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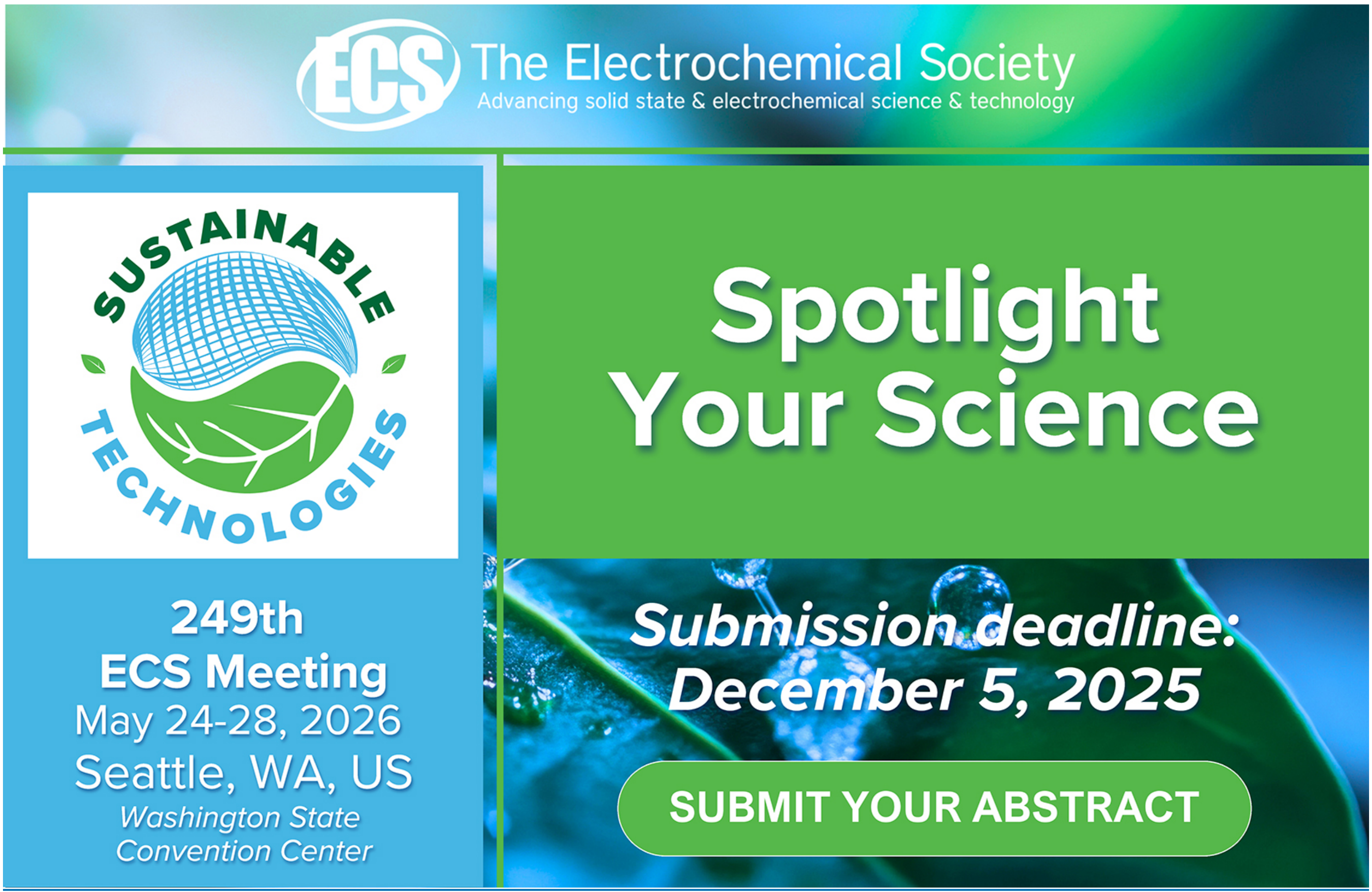

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LETTER

Climate change and federal aid disbursements after Hurricane Harvey: an extreme event attribution analysis

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Abstract

The role climate change plays in increasing the burden placed on governments and insurers to pay for recovery has not been extensively explored and is the focus of this study. This study examines the impacts of climate change attributed flooding on federal disaster aid disbursement in Harris County, Texas following Hurricane Harvey in 2017. Our approach uses flood models to estimate the amount of flood damages attributable and not attributable to climate change under two climate change attribution scenarios from peer reviewed studies: 20% and 38% increases in rainfall associated with the hurricane due to climate change. These estimates are combined with census tract-level disbursement data for FEMA's National Flood Insurance Program (NFIP) and the Individual Assistance (IA) part of the Individuals and Households Program. We employ spatial lag regression models with direct and spatial spillover effects to analyze the relationship between a tract's flood damages—both attributed and not attributed to climate change—and federal disaster aid. We find that both types of flood damage shape federal aid disbursements, but that climate change attributed damages tend to have larger effect sizes (elasticities) especially for IA. Specifically, for a 1% increase in additional climate change attributed damages per household in a census tract (under the 20% scenario), expected NFIP levels in that census tract are 0.26% higher and IA levels are 0.3% higher. Implications center on federal funding in an era of climate change.

1. Introduction

Climate change is increasing the severity of many classes of extreme weather (Seneviratne *et al* 2023). Advances in climate science now allow researchers to directly quantify the influence of anthropogenic climate change in altering the weather conditions that shape specific weather events. Still, the role climate change plays in increasing the direct damage from these disasters has only recently started to be quantified in a new literature on Extreme Event Impact Attribution (EEIA); see Noy *et al* (2024) and Perkins-Kirkpatrick *et al* (2022) for surveys of this new literature. The direct damage from extreme weather typically leads to a fiscal response from government. Quantifying the relationship between the attributed damage from climate change and this governmental response is the focus of this study.

EEIA is part of a broader field of Extreme Event Attribution (EEA) which attempts to determine how much of a given storm's physical characteristics would not have occurred in a world without anthropogenic climate change (NASEM, 2016, Otto 2017, Perkins-Kirkpatrick *et al* 2022). To do this, climate scientists use a variety of methods exploiting observational data and climate or weather forecast models (Wehner 2023). The often used 'storyline approach' compares simulations of individual extreme weather events performed to be as realistic as possible to counterfactual simulations with the human interference in the thermodynamic components of the climate system removed. By comparing the actual storm that happened and the counterfactual storm, this research can identify differences that can be understood as attributed to climate change. More recently, researchers have started to incorporate quantifications from EEA with social and economic data in order to quantify the impact of these attributed events—this is EEIA (Noy *et al* 2024).

In parallel to this work is research that seeks to understand societal responses to climate change, most notably responses shaped by governments' attempts to aid in disaster recovery. Of particular interest in this study are programs that provide aid to homes damaged by flooding in the United States: The National Flood Insurance Program (NFIP) and the Individual Assistance (IA) part of the Individuals and Households Program—both administered by the Federal Emergency Management Agency (FEMA). The NFIP is one of FEMA's primary policy instruments for managing flood risk. Standard home insurance does not typically cover damage from flooding, so NFIP policies are sold separately to cover this risk. Properties located within a FEMA-delineated 100 year floodplain (i.e. the Special Flood Hazard Area [SFHA]) with a federally backed mortgage are required to have flood insurance, though this is not always enforced. Residents outside of the 100 year floodplain can elect to buy flood insurance but are not mandated to do so (Title 24, 2025). IA is part of the Individuals and Households Program (IHP), which provides aid for many different needs, and we study home repair in particular. Flood insurance holders rarely need IA, but IA's home repair grants are a primary federal option for households without flood insurance. The IA was capped at $33 000 for households at the time of Hurricane Harvey—much lower than the NFIP cap: up to $250 000 for property damages and $100 000 for home contents (Lindsay and Reese 2018). A third program, the Federal Disaster Loan Program from the Small Business Administration (SBA), provides loans for homeowners and disbursed larger sums on average than the IA program, but these data are not readily available at the spatial scale (i.e. census tract) for this study (see Billings *et al* 2022).

Recent trends show that there has been a dramatic expansion of federal aid after disasters in recent decades, and climate change could be one of the reasons why this aid is increasing. From 1992 to 2022, a total of $347 billion (in 2022 dollars) was spent by FEMA's Disaster Relief Fund (CBO 2022). Of the ten years with the highest outlays, all have occurred since 2003, including each of the last five years of this period. A recent Congressional Budget Office report observes that '…spending has been driven less by the number of disasters declared and more by the size and severity of individual disasters' (CBO 2022, p 2). Approximately 75% of funds for the Disaster Relief Fund come from one-time supplemental appropriations for major disaster events, indicating that the ad-hoc funding model could lead to increasing financial outlays as climate change increases impacts from extreme weather. Indeed, an emergent set of work estimates the economic costs of climate change through extreme weather events (e.g. Newman and Noy 2023, WMO 2023). Smiley *et al* (2022) provide one of the first studies linking extreme event attribution to micro-level economic impacts, estimating that climate change was responsible between $2.4 billion (37.2%) and $3.7 billion (57.8%) of residential damage in Harris County, Texas during Hurricane Harvey. These findings highlight the substantial fiscal impact of climate change on disasters, which reinforces the escalating costs borne by the federal disaster relief programs.

To examine the connection between climate change and disaster policy, our research bridges scientific data on climate change attribution with social scientific research designs to study an essential question: how do the impacts of climate change from extreme weather events shape U.S. recovery aid in the case of Hurricane Harvey? More specifically, did climate change increase federal aid expenditures for this storm? Whether climate change increases expenditures, and by how much, are both important questions for understanding how government and households will recover from flooding in decades to come.

To investigate these differences, we extend our analysis of the effect of climate change on the flood impacts resulting from Hurricane Harvey in Greater Houston in 2017—an important case study due to the magnitude of this event (the second costliest hurricane in US history), and its mix of insured and uninsured households across diverse socio-economic backgrounds. A key contribution of this paper is its research design. Following the logic of end-to-end extreme event attribution (Smiley *et al* 2022), this design first disaggregates floodwaters into amounts that can be attributed to climate change and those not attributed to climate change using outputs from extreme event attribution research paired with flood modeling (Risser and Wehner 2017, van Oldenborgh *et al* 2017, Wang *et al* 2018, Wehner and Sampson 2021). Next, we translate these flood depths—attributed to climate change and flooding that would have occurred regardless of climate change—to financially measured damage to residential properties. Here, we use these disaggregated measures as independent measures of damage and correlate them with fiscal consequences. Using disaster impacts as an independent variable in a regression framework is common (Logan *et al* 2016, Fussell *et al* 2017, Chakraborty *et al* 2019, Howell and Elliott 2019), but the heart of our approach is quantifying the increasing impacts due to climate change. This is a transposable research design: future research could similarly use insights from climate scientists and damage modelers to determine how much impacts from hazards is attributed to climate change and if, and how, this affects other social outcomes.

By integrating these datasets, our research links extreme event attribution with disaster recovery policy, revealing whether climate change attributed damages relate to greater government expenditures. Different areas do not necessarily experience impacts from climate change equally, and, noting this, we assess the geographic disparities of these climate change attributed damages and of FEMA aid. If federal aid disproportionately covers damages in areas impacted by climate change, it suggests that climate-driven impacts are imposing financial burdens on the U.S. government—a finding with significant implications for the future of federal disaster policy, and for the fiscal benefits associated with more aggressive greenhouse gas mitigation policies.

2. Data and methods

To examine the association between climate change attributed flooding and federal aid disbursement, data from three sources are utilized: OpenFEMA (FEMA 2024a, 2024b), climate change attribution flood models (Smiley *et al* 2022, Wehner and Sampson 2021), and American Community Survey 5 year estimates. Census tracts are chosen as the unit of analysis because tracts allow for a localized examination of the relationship between federal aid payouts and damages linked to climate change. Moreover, census tracts are widely recognized as a standard unit of analysis in U.S. urban studies (Krivo and Peterson 1996, Akins 2009, Neckerman *et al* 2009), affirming their validity as reasonable representations of neighborhood dynamics. Our population of census tracts is from Harris County, Texas, which had approximately 4.6 million residents at the time of Hurricane Harvey and includes Houston as its major city. There are 764 census tracts in Harris County with the required data[6].

2.1. Dependent variables

Federal aid disbursement data came from two open-sourced datasets provided by OpenFEMA, which provide details on NFIP (FEMA 2024a) and IA (FEMA 2024b) claim-level transactions. For both the NFIP and the IA, dollar amounts of successfully paid claims from Hurricane Harvey were aggregated to the census tract level then divided by the number of occupied residences within that tract. For IA, we specifically focused on home repair assistance under the IHP. While IA provides aid for a range of immediate needs—including temporary housing, medical expenses, and personal property losses—our analysis is limited to home repair grants, which support individuals without flood insurance.

2.2. Focal explanatory variables

The focal explanatory variables are damages attributed and not attributed to climate change. Flood models developed by Wehner and Sampson (2021) were used to create these measures. Estimates of the portion of Hurricane Harvey's rainfall attributable to climate change were calculated in three studies (Risser and Wehner 2017, van Oldenborgh *et al* 2017, Wang *et al* 2018). The current analysis uses a best estimate of 20% from Wang *et al* (2018), and a high estimate of 38%, which refers to the best small area estimate from Risser and Wehner (2017), an area that partly corresponds to the study area of Harris County.

Building-level damages were calculated using flood simulations based on observed rainfall estimated during Hurricane Harvey and estimates with counterfactual flood simulations based on 17% and 27% less rainfall than observed corresponding to a 20% and 38% increase in rainfall attributable to climate change, respectively. These flood models mitigate potential concerns over endogeneity by utilizing depth-damage curves based on building characteristics rather than market values, meaning that estimates of physical damage are not directly influenced by housing market conditions and residents' wealth. This reduces concerns that property values, which are partly shaped by neighborhood socioeconomic factors, might bias the damage estimates[7]. Total residential building-level damages attributed to climate change and not attributed to climate change (i.e. would have occurred regardless of climate change) were aggregated to the census tract-level. Both of these estimates were then divided by the number of occupied housing units in each tract. In all, the two focal explanatory variables are: (1) property damages not attributed to climate change per occupied residence (which we term non-climate change attributed damage), and (2) property damages attributed to climate change per occupied residence (which we term climate change attributed damage).

2.3. Control variables

Tract-level socio-demographic control variables were computed using five-year pooled estimates from the American Community Survey (2012–2016), sourced from the National Historical Geographic Information Systems (Manson *et al* 2023). These variables include

[6] Twenty-two tracts were missing information on their median housing value, and were therefore dropped from the analysis. These dropped census tracts account for only about 2% of the total damage caused by Hurricane Harvey in Harris County.

[7] For further details on flood models and construction of impact measures, see (Wehner and Sampson 2021, Smiley *et al* 2022, Wing *et al* 2022).

racial composition, including the proportion of black residents, the proportion of Hispanic or Latino (Latina/x/o) residents, and the proportion of residents who are not white, black, or Latina/x/o. Additionally, models control for median income and proportion of owner-occupied homes before the storm. The analysis also accounts for the number of NFIP policyholders at the time of Hurricane Harvey, divided by the number of occupied residences; these data are available from OpenFEMA. Finally, baseline flood risk is controlled for using the proportion of residential buildings in each tract that intersect with the 100 year FEMA-delineated floodplain (i.e. SFHA) divided by the number of residential parcels in that tract.

2.4. Analytic strategy

To analyze the relationship between federal aid disbursements and flood damage, four regression models were estimated. Model 1 and Model 3 analyze NFIP and IA paid claims, respectively, with four independent variables: non-climate change attributed damage, climate change attributed damage, NFIP policyholders, and baseline flood risk. Model 2 and Model 4 include the same variables, plus socio-demographic controls like racial composition, homeownership, and median income. All analyses were conducted at the census tract-level, and all variables were logged to account for skew. Initial model selection used nonspatial ordinary least squares (OLS) models, and variance inflation factors (VIFs) indicated no multicollinearity (VIF < 5).

Global Moran's I statistics based on a queen's first order contiguity matrix revealed statistically significant spatial autocorrelation in OLS residuals (Moran's I between 0.247 and 0.368, $p < 0.001$), violating OLS independence assumption and necessitating a spatial regression approach (Golgher and Voss 2016, Anselin 2022). Robust LM tests for a missing spatially lagged variable indicated spatial lag terms as the appropriate specification of spatial dependence ($p < 0.001$). A spatial lag model accounts for this spatial dependence, as NFIP and IA payouts may directly influence or spill over into neighboring areas. Additionally, lower Akaike Information Criterion values for the spatial lag model suggest a better fit than the spatial error model. The spatial lag model can be expressed as:

$$y_i = \rho W y_{-i} + \beta X_i^{\mathrm{dam}} + \gamma X_i^{\mathrm{soc}} + \varepsilon_i \qquad (1)$$

where y_i represents the values of the dependent variables in each census tract i (the NFIP and IA disbursements). ρ is a spatial autoregressive parameter we estimate, while $W y_{-i}$ is the spatially lagged dependent variable with spatial weights W, based on a queen-one contiguity matrix. X_i^{dam} is a vector of the main variables we are interested in (the damage attributed or not attributed to climate change), β is a vector of coefficients associated with these explanatory variables, X_i^{soc} is a vector of other socio-economic control variables with its accompanying coefficient vector γ, and ε is the error term.

3. Results

3.1. Descriptive analysis

Table 1 provides descriptive statistics for all study variables. Compared to the IA program, the NFIP allocated much more funding following Hurricane Harvey in Harris County. The mean tract allocation was \$3973 of NFIP outlays per household, but the equivalent value for IA was only approximately one tenth of this figure (\$404). This was anticipated, as the NFIP offers a much higher cap on its disbursements (Lindsay and Reese 2018, Emrich *et al* 2022). Figure 1 shows a positive correlation, albeit with a moderate amount of variation, between the two programs.

Moreover, and not surprisingly, there was greater damage per household that was not linked to climate change than there were damages attributable to climate change. Still, there was substantial damage attributed to climate change. Specifically, under the 20% rainfall scenario, approximately \$8030 of mean damages per household were attributable to climate change during Hurricane Harvey, while \$14 711 per household were not attributable to climate change. Still, this indicates a degree of disproportionality: the extreme event attribution suggested a 20% increase in rainfall attributed to climate change, but this corresponded to approximately 35% of the damages. The data is similarly disproportionate for the 38% scenario, in which 53% of the damage was attributable. This is to be expected given that flood hazard damage functions used are non-linear (see Wehner and Sampson 2021).

Figure 2 maps these outcomes with a bivariate analysis with a recoding of the two flood damage variables into terciles. While many tracts correspond to low values on both variables (i.e. the tracts in light gray) or high on both variables (i.e. the tracts in brown) as would be expected, there are still many tracts that are disproportionately higher in climate change attributed damage compared to damage not attributed to climate change (i.e. purple), and vice versa (i.e. dark yellow). The two types of damage exhibit only a moderate positive correlation ($r = 0.46$ under the 20% scenario; $r = 0.51$ under the 38% scenario).

3.2. Multivariate regressions

Tables S1 and S2 in the Supplementary Material display results of spatial lag models predicting NFIP and IA award amounts under the two climate change scenarios (20% and 38%). In each of these models, the spatial autoregressive parameter is statistically significant. This suggests that for both the NFIP and

Table 1. Descriptive statistics for all study variables.

	Mean	St.Dev.	Min	Max
NFIP aid per household	3973	11 611	0	132 027
IA aid per household	404	885	0	9249
Non-CC Damage (20%) per household	14 711	106 992	0	2 673 068
Non-CC Damage (38%) per household	10 633	92 965	0	2 401 307
CC Attributed Damage (20%) per household	8030	35 877	0	611 785
CC Attributed Damage (38%) per household	12 108	51 821	0	789 221
Prop. NFIP policy holders	0.16	0.15	0.00	0.85
Prop. FEMA 100 year floodplain	0.10	0.20	0.00	0.98
Prop. Black	0.19	0.21	0.00	0.92
Prop. Latina/x/o	0.42	0.26	0.02	0.99
Prop. other race	0.08	0.08	0.00	0.56
Prop. homeowners	0.55	0.24	0.02	0.99
Median Income	62 456	36 716	9015	250 001

Note: Descriptive statistics are not logged.

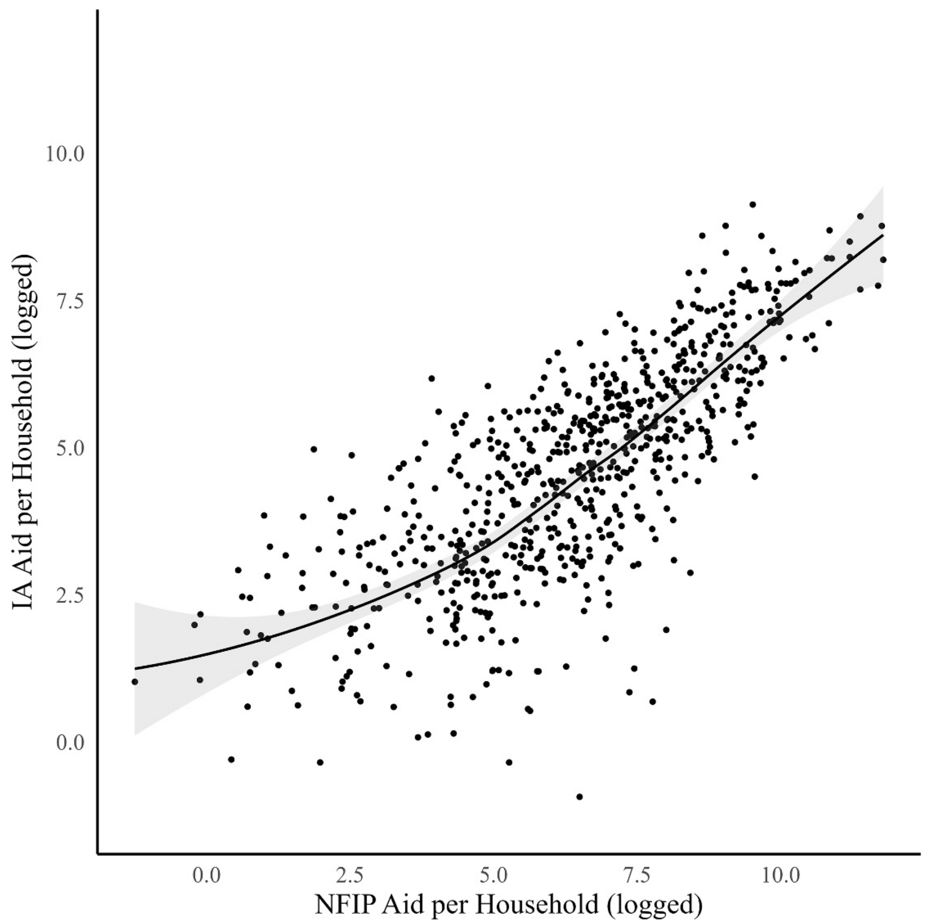

Figure 1. NFIP Aid per Household v. IA Aid per Household among census tracts that received aid in Harris County, Texas after Hurricane Harvey ($N = 732$).
Note: 32 tracts did not receive NFIP aid and are not shown in this plot.

IA program, payouts in a given tract tend to be higher when neighboring tracts receive larger payouts. Because coefficients for the explanatory variables represent spatial interaction effects and cannot be interpreted as in standard linear models (Golgher and Voss 2016), direct effects, indirect effects (i.e. spillovers), and total effects of the explanatory variables from the fully specified models are estimated for each of the climate change attribution scenarios. These results are presented in table 2. Additionally, supplemental analysis (see table S3 in Supplementary Material) shows that total damage (i.e. climate change attributed and non-attributed damages combined) is associated with higher NFIP and IA aid—i.e. areas with greater damage received more assistance from both programs.

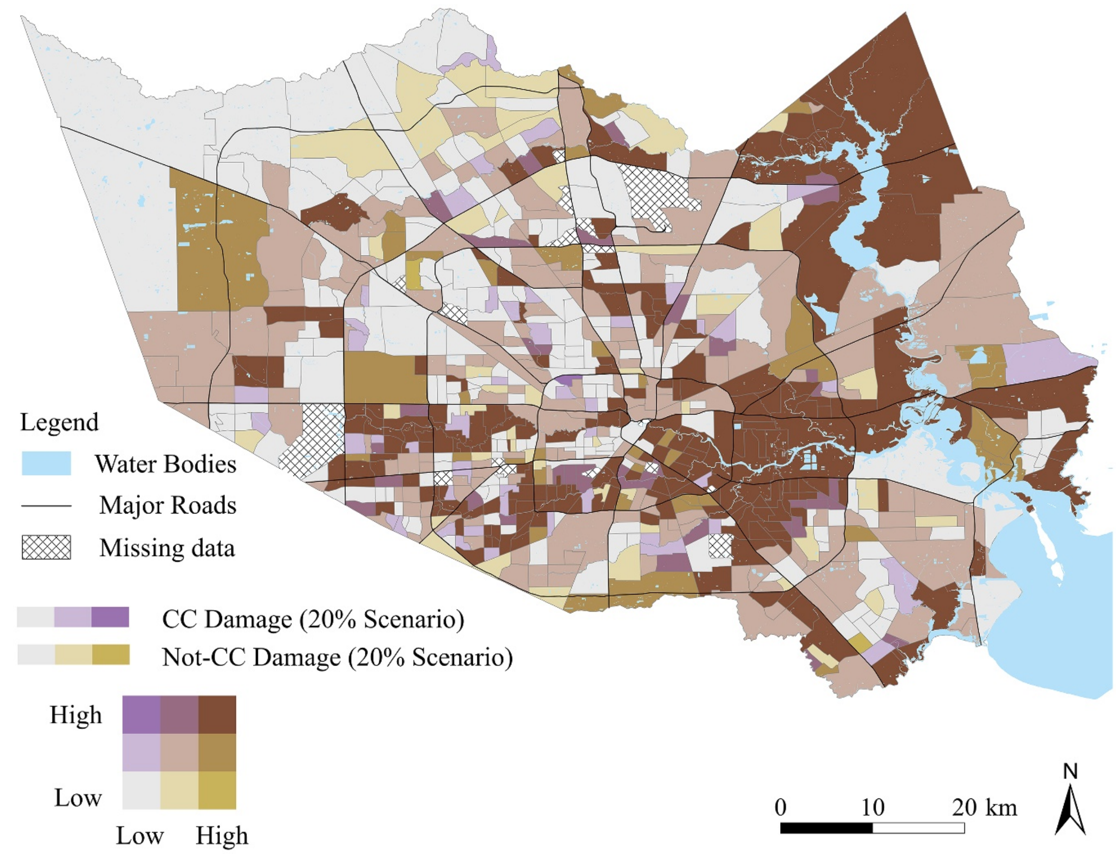

Figure 2. Climate change and non-climate change attributed damages.
Note: Cutoffs based on terciles.

Table 2. Direct and indirect effects for NFIP and IA Aid per residence under different attribution scenarios.

	20% Rainfall Attributed to Climate Change					
	NFIP			IA		
	Direct	Indirect	Total	Direct	Indirect	Total
Non-CC Damage	0.17***	0.15**	0.32***	0.05	0.08	0.13
CC Attributed Damage	0.14**	0.12**	0.26**	0.11***	0.19***	0.30***
Prop. NFIP policy holders	1.55***	1.32***	2.88***	0.46***	0.76***	1.23***
Prop. FEMA 100 year floodplain	−0.14	−0.12	−0.26	0.14	0.24	0.38
Prop. Black	0.03	0.03	0.06	0.11**	0.18**	0.29**
Prop. Latina/x/o	0.18	0.16	0.34	0.20*	0.32*	0.52*
Prop. other race	−0.07**	−0.06**	−0.13**	−0.04**	−0.07**	−0.12**
Prop. homeowners	−0.07	−0.06	−0.13	0.46***	0.76***	1.22***
Median income	−0.77**	−0.66**	−1.43**	−0.63***	−1.05***	−1.68***
	38% Rainfall Attributed to Climate Change					
	NFIP			IA		
	Direct	Indirect	Total	Direct	Indirect	Total
Non-CC Damage	0.08*	0.07*	0.15*	0.06**	0.10*	0.16**
CC Attributed Damage	0.23***	0.20***	0.42***	0.10***	0.18***	0.28***
Prop. NFIP policy holders	1.54***	1.32***	2.86***	0.47***	0.79***	1.26***
Prop. FEMA 100 year floodplain	−0.16	−0.14	−0.29	0.14	0.23	0.37
Prop. Black	0.03	0.03	0.06	0.11**	0.18**	0.29**
Prop. Latina/x/o	0.18	0.16	0.34	0.19**	0.33*	0.52**
Prop. other race	−0.07*	−0.06*	−0.13*	−0.05**	−0.08**	−0.12**
Prop. homeowners	−0.08	−0.07	−0.15	0.45***	0.75***	1.19***
Median income	−0.75***	−0.64**	−1.39***	−0.64***	−1.07***	−1.70***

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

3.2.1. 20% scenario

Table 2 (top panel) shows that for the 20% scenario, the direct effects, indirect spillover effects, and total effects of non-climate change attributed damage on NFIP aid were 0.17, 0.15, and 0.32, respectively. As these independent variables and dependent variables are logged, these regression coefficients are elasticities and interpreted as such below. Each coefficient was statistically significant, suggesting that damages not linked to climate change within a tract were associated with greater NFIP payouts in that tract (i.e. the direct effect) and in neighboring tracts (i.e. the indirect effect). However, the effects of non-climate change attributed damage were not statistically significant in predicting IA payment amounts. Put differently, within a particular tract, experiencing greater damages that would have occurred regardless of climate change was better linked to greater NFIP than IA payments. In contrast to these results, climate change attributed damages had statistically significant direct and spatial spillover effects for both NFIP aid and IA aid. For each 1% increase in additional climate change attributed damages per household in a given tract, the expected IA payout per occupied residence was higher by 0.11% in that tract (i.e. the direct effect) and by 0.19% in neighboring tracts (i.e. the indirect effect).

For the control variables (X_i^{soc}), the proportion of NFIP policy holders is always associated positively (and statistically) with both the NFIP and IA. While expected for NFIP payments, the IA results are less intuitive, and the coefficients are indeed smaller. Median income is consistently negatively associated for both programs. While the NFIP and median income finding may be somewhat surprising, controlling for NFIP policyholder penetration (which is positive) likely explains it. Indeed, bivariate regressions (see table S4) show that median income is positively related to NFIP but remains negative for IA.

For NFIP payments in the 20% scenario, tract racial composition was not a strong predictor, except for a small but statistically significant negative impact of the proportion of other races (not Black or Latina/x/o). For IA payments, tracts with higher proportions of Black or Latina/x/o residents received more funding. These findings for race should be noted in the context that Latina/x/o residents (Chakraborty *et al* 2019, Smiley 2020, Smiley *et al* 2022) experienced greater impacts during Hurricane Harvey, relative to White residents, and therefore these federal disbursements may correspond to those greater impacts[8].

[8] Supplemental analyses examining interactions between racial composition variables and damage variables (i.e. attributed to and not attributed to climate change) did not yield large effect sizes or statistically significant results.

3.2.2. 38% scenario

The direct effects, indirect effects, and total effects of the explanatory variables on NFIP and IA assistance when a 38% increase in rainfall is attributed to climate change are presented in the bottom panel of table 2. As with the 20% results, non-climate change attributed damage has statistically significant effects on NFIP aid, indicating that experiencing greater damages not attributable to climate change within a particular tract was associated with larger NFIP payouts. For IA, small direct and indirect effects for non-climate change attributed damage emerged. Climate change attributed damage was positive and statistically significant for both programs, as was the case for the 20% scenario. Here, a 1% increase in additional climate change attributed damage per household translates an increase of 0.42% in NFIP and 0.28% in IA aid.

Similar to 20% scenarios, NFIP policyholder proportion had statistically significant direct and indirect effects on both programs, though smaller in magnitude for IA. Median income remained statistically significant and negative for both types of aid. Proportion Black, proportion Latina/x/o, and proportion homeowners positively predicted IA aid but not NFIP aid. The proportion of other races had a negative and statistically significant effect.

4. Discussion and conclusion

The objective of this study was to assess the contemporary impacts of climate change on federal post-disaster assistance disbursements, particularly as they intersect with disaster impacts. By utilizing an EEIA perspective, we differentiated between additional flood damages attributable to climate change and those likely to have occurred regardless. Findings show that both are important in determining the amounts of federal post-disaster disbursements from FEMA, but in different ways depending on the funding program being examined and the climate change scenario being assessed. Damage attributed to climate change was linked to greater NFIP and IA payments in both the 20% and 38% scenario. Damages that were not attributed to climate change were linked to greater NFIP payments for both the 20% and 38% scenario and were only linked to greater IA payments in the 38% scenario.

Why these differences? It might be reasonable to expect that more damage means more paid claims, regardless of the cause. Our results, though, show that this is not always the case. Because damage is often a non-linear function of hazard exposure, the additional floodwaters from the amplified rainfall because of climate change had disproportionate impacts. Further, this additional flooding because of climate change is linked in different ways to localized federal aid disbursement levels.

One possible explanation for the NFIP results is that non-climate change attributed flooding adheres to historical norms and is better anticipated by FEMA's flood risk framework. This explanation corresponds with the finding that NFIP payouts were associated with non-attributable flooding. Because FEMA flood maps and insurance requirements are based on historical flood risk, homeowners in these areas may be more likely to hold flood insurance policies, leading to higher NFIP payments when damages occur. Conversely, climate change attributed flooding represents flooding that is more unprecedented and more intense than what is expected by historical norms and risk modeling based on past experiences. For both the IA and the NFIP, climate change attributed damages were linked with larger disbursements in both scenarios (20% and 38%). For the NFIP, these findings suggest that in a flood-prone city like Houston, there is a degree of proportionality between flood insurance payouts and impacts from climate change.

For IA, climate change attributed flooding is more strongly linked to disbursements than non-climate change attributed flooding. Compared to the NFIP, IA is a program designed as a secondary support mechanism. It does not entail advance payments of insurance premiums, and it features lower disbursements overall (with more than 90% of funds from these programs after Harvey distributed through the NFIP), lower disbursements per claim (with a cap of $33 000 for IA compared to $250 000 for home damage for NFIP), and high rates of claims denied (an issue not directly examined here; see Raker 2023, Raker and Woods 2023). And, yet IA is an essential mechanism for recovery (alongside SBA loans) for those who cannot afford flood insurance or did not purchase flood insurance.

Taken together, these findings suggest that these dynamics may operate as inequality-generating mechanism in that households dependent on IA will have less means to recover (even if their claims are successful) compared to households with NFIP policies. More broadly, the findings indicate that if climate change increases the severity of storm impacts (as we identify for Hurricane Harvey in Harris County), then increases in federal aid are essential for residents to recover from the storm. The findings further suggest that a primary way to limit these increases in federal aid outlays after disasters is long-term mitigation of climate change-causing emissions.

Still, our analysis cannot fully address all interpretive possibilities. Future data and analysis might employ multi-scalar and multi-method frameworks to uncover more mechanisms driving these dynamics. We investigate only one case (Hurricane Harvey in 2017), and it is difficult to draw conclusions for other disasters from this single event without similar research on other events. Future expansion of this approach might study additional cases as particular storms and places have their own individual idiosyncrasies. We also do not examine SBA loans as data is not available at the census tract level, although this is a major type of aid (Billings *et al* 2022).

This study provides clear empirical evidence that climate change is increasing federal disaster relief expenditures and that these expenditures are structured in ways that reinforce existing social inequalities. NFIP disbursements align more closely with historical flood risk expectations, while IA assistance may play a larger role in addressing unexpected climate change-driven damages. Ultimately, as climate change continues to reshape the landscape of disaster risk, federal disaster aid must evolve to better address both the financial and social consequences of these increasingly frequent and severe events.

Data availability statement

The data that supports the study are available from multiple sources. Data on flood depths and damages at the building level used to create census tract-level figures are available from Fathom but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available; these data can be made available for non-commercial academic research from Fathom upon reasonable request. Data on NFIP claims, IA claims, and NFIP policies are available from the OpenFEMA dataset: www.fema.gov/about/reports-and-data/openfema. Data on social and demographic composition of neighborhoods are available from the National Historical Geographic Information Systems: www.nhgis.org/.

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