tracts are missing from FEMA EAL data. The missing FEMA data are disproportionately concentrated in neighborhoods of color, particularly low-to-moderate-income (LMI) neighborhoods of color (table 1). FEMA data also tend to underestimate the level of riverine flood risk for two primary reasons. First, when assessing riverine flooding risk, FEMA models based only on historical events. If a flooding event has never occurred in a given neighborhood, FEMA's model will not predict future floods. FEMA also does not cover either flooding from smaller bodies of water or pluvial flooding events. Pluvial flooding occurs when increased rainfall creates a flood independent of an existing body of water. These floods can occur in any location, even without nearby water bodies.

TABLE 1

Share of Census Tracts with Missing FEMA Data, by Neighborhood Race and Income

	LMI neighborhoods	Middle-income neighborhoods	Upper-income neighborhoods	All neighborhoods
Neighborhood of color	43.1%	38.9%	38.5%	41.4%
Majority-white neighborhood	24.3%	15.8%	20.8%	19.1%
All neighborhoods	34.7%	20.1%	22.8%	25.6%

Sources: FEMA and Verisk data.

Notes: AMI = area median income; FEMA = Federal Emergency Management Agency; LMI = low- and moderate-income. Neighborhoods of color are census tracts where the share of households of color exceeds 50 percent. Majority-white neighborhoods are census tracts where the share of white households exceeds 50 percent. LMI neighborhoods are those where the median income in the census tract is less than 80 percent of the AMI. Middle-income neighborhoods are those where the median income in the census tract is at least 80 percent of the AMI but less than 120 percent of the AMI. Upper-income neighborhoods are those where the median income in the census tract is at least 120 percent of the AMI.

To overcome some of the shortcomings of the FEMA data, we use a proprietary dataset from Verisk, an analytics and risk assessment firm, alongside measures of social vulnerability and community resilience to recalculate riverine flood risk by community-level race and ethnicity, and assess independently of FEMA. The Verisk dataset is derived from output of Verisk's catastrophe models. This measure of climate risk is informed by thousands of simulations of potential events that could occur in a given year.[3] The probabilistic analytics are informed by historical experience and recent climate trends, thus accounting for natural catastrophes that have not yet occurred but are possible in a near-present climate.

Verisk also develops a representation of the exposure, or built, environment, including building counts, characteristics, and total replacement values (TRVs). The high-resolution Verisk exposure is aggregated into census tracts using the appropriate US Department of Housing and Urban Development–US Postal Service zip code crosswalk files.

Verisk characterizes flood types different from FEMA. Verisk models separately calculate inland floods, hurricane precipitation–induced floods, and hurricane storm surges. In our analysis, we combine inland flood risk and hurricane precipitation–induced flood risk and define it as riverine flood risk. Using the losses and exposure values above, Verisk calculates an EAL value as a dollar amount. Using the Verisk TRV, we create a normalized (percentage) measure of loss by dividing the EAL by the TRV (EAL_TRV). Verisk has separately compared locations' relative riskiness based on its model to the FEMA riverine flooding NRI metrics. Despite differences owing to methodologies, Verisk results are broadly consistent with the FEMA NRI risk measures.

Verisk data have comprehensive geographic coverage. Many census tracts do not have a FEMA NRI riverine flood score but do have a Verisk result. This is because FEMA does not calculate an NRI score if any component has a score of zero or if there is no historical record in the NRI source data and the hazard type is not geographically possible (e.g., a coastal flood in an inland area). Verisk data allow us to examine areas where no flooding has previously occurred but where floods could occur in the future so that we can better consider future risk and expected losses by race and ethnicity. The Verisk data fill in 89 percent (22.8 percent / 25.6 percent) of missing values in the FEMA dataset (table 2). The Verisk data cover 95.6 percent of the census tracts under consideration. The remaining gap is related to small discrepancies when crosswalking from zip codes to census tracts.

TABLE 2

FEMA versus EAL Missing Data

	Verisk EAL		
FEMA EAL	**Valid**	**Missing**	**Total**
Valid	72.8%	1.6%	74.4%
Missing	22.8%	2.8%	25.6%
Total	95.6%	4.4%	100.0%

Sources: FEMA and Verisk data.

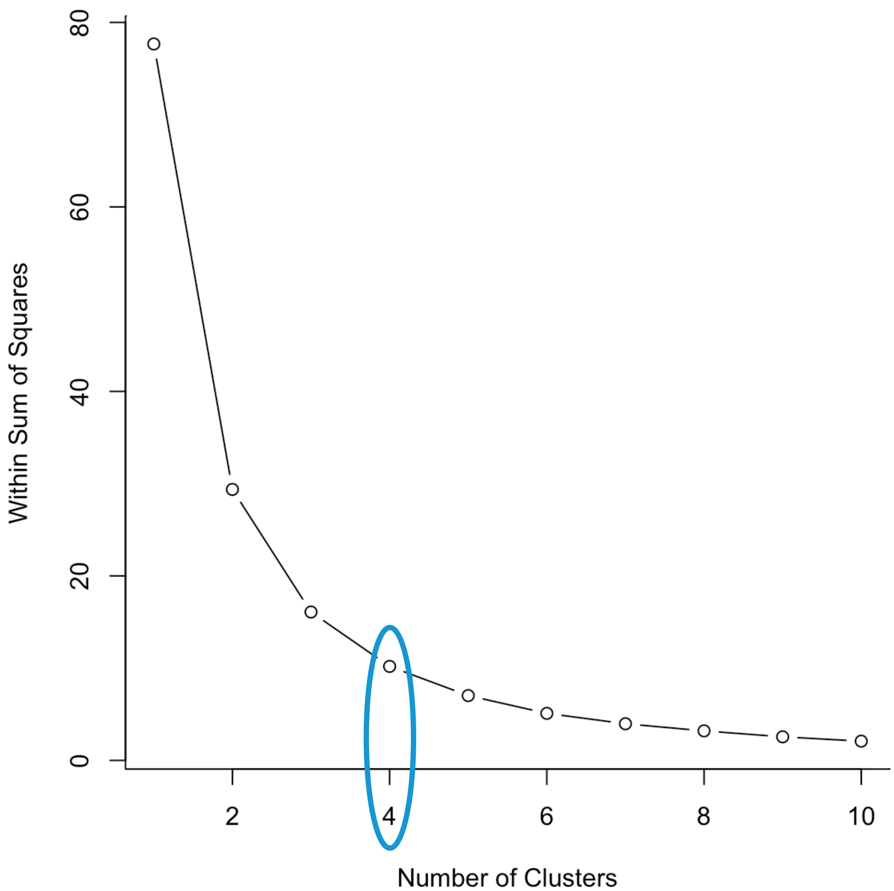
Note: EAL = expected annual loss; FEMA = Federal Emergency Management Agency.

EAL Values Adjusted by Replacement Values Are Foundational to Measuring Climate Risk

To convert EAL from a dollar amount to a risk rating, we use a *k*-means clustering approach. This unsupervised machine learning technique divides all neighborhoods into clusters such that the neighborhoods within each cluster are as similar as possible (i.e., variables are minimized, also known as "inertia") while the clusters themselves are as different as possible from one another (i.e., variance is maximized between clusters). We chose *k*-means clustering because it is fairly simple to implement and scales easily to large datasets such as ours. It also easily adapts to new examples and clusters of different shapes and sizes, and we wanted to create risk rating groups for different datasets. Given the distribution of Verisk EAL and EAL_TRV, the optimal number of clusters is four. Figure 3 visualizes minimized inertia and maximized variance to show how the number of clusters is optimized.

FIGURE 3

***K*-Means Clustering Analysis: Determining Risk Rating**

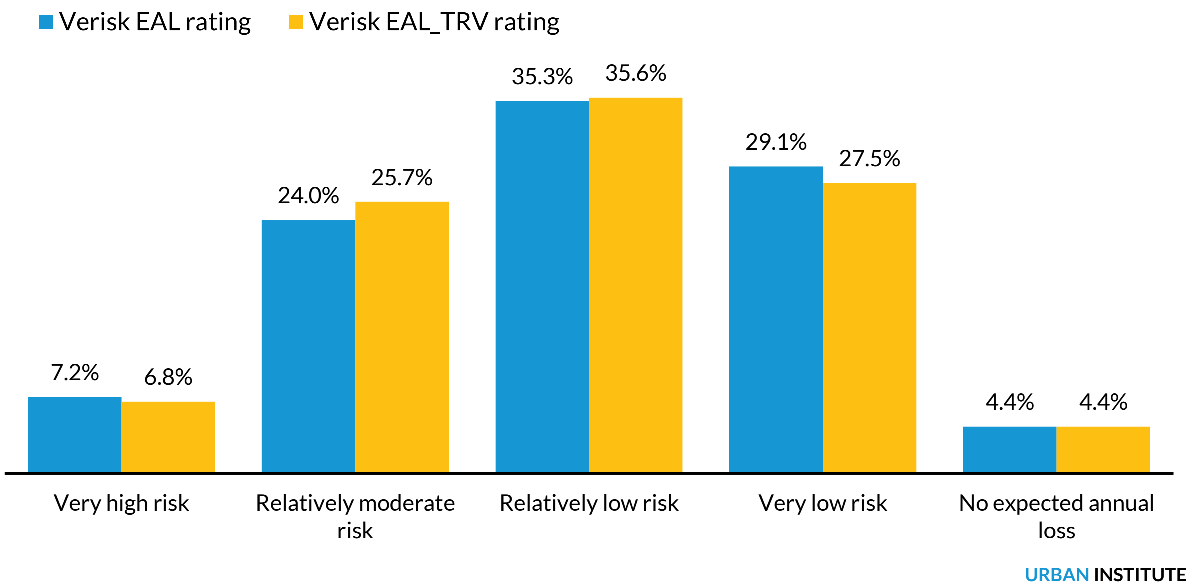


Using the *k*-means clustering approach with *k* = 4, we get four risk-rating groups: very high risk, relatively moderate risk, relatively low risk, and very low risk. For both Verisk EAL and Verisk EAL_TRV, there are a few tracts for which there was no EAL predicted. Verisk EAL and EAL_TRV give comparable overall risk distributions (figure 4).

FIGURE 4

Verisk Riverine Flood Risk Rating

EAL versus EAL_TRV



Sources: Verisk and American Community Survey data.
Note: EAL = expected annual loss; TRV = total replacement value.

Although the overall risk distributions are comparable between EAL and EAL_TRV, EAL_TRV, the expected annual loss amount adjusted by replacement value, indicates that a greater share of LMI neighborhoods that are predominantly neighborhoods of color is severely affected by riverine flooding. That is, although the EALs are lower in LMI neighborhoods, as buildings' values are lower, the cost as a percentage of the structures' values is higher. Nearly 8 percent of LMI neighborhoods that are predominantly households of color have very high flood risk using EAL adjusted by TRV, compared with fewer than 4 percent when using only EAL (table 3).

This comparison underscores the importance of adjusting EAL by replacement values when measuring riverine flood risk, particularly in the context of equitable risk assessment. Using EAL in isolation can lead to skewed perceptions of risk, disproportionately reflecting the financial exposure of more affluent neighborhoods with higher property values. This methodology inherently biases risk assessment toward those with more to lose financially, neglecting the proportionally greater impact on marginalized communities.

The EAL_TRV is a more equitable measure of flood risk and highlights the acute need for targeted policy interventions that address the vulnerabilities of these neighborhoods. The measure ensures risk assessments reflect the true scale of impact on LMI neighborhoods.

TABLE 3

Share of Tracts with Very High Riverine Flood Risk, by Neighborhood Income and Race

EAL versus EAL_TRV

	LMI neighborhoods	Middle-income neighborhoods	Upper-income neighborhoods	All neighborhoods
EAL_TRV				
Neighborhood of color	7.8%	7.7%	8.0%	7.8%
Majority-white neighborhood	6.9%	7.5%	5.9%	6.8%
All neighborhoods	7.4%	7.5%	6.2%	7.1%
EAL				
Neighborhood of color	3.8%	5.7%	9.1%	4.9%
Majority-white neighborhood	5.2%	8.6%	10.6%	8.7%
All neighborhoods	4.5%	8.1%	10.5%	7.7%

Sources: Verisk and American Community Survey data.

Notes: AMI = area median income; EAL = expected annual loss; LMI = low- and moderate-income; TRV = total replacement value. Neighborhoods of color are census tracts where the share of households of color exceeds 50 percent. Majority-white neighborhoods are census tracts where the share of white households exceeds 50 percent. LMI neighborhoods are those where the median income in the census tract is less than 80 percent of the AMI. Middle-income neighborhoods are those where the median income in the census tract is at least 80 percent of the AMI but less than 120 percent of the AMI. Upper-income neighborhoods are those where the median income in the census tract is at least 120 percent of the AMI.

Adding Measures of Social Vulnerability and Community Resilience Amplify the Climate Risk Communities of Color Face

So far, in our quest to examine the impact of riverine flooding risk, we have assessed the risk distribution using the EAL, normalized by the TRV at the census tract level, providing an assessment of the potential economic repercussions. Yet we recognize that mere economic metrics can sometimes fail to provide a robust measure of the community impact or capture the full spectrum of flood risk implications. Such an approach often bypasses the integral considerations of social vulnerability and community resilience, elements that can significantly alter the real-world postdisaster impact of riverine flooding events.

FEMA's NRI is made up of two components: (1) EAL attributed to riverine flooding and (2) a community risk factor, which is the combination of social vulnerability and community resilience. In FEMA's NRI, areas of exposure are determined by intersecting the riverine floodplain polygons with the census block developed-area polygons within the processing database.

Social vulnerability is a community-level risk factor that represents the susceptibility of social groups to the adverse impact of a given natural hazard. The higher an area's social vulnerability, the greater the risk. The underlying data come from the Agency for Toxic Substances and Disease Registry, which uses 16 variables from the US Census Bureau that can help local officials identify communities most in need of support.[4] Community resilience is a community-level risk factor that represents a given community's ability to prepare for anticipated natural disasters, adapt to changing conditions, and how quickly they can recover from a disruption. The underlying data come from the Hazards Vulnerability and Resilience Institute's Baseline Resilience Indicators for Communities.[5] The index considers six main categories of disaster resilience: social, economic, community capital, institutional, infrastructural, and environmental. The smallest geography at which the index is available is the county level, so each tract is assigned the community resilience score of its parent county by FEMA.

The concept of social vulnerability is crucial for understanding the uneven impact of flood risks across different demographics. Social vulnerability refers to a community's inability to withstand environmental hazards attributable to such factors as poverty, lack of access to resources, lack of social capital, and concentration of vulnerable populations. In the context of riverine flooding, socially vulnerable communities, which often include LMI neighborhoods of color, are at a higher risk of experiencing flood damage and face greater challenges in recovery and rebuilding efforts. Nearly 70 percent of census tracts in LMI neighborhoods of color are classified as highly socially vulnerable, compared with 20 percent of neighborhoods nationwide (table 4). This stark contrast highlights the heightened risk these communities face and underscores the urgent need to integrate social vulnerability into flood risk assessments more robustly.

Community resilience is another factor in our composite risk metric. It encompasses a community's ability to anticipate, prepare for, respond to, and recover from adverse events. Resilience is about having the physical infrastructure to withstand floods and includes characteristics such as community networks, access to information, and the capacity to adapt to changing circumstances. Traditional flood risk assessments often overlook these softer elements, focusing instead on physical and economic metrics. Table 4 shows 30.4 percent of LMI neighborhoods of color exhibit low community resilience, significantly higher than the national average of 20.0 percent. Traditional flood risk assessments that focus mainly on physical and economic metrics fail to capture this nuanced picture.

TABLE 4

Social Vulnerability and Community Resilience, by Neighborhood Income and Race

	LMI neighborhoods	Middle-income neighborhoods	Upper-income neighborhoods	All neighborhoods
Share of tracts with high social vulnerability				
Neighborhoods of color	69.9%	26.9%	5.7%	50.9%
Majority-white neighborhoods	27.4%	5.7%	0.7%	8.1%
All neighborhoods	51.0%	9.7%	1.2%	20.0%
Share of tracts with low community resilience				
Neighborhoods of color	30.4%	40.5%	41.0%	34.4%
Majority-white neighborhoods	14.0%	14.1%	14.7%	14.3%
All neighborhoods	23.1%	19.0%	17.6%	20.0%

Source: American Community Survey data.

Notes: AMI = area median income; LMI = low- and moderate-income. Neighborhoods of color are census tracts where the share of households of color exceeds 50 percent. Majority-white neighborhoods are census tracts where the share of white households exceeds 50 percent. LMI neighborhoods are those where the median income in the census tract is less than 80 percent of the AMI. Middle-income neighborhoods are those where the median income in the census tract is at least 80 percent of the AMI but less than 120 percent of the AMI. Upper-income neighborhoods are those where the median income in the census tract is at least 120 percent of the AMI.

An illustrative example of the importance of having a composite risk metric is when comparing two neighborhoods that suffer the same economic losses in terms of EAL. If one neighborhood has strong community resilience while the other exhibits low resilience, the latter will require substantially more resources and support to facilitate effective postdisaster recovery. This difference highlights that economic loss alone is an insufficient measure of flood impact. The levels of community resilience and social vulnerability are crucial determinants of the actual resources needed for recovery and should be a key consideration in allocating aid and designing recovery strategies. Thus, integrating social vulnerability and community resilience into our composite risk metric is a vital step toward a more equitable and effective flood risk assessment and management approach.

Composite Risk Metric

To construct a composite risk metric incorporating both economic losses and location-specific risk factors related to social vulnerability and community resilience, we use the EALs normalized by the TRV from Verisk, the social vulnerability score from Centers for Disease Control and Prevention, and the community resilience score from the Hazards Vulnerability and Resilience Institute used in FEMA's NRI.

We follow the three-point estimation, a parametric approach employed by FEMA in its calculations of the NRI. In the NRI, using a triangular distribution, a community risk factor is created to be a scaling factor to integrate aspects of social vulnerability and community resilience. For each census tract, a community risk factor value is derived by a triangular distribution mapping based on the ratio of its social vulnerability value over community resilience value. By design, the community risk factor ensures that communities with higher social vulnerability and lower community resilience will result in a higher overall risk rating for a given level of EAL.

Almost 11 percent of LMI neighborhoods of color are rated as very high risk, compared with 7.8 percent when assessing risk using only the EAL_TRV, a 2.8 percentage-point difference (table 5). This indicates a more pronounced risk perception when the metric incorporates factors of social vulnerability and community resilience. For middle-income neighborhoods, the disparity is less marked. The composite risk metric rates 8.3 percent of neighborhoods of color as very high risk, which is slightly higher than the 7.7 percent determined by EAL_TRV alone.

Majority-white neighborhoods present a different profile. The composite risk metric results in 7.2 percent of LMI neighborhoods being classified as very high risk, whereas EAL_TRV alone indicates a slightly lower risk (6.9 percent). In middle-income and upper-income neighborhoods, composite risk assessment identifies less concentration of very high–risk areas compared with using EAL_TRV only.

These findings underscore the importance of incorporating social vulnerability and community resilience alongside traditional economic loss evaluations, particularly for LMI neighborhoods of color.

TABLE 5

Share of Tracts Rated as Very High Risk, by Neighborhood Income and Race

	LMI neighborhoods	Middle-income neighborhoods	Upper-income neighborhoods	All neighborhoods
Composite risk metric				
Neighborhoods of color	10.6%	8.3%	6.0%	9.5%
Majority-white neighborhoods	7.2%	5.9%	3.4%	5.3%
All neighborhoods	9.1%	6.4%	3.7%	6.4%
EAL_TRV only				
Neighborhoods of color	7.8%	7.7%	8.0%	7.8%
Majority-white neighborhoods	6.9%	7.5%	5.9%	6.8%
All neighborhoods	7.4%	7.5%	6.2%	7.1%

Sources: Verisk and American Community Survey data.

Notes: AMI = area median income; EAL = expected annual loss; LMI = low- and moderate-income; TRV = total replacement value. Neighborhoods of color are census tracts where the share of households of color exceeds 50 percent. Majority-white neighborhoods are census tracts where the share of white households exceeds 50 percent. LMI neighborhoods are those where the median income in the census tract is less than 80 percent of the AMI. Middle-income neighborhoods are those where the median income in the census tract is at least 80 percent of the AMI but less than 120 percent of the AMI. Upper-income neighborhoods are those where the median income in the census tract is at least 120 percent of the AMI.

Conclusions and Policy Implications

This research builds upon previous studies that have explored the profound impacts of shock events, such as recessions and fluctuations in mortgage rates, on communities of color. Using a focused analysis of riverine flood risk, our findings illustrate how communities of color are disproportionately affected by natural disaster shocks and how the impact is magnified because of these communities' greater vulnerability and weaker resilience. Riverine flooding events can lead to disproportionately larger impacts on these communities, exacerbating existing disparities and resulting in prolonged recovery periods.

In the realm of riverine flood risk, understanding and preparation are paramount. This study reaffirms the importance of broadening our methods of assessment and enhancing data quality to ensure the most vulnerable communities are adequately supported. The findings of this study prompt a critical examination of current methodologies and underscore the need for comprehensive policy responses to riverine flood risks. Four key takeaways have emerged:

1. Revisiting FEMA's risk assessment of riverine flooding risk. There is an essential need for FEMA to adopt a more inclusive definition and forward-looking assessment approach for riverine flooding risk.

Data on pluvial flooding events should be included. Reliance on historical data alone is insufficient in a changing climate. Risk assessments must evolve to capture observed climatic trends and possible events beyond those observed in the historical record and must incorporate predictive models that account for future climatic events and their potential impacts, ensuring that all communities, especially historically underserved communities, are adequately considered in risk mitigation strategies. Increased precision in these models does not inherently mean better accuracy. Therefore, special attention must be given to ensure these forward-looking estimates accurately reflect the potential risks, thus providing a reliable basis for decisionmaking and resource allocation.

2. Normalizing EAL with TRV. To grasp the full extent of the impact on communities, especially marginalized ones, the EAL needs to be normalized by the TRV. This scaling provides a more equitable measure of risk, reflecting the disproportionate impact marginalized communities bear, particularly LMI neighborhoods of color.

3. Incorporating social vulnerability and community resilience to formulate composite risk metrics. It is imperative to integrate social vulnerability and community resilience into risk assessment models. Our study has shown that communities of color, particularly in LMI areas, are disproportionately affected by riverine flooding when accounting for social vulnerability. A holistic risk assessment that includes these factors can lead to a more comprehensive understanding of risk and more effective postdisaster recovery strategies.

4. Attention to racial equity in ESG frameworks. Environmental, social, and governance (ESG) frameworks highlight the importance of considering racial equity issues. Our analysis—which integrates EAL_TRV, social vulnerability, and community resilience—demonstrates the disproportionate impact of riverine flooding on marginalized communities. This integration aligns with the ESG imperative to pay attention to how environmental risks, such as flooding, exacerbate existing social inequities.

In light of these takeaways, policymakers must consider a multifaceted approach to flood risk assessment. Such an approach should consider historical patterns and future predictions, the economic burden relative to community wealth, and the compounding factors of social vulnerability and resilience. Doing so ensures that interventions and resources are equitably distributed, particularly to communities most at risk and least able to recover from disaster events. As we continue to face climate change, our policies must be informed by data and methodologies that encompass the full scope of risk and prioritize all communities' well-being and sustainability.

The phenomenon of "bluelining," where communities at high flood risk face exclusion from essential financial services and insurance coverage, calls for immediate and concrete policy actions. On one hand, insurance coverage policies need urgent reform to ensure fair and affordable access for marginalized and historically underserved communities, often situated in flood-prone zones. These changes may involve regulatory reforms to mandate fair access to insurance and government-backed insurance solutions. On the other hand, financial service policies must be crafted to enhance the resilience of these vulnerable communities. Marginalized and historically underserved communities are at a heightened risk of suffering disproportionate hardships attributable to climate- or disaster-driven financial exclusion. To combat this, policies must be enacted to ensure these vulnerable populations are not denied access to the financial products necessary for their postdisaster economic stability and recovery. Policy frameworks such as the Community Reinvestment Act and the Inflation Reduction Act's Greenhouse Gas Reduction Fund could mitigate the adverse effects of bluelining and foster a more equitable and resilient financial system that upholds the rights and needs of all communities, regardless of their geographic or socioeconomic status.

Moreover, the historical approach to the allocation of support and subsidies in the aftermath of disasters has often been driven by visible, immediate losses, overshadowing the less quantifiable yet critical elements of social vulnerability and community resilience. The long-term effectiveness and sustainability of recovery efforts are inextricably linked to these aspects. Communities burdened with high levels of social vulnerability encounter challenges that transcend the apparent economic damages. Likewise, regions with low resilience capacities require recovery assistance and proactive measures to strengthen them against future incidents. Therefore, policy frameworks should be restructured to fully encompass and respond to the broader spectrum of social vulnerability and resilience. For example, Community Disaster Resilience Zones (CDRZs) are a stride toward such restructuring. The CDRZ Act requires FEMA to identify areas most susceptible to natural hazards and climate change through detailed and comprehensive risk assessment. Based on the FEMA NRI, communities recognized as CDRZs will gain access to enhanced federal support, becoming hubs for significant investments from government sources and from philanthropic organizations, nonprofits, and private-sector entities. Such a recalibration would allow for a more equitable distribution of resources, ensuring that those most in need of support—communities that are most vulnerable and least resilient—are given priority.

Notes

[1] Justin Dorazio, “How FEMA Can Prioritize Equity in Disaster Recovery Assistance,” Center for American Progress, July 19, 2022, https://www.americanprogress.org/article/how-fema-can-prioritize-equity-in-disaster-recovery-assistance/.

[2] Andy Olin, “How Inequalities Made Harvey Recovery Harder for Many Nonwhite Houstonians,” *Urban Edge* (blog), Rice University Kinder Institute for Urban Research, May 6, 2021. https://kinder.rice.edu/urbanedge/how-inequalities-made-harvey-recovery-harder-many-nonwhite-houstonians.

[3] Verisk models flood risk using stochastic event generation as part of its catastrophe model, a fully probabilistic model that covers pluvial and fluvial flooding. The simulated events are informed from output of a coupled General Circulation Model and Numerical Weather Prediction model, which simulate realistic and statistically robust precipitation patterns in space and time after downscaling the output of the coupled models.

[4] The underlying social vulnerability data and documentation are available at “CDC/ATSDR SVI Data and Documentation Download,” Agency for Toxic Substances and Disease Registry, last updated October 26, 2022, https://www.atsdr.cdc.gov/placeandhealth/svi/data_documentation_download.html.

[5] The underlying community resilience data and documentation are available at “BRIC,” University of South Carolina, College of Arts and Sciences, accessed March 1, 2024, https://www.sc.edu/study/colleges_schools/artsandsciences/centers_and_institutes/hvri/data_and_resources/bric/index.php.

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