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## Climate Change and Federal Aid Disbursements After Hurricane Harvey: An Extreme Event Attribution Analysis

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# Climate Change and Federal Aid Disbursements After Hurricane Harvey: An Extreme Event Attribution Analysis

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# Climate Change and Federal Aid Disbursements After Hurricane Harvey: An Extreme Event Attribution Analysis

## Abstract

The role climate change plays in increasing the burden on governments and insurers to pay for recovery is an area not examined by extreme event attribution research. To study these impacts, we examine the impacts of climate change attributed flooding on federal disaster aid disbursement in Harris County, Texas following Hurricane Harvey. Our approach uses flood models to estimate in dollars the amount of flood damages not attributable to climate change and the amount of flood damages attributable to climate change under two climate change attribution scenarios estimated in peer reviewed studies (20% and 38% additional rainfall 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 and estimate 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, with impacts varying based on the percentage of rainfall attributed to climate change and the specific aid program. Our discussion centers on how these differences might reflect what we term “typical” and “(a)typical” flooding.

JEL-Codes: Q540.

Keywords: extreme weather attribution, federal disaster aid, FEMA, NFIP, Hurricane Harvey.

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**Competing Interests:** The authors declare no competing interests.

## 1. INTRODUCTION

Climate change is increasingly seen as a cause of severe weather disaster events. Scientific research is quantifying this directly in a field called *extreme event attribution* (EEA). EEA, for example, attempts to determine how much of a given storm's physical characteristics would not have occurred in a world without anthropogenic climate change (Otto 2017; Reed et al. 2022; van Oldenborgh et al. 2021; Wehner and Reed 2022). To do this, climate scientists use meteorological, atmospheric, and physical data of a given storm, embedded within a climate model, and then run counterfactual scenarios that recreate climate conditions from before human-induced changes began altering earth system processes. By comparing the actual storm with the counterfactual storm, this research can identify the differences attributable to climate change. 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 Weather Impact Attribution (EEIA; see Noy et al. [2024] for a survey of this new literature). The direct damage from extreme weather is important because it often generates a response from government. Quantifying the relationship between the attributed damage from climate change and this government response is the focus of this study.

In parallel to this work is research that studies societal responses to climate change, and we examine an important response: governmental disaster recovery aid. 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 National Flood Insurance Program, or 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 100-year floodplain with a federally subsidized mortgage are required to have flood insurance. New property owners within these areas are usually mandated to purchase NFIP cover at the initiation of the mortgage (although the continued re-purchase of cover is not always monitored by the mortgage holder). Residents living outside of the 100-year floodplain can elect to buy flood insurance but are not mandated to do so.

The Individual Assistance (IA) program, part of the Individuals and Households Program (IHP), provides aid for residents for many different needs from lodging expenses to loss of personal property. One of IA's most important components for disaster recovery funding is home repair. An important distinction between IA and the NFIP is that the IA's home repair grants are typically granted for residents who do *not* have flood insurance. Put differently, flood insurance holders rarely need IA, but IA's home repair grants are the only federal aid option for households who do not have flood insurance. At the time of Hurricane Harvey, the IA was capped at \$33,000 for households. This is much lower than the caps for coverage through the NFIP: up to \$250,000 for property damages and \$100,000 for home contents (Lindsay and Reese 2018).

In the context of EEIA, a pressing question emerges about these federal programs: do they face greater outlays because of climate change? Indeed, these parallel strands of work on extreme event impact attribution and post-disaster recovery response are yet to intersect. We suggest three important reasons why they should. The first is that there has been a dramatic expansion of federal aid after disasters in recent decades. 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, which further indicates that the baseline funding model is not sufficient to respond to increasingly severe impacts from extreme weather.

The second reason is that climate change making extreme weather more severe may be a key driver of rising FEMA expenditures. An emergent set of work estimates the economic costs of climate change through extreme weather events revealing significant socio-economic consequences (e.g., Callahan and Mankin 2022; Frame et al. 2020; Newman and Noy 2023; WMO 2023). In the first study of its kind to connect extreme event attribution to micro-level socio-economic impacts, Smiley et al. (2022) found that as many as 50,000 residences – half of the total number of flooded properties – in Harris County, Texas would not have flooded during Hurricane Harvey if not for climate change. These impacts were unequal: low-income, Latina/x/o neighborhoods outside the (better insured) flood zones disproportionately experienced this climate change-attributed flooding.

The third reason comes from rich strand of research that examines how federal policy can exacerbate inequalities in disaster recovery (Domingue and Emrich 2019; Emrich et al. 2022; Howell and Elliott 2019; Raker 2023; Raker and Woods 2023; Rhodes and Besbris 2022). Howell and Elliott (2019) show that counties that received more FEMA aid tended to also have widening wealth inequalities by race, education, and home ownership. The mechanisms at work creating these inequalities are identified by recent research and can pattern on existing modes of



risk delineation (Smiley 2020). Flood insurance (i.e., NFIP), for instance, enabled insured homeowners to undertake faster and more successful recoveries compared to similar owners without flood insurance (Kimbrow 2021; Rhodes and Besbris 2022). For individual assistance (IA), Raker (2023) and Raker and Woods (2023) find multiple mechanisms at work in the multi-step process of award assistance, with high rates of denial because of racial disparities in damage appraisals. This is further elucidated by Emrich et al. (2022), who showed that underlying social vulnerabilities, most notably related to race and ethnicity, were linked to the allocation of IA. Although the mechanisms generating these inequalities may not be overt (Stanley et al. 2023), outlays from federal sources can result in exacerbation of inequalities during disaster recovery.

While much of this emergent research on disaster policy and socially unequal recoveries refers casually to climate change as an exacerbating factor, it does not quantify climate change's role directly. Research on disaster policy remains largely unconnected from extreme event attribution research. To establish this connection, our research bridges scientific data on climate change attribution with a social scientific research design to ask: how do the impacts of climate change from extreme weather events shape U.S. disaster recovery funding to households?

To answer this question, we analyze flood impacts from Hurricane Harvey in Greater Houston in 2017. Our data synthesis combines work on climate change attribution (Wehner and Sampson 2021; Smiley et al. 2022) with FEMA aid and insurance coverage (FEMA 2024a; FEMA 2024b) alongside socio-demographic neighborhood census data (Manson et al. 2023). This synthesis offers the possibility to braid together threads of research on extreme event attribution and on disaster recovery aid.

## 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; FEMA 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 damages linked to climate change and federal aid disbursements. Moreover, census tracts are widely recognized as a standard unit of analysis in U.S. urban studies (Akins 2009; Krivo and Peterson 1996; Neckerman et al. 2009), affirming their validity as reasonable representations of neighborhood dynamics. Our population of census tracts is from Harris County, Texas, a county of approximately 4.6 million residents at the time of Hurricane Harvey. Houston is the major city in Harris County. There are 764 census tracts in Harris County with the valid data across all measures.<sup>1</sup>

### *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) claims. These claim-level data includes geographic identifiers indicating the census tract where each claim was filed. 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.

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<sup>1</sup> 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.

## *2.2. Focal Explanatory Variables*

The focal explanatory variables under consideration are climate change-attributed damages and non-climate change-attributed flood damages. To obtain 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 an estimate of 38% from Risser and Wehner (2017), an area that partly corresponds to the study area of Harris County.

Building-level damages were calculated using flood models based on observed rainfall estimated from Hurricane Harvey and counterfactual estimates with 20% less rainfall and 38% less rainfall (Smiley et al. 2022; Wehner and Sampson 2021; Wing et al. 2022). Total residential building-level damages attributed to climate change and not attributed to climate change were aggregated to the census tract-level. Both of these estimates were then divided by the number of occupied residences within that tract. In all, the two focal explanatory variables are: (1) property damages not attributed to climate change per household (which we term non-climate change attributed damage), and (2) property damages attributed to climate change per household (which we term climate change attributed damage).

## *2.3. Control Variables*

A series of 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 database (Manson et al. 2023). Racial composition measures include 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. Additional measures include household median income and proportion of owner-occupied homes. Finally, the analysis 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.

#### *2.4 Analytic Strategy*

In analyze the relationship between flood damages and federal aid disbursements and, four regression models were estimated. Model 1 and Model 3 analyze NFIP and IA paid claims, respectively, with three independent variables: non-climate change attributed damages, climate change attributed damages, and NFIP policyholders. Model 2 and Model 4 analyze NFIP and IA paid claims, respectively, with the same independent variables and the addition of socio-demographic variables measuring the racial composition, homeownership, and median income in each tract.

All analyses were conducted at the census tract-level, and all variables were logged to account for skew. Initial model selection involved the use of nonspatial ordinary least squares (OLS) models. Variance inflation factors were utilized to evaluate multicollinearity for each OLS model, with no indications of multicollinearity observed ( $VIF < 5$ ). Following this, Global Moran's I statistics based on a queen's first order contiguity matrix were used to detect any presence of spatial autocorrelation within OLS regression model residuals. Moran's I values were moderately large (between 0.247 and 0.368) and statistically significant ( $p < 0.001$ ) in all four models. This suggests that the model residuals are spatially autocorrelated, which violates the assumption of independence in OLS regression and necessitates a spatial regression

approach. Lagrange Multiplier (LM) tests were then used to determine the appropriate form of spatial dependence within the models. Both the simple LM test for error dependence and the simple LM test for a missing spatially lagged variable were statistically significant, suggesting the presence of spatial dependence for both. Moreover, the statistically significant robust LM tests suggest that spatial lag terms are the more appropriate specification of the dependence within the residuals. We therefore incorporate a spatial lag term into the model to account for spatial dependence. Additionally, lower Akaike Information Criterion (AIC) values in the spatial lag models compared to the spatial error models indicate that the spatial lag models provide a better fit for the data. The spatial lag model can be expressed as:

$$y_i = \rho W y_{-i} + \beta X_i^{dam} + \gamma X_i^{soc} + \varepsilon_i$$

where  $y_i$  represents the values of the dependent variables in each census tract  $i$  (the NFIP and IA disbursements).  $\rho$  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. The  $X_i^{dam}$  denotes the vector of the main variables we are interested in (the damage attributed or not attributed to climate change),  $\beta$  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  $\gamma$ , and  $\varepsilon$  is the error term. Because coefficients for the explanatory variables represent spatial interaction effects and cannot be interpreted as standard linear models (Golgher and Voss 2016), direct effects, indirect (i.e., spillover) effects, and total effects of the explanatory variables from the fully specified models are estimated for each of the climate change attribution scenarios. Supplemental materials show the results of the spatial lag models used to generate these direct, indirect, and total effects.

### 3. RESULTS

#### *3.1. Descriptive Analysis*

Table 1 provides descriptive statistics for all variables included in the study. Compared to the IA, the NFIP allocated much more funding following Hurricane Harvey in Harris County. The mean tract allocation was \$3,973 of NFIP outlays per household, but the equivalent value for IA was only approximately one tenth of this figure (\$404). This outcome was anticipated, as the NFIP offers a much higher cap on its disbursements (Emrich et al. 2022; Lindsay and Reese 2018). Figure 1 is a scatterplot (with a line of best fit and confidence interval) that shows that there is a positive correlation, albeit with a moderate amount of variation, between the two programs.

[Table 1 about here]

[Figure 1 about here]

Moreover, across the tracts, there was substantial damage attributed to climate change. Specifically, under the 20% rainfall scenario, approximately \$8,030 of mean damages per household were attributable to climate change during Hurricane Harvey, while \$14,711 per household were not attributable to climate change. This indicates a degree of disproportionality: the extreme event attribution models suggested that 20% of rainfall was attributed to climate change, but this corresponded to approximately 35% of the damages. The data is similarly disproportional for the 38% scenario (38% of the rain is attributable to climate change), in which 53% of the damage was attributable.

Figure 2 maps these outcomes with a bivariate analysis with recoding of the two flood damage variables (i.e. attributed and not attributed to climate change) in 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, and vice versa.

[Figure 2 about here]

### *3.2. Multivariate Regressions*

#### *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 disbursements 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 of these coefficients were statistically significant, suggesting that damages not linked to climate change within a tract were associated with greater NFIP disbursements in that tract (i.e., the direct effect) and in neighboring tracts (i.e., the indirect effect). In contrast to the NFIP findings, the direct, indirect, and total effects of non-climate change attributed damage were not statistically significant in predicting IA award amounts. Put differently, within a particular tract, experiencing greater damages that would have occurred regardless of climate change was not associated with larger IA disbursements within that tract or its neighboring tracts but was associated with greater NFIP amounts. In contrast to these results, climate change attributed damages had statistically significant direct effects and spatial spillover effects for both NFIP aid and IA aid. For each 1% increase in climate change attributed damages per household in a given tract, the expected IA disbursement per occupied residence was higher by 0.12% in that tract (i.e., the direct effect) and by 0.19% in neighboring tracts (i.e., the indirect effect).

For the other control variables ( $X_i^{soc}$ ), the proportion of NFIP policy holders is associated positively, and is statistically significant, with both the NFIP and IA. This result is of course to be expected for NFIP payments, but it is less obvious for the IA outlays, and the coefficients for these are indeed much smaller. Median income is consistently negatively associated for all types of effects for NFIP and IA. While the NFIP and median income finding may be somewhat surprising, we believe it is partly an artifact of controlling for NFIP policyholder penetration (which is positive); indeed, bivariate regression analyses (supplemental analysis available on request) of median income and NFIP show a positive relationship but it remains negative for IA.

For NFIP payments in the 20% scenario, the racial composition of the tracts was not a strong predictor, except for a small but statistically significant negative impact of the proportion of other races (other than Black, Latina/x/o, and White). For IA payments, tracts that had a higher proportion of Blacks 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.<sup>2</sup>

### 3.2.2. 38% Scenario

The direct effects, indirect effects, and total effects of the explanatory variables on NFIP and IA assistance when 38% of rainfall is attributed to climate change are presented in the bottom panel of Table 2. In a marked change from the 20% results, non-climate change

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<sup>2</sup> 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.



attributed damage does not have any statistically significant effects on NFIP aid, indicating that experiencing greater damages not attributable to climate change was not associated with larger NFIP disbursements. For IA, there is a small, positive indirect effect for non-climate change attributed damage but no statistically significant direct effect. However, climate change attributed damage was positive and statistically significant for both programs, as was also the case for the 20% scenario. For this scenario, within a given tract, a 1% increase in climate change attributed damage per household translates to increases for the total effects of 0.42% in NFIP aid and 0.28% in IA aid.

Similar to the 20% scenario, the proportion of NFIP policy holders had statistically significant direct and indirect effects on both types of funding. Also similar to the 20% scenario for both NFIP and IA, proportion other race had a negative and statistically significant effect, while median income also retained its statistical significance and negative relationship. Proportion Black and proportion homeowners were also both positively associated with IA aid but not NFIP aid.

#### 4. DISCUSSION AND CONCLUSION

The objective of this study was to quantitatively assess the contemporary impacts of climate change on federal post-disaster assistance disbursements. To do this, we differentiated between flood damages that were attributable to climate change and those likely to have occurred regardless of climate change by using Extreme Event Impact Attribution (EEIA) science. This framework studies how human-driven changes in our climate operates as a process generating greater disaster vulnerability.

Findings show that while both of these impact measures are important in determining the amounts of federal post-disaster disbursements from FEMA, the way in which they do so depends on the funding program being examined and the climate change scenario being assessed. Damage attributed to climate change was linked to greater NFIP payments and for IA payments in both the 20% and 38% scenario. Damages that were not attributed to climate change were linked to greater NFIP payments for the 20% scenario (but not the 38% scenario) and was only linked to greater IA payments through indirect effects only in the 38% scenario. Taken together, damages attributed to climate change were a more consistent predictor of federal aid disbursements than damages not attributed to climate change.

Why these differences? It might be reasonable to expect that more damage means more paid claims, regardless of the provenance of the damages. Our results, though, show that this is not always the case. We believe that the findings for the NFIP paid claims may be because non-climate change attributed flooding might be considered what we term “typical flooding.” This “typical flooding” corresponds to the lower climate change attribution scenario (20%) and for NFIP aid only. This “typical flooding” risk is well known, and consequently the existing risk transfer instruments (guided by FEMA’s flood maps) can drive higher flood insurance penetration to cover these “typical” flood losses. Put differently, this kind of “normal” flooding is driven primarily by anthropogenic factors other than climate change (see Raju et al. 2022).

The climate change attributed flooding we identified may be considered what we term “(a)typical flooding,” that is flooding that is harder to account for because it is being exacerbated by climate change. Hurricane Harvey, for example, was cited as being a 1-in-2,000 year event by 20th century standards (Emanuel 2017). Yet, we refrain from fully using the standalone *a* instead opting for *(a)typical* because these kinds of events will only be atypical temporarily. As our data

demonstrates in conjunction with a growing body of climate change attribution research (Smiley et al. 2022), what might be difficult to anticipate now is becoming a new normal, i.e. (a)typical weather.

The findings for each program align with this (a)typical framing. For both the IA and the NFIP, climate change attributed damages were linked with 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 disbursements (and, correspondingly, flood insurance rates) and impacts from climate change. It may be the case that residents who have the means to buy flood insurance are anticipating increasingly severe weather because of climate change. Put differently, they may foresee (a)typical impacts of the type characterized by Hurricane Harvey.

For IA, climate change attributed flooding is more strongly linked to disbursements than non-climate change attributed flooding. This especially calls to mind the (a)typical framing because IA, compared to the NFIP, is a more (a)typical funding mechanism. It is a program designed as secondary to other programs like the NFIP because it features lower disbursements overall (with more than 90% of FEMA money during Harvey distributed through the NFIP and not IA), 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 (Raker 2023; Raker and Woods 2023). And, yet, IA is an essential mechanism for recovery such as for those who cannot afford flood insurance, and for those who thought of their homes as at less risk. 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.

These interpretive possibilities are made possible by our research design, which we believe has much to offer transdisciplinary research on the social consequences of climate change and extreme weather. This design first disaggregates floodwaters into amounts that can be attributed to climate change and those not attributed to climate change, and then translate them to financially measured damage. Here, we use these disaggregated measures as independent measures of damage and correlate them with fiscal consequences.

This is a transposable research design: future research could similarly use insights from climate scientists and damage modelers to determine how much flooding (or, possibly, impacts from other hazards) is attributed to climate change and if, and how, this affects other social outcomes. Our social outcome was the different FEMA fiscal disbursements, but these disaggregations could be paired with other data in a multilevel framework (e.g., predicting health outcomes or recovery trajectories), place-based data (e.g., on neighborhood economic change or migration and displacement), and more. Using disaster impacts as an independent variable in a regression framework is common (e.g., Chakraborty et al. 2019; Fussell et al. 2017; Howell and Elliott 2019; Logan et al. 2016; Smiley et al. 2018), but the heart of our approach is quantifying the oft mentioned but infrequently measured increasing impacts due to climate change.

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 future expansion of this approach might study additional cases as particular storms and places have idiosyncrasies.

**Data Availability:** 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: <https://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: <https://www.nhgis.org/>.

Figure 1: Correlation of NFIP and IA assistance per household

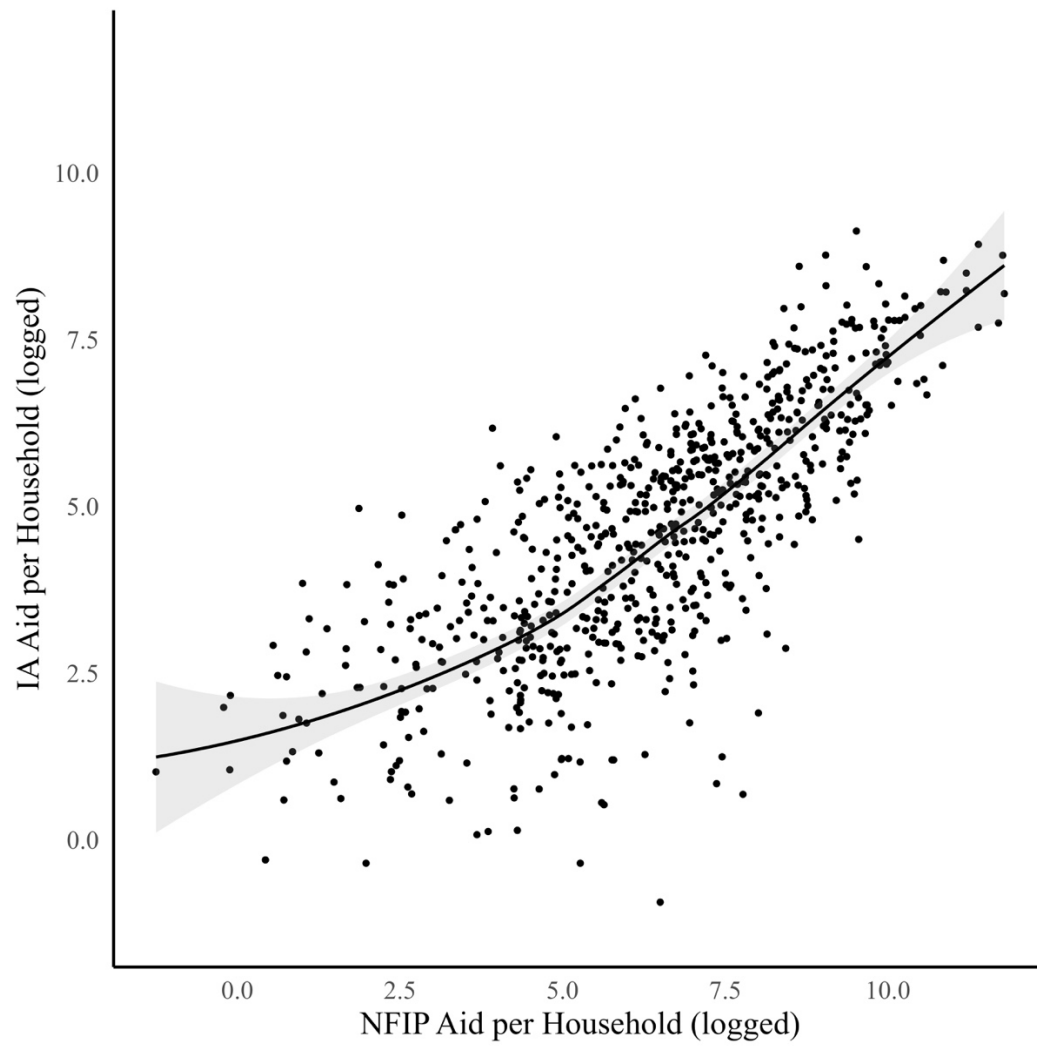
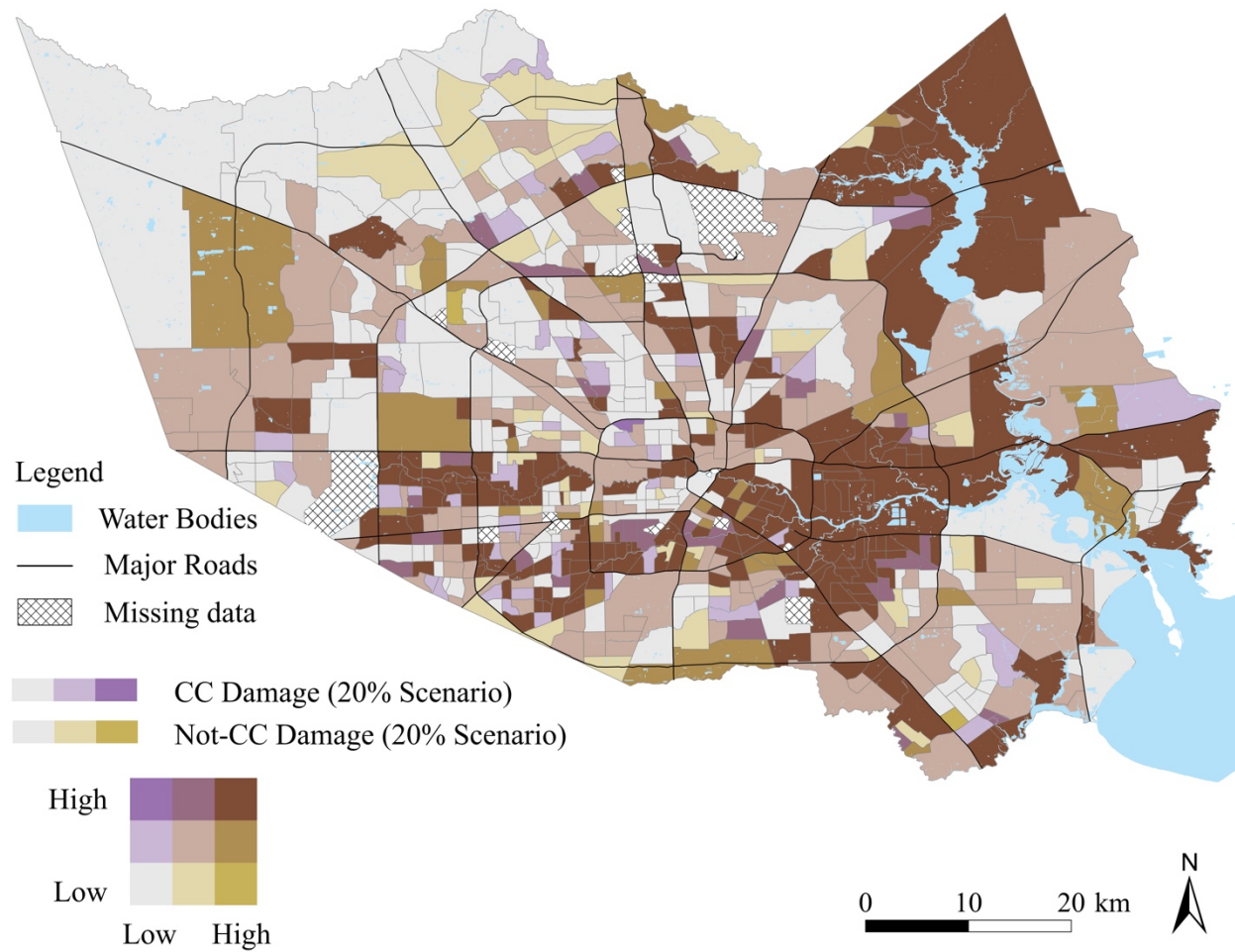


Figure 2: Climate Change Attributed Damage and Non-Attributed Damage per Census Tract



**Table 1.** Descriptive Statistics for All Study Variables

	Mean	St.Dev.	Min	Max
NFIP aid per household	3,973	11,611	0	132,027
IA aid per household	404	885	0	9,249
CC Attributed Damage (20%) per household	8,030	35,877	0	611,785
CC Attributed Damage (38%) per household	12,108	51,821	0	789,221
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
Prop. NFIP policy holders	0.16	0.15	0.00	0.85
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	9,015	250,001

Note: Descriptive Statistics are not logged.



**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
CC Attributed Damage	0.14**	0.12**	0.26**	0.12***	0.19***	0.31***
Non-CC Damage	0.17***	0.15***	0.32***	0.05	0.08	0.13
Prop. NFIP policy holders	1.53***	1.30***	2.84***	0.49***	0.80***	1.29***
Prop. Black	0.03	0.03	0.06	0.11***	0.18***	0.29***
Prop. Latina/x/o	0.18	0.15	0.34	0.20*	0.33*	0.53*
Prop. other race	-0.07**	-0.06*	-0.13*	-0.04**	-0.07**	-0.12**
Prop. homeowners	-0.06	-0.05	-0.10	0.45***	0.74***	1.18***
Median income	-0.75**	-0.64**	-1.39**	-0.65***	-1.08***	-1.73***
38% Rainfall Attributed to Climate Change						
	NFIP			IA		
	Direct	Indirect	Total	Direct	Indirect	Total
CC Attributed Damage	0.23***	0.19***	0.42***	0.11***	0.18***	0.28***
Non-CC Damage	0.08	0.07	0.15	0.06	0.10*	0.16*
Prop. NFIP policy holders	1.52***	1.30***	2.81***	0.49***	0.83***	1.32***
Prop. Black	0.03	0.03	0.06	0.11**	0.18**	0.29*
Prop. Latina/x/o	0.18	0.15	0.34	0.20	0.33*	0.53*
Prop. other race	-0.07*	-0.06*	-0.13*	-0.05**	-0.08**	-0.12*
Prop. homeowners	-0.06	-0.05	-0.11	0.43***	0.72***	1.15***
Median income	-0.73**	-0.62**	-1.35**	-0.65***	-1.10***	-1.75***

\*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1

**Table S1.** Log-Log Spatial Lag Model Regressing NFIP and IA Aid per Residence under the 20% Scenario

	NFIP	NFIP	IA	IA
CC Attributed Damage	0.16 *** (0.05)	0.13 ** (0.05)	0.11 *** (0.03)	0.10 *** (0.03)
Non-CC Damage	0.15 *** (0.06)	0.16 *** (0.06)	0.03 (0.03)	0.04 (0.03)
Prop. NFIP policy holders	1.09 *** (0.09)	1.46 *** (0.13)	0.29 *** (0.05)	0.44 *** (0.07)
Prop. Black		0.03 (0.07)		0.10 ** (0.04)
Prop. Latina/x/o		0.17 (0.15)		0.18 ** (0.09)
Prop. other race		-0.07 ** (0.03)		-0.04 ** (0.02)
Prop. homeowners		-0.05 (0.18)		0.40 *** (0.11)
Median income		-0.72 ** (0.29)		-0.59 *** (0.18)
Rho	0.50 *** (0.04)	0.48 *** (0.04)	0.74 *** (0.03)	0.66 *** (0.03)
Intercept	3.43 *** (0.39)	12.26 *** (3.27)	0.89 *** (0.21)	8.53 *** (1.98)
Num. obs.	764	764	764	764
Parameters	6	11	6	11
Log Likelihood	-1751.37	-1737.40	-1385.58	-1352.92
AIC (Linear model)	3637.22	3610.86	3159.35	3009.93
AIC (Spatial model)	3514.74	3496.81	2783.15	2727.84
LR test: statistic	124.48	116.05	378.19	284.09
LR test: p-value	0.00	0.00	0.00	0.00

\*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1

Standard errors in parentheses.

**Table S2.** Log-Log Spatial Lag Model Regressing NFIP and IA Aid per Residence under the 38% Scenario

	NFIP	NFIP	IA	IA
CC Attributed Damage	0.25 *** (0.05)	0.22 *** (0.05)	0.10 *** (0.03)	0.10 *** (0.03)
Non-CC Damage	0.06 (0.05)	0.08 (0.05)	0.04 (0.03)	0.05 * (0.03)
Prop. NFIP policy holders	1.08 *** (0.09)	1.45 *** (0.13)	0.29 *** (0.05)	0.44 *** (0.07)
Prop. Black		0.03 (0.07)		0.10 ** (0.04)
Prop. Latina/x/o		0.17 (0.15)		0.18 * (0.09)
Prop. other race		-0.07 ** (0.03)		-0.04 ** (0.02)
Prop. homeowners		-0.06 (0.18)		0.39 *** (0.11)
Median income		-0.69 ** (0.30)		-0.59 *** (0.18)
Rho	0.50 *** (0.04)	0.49 *** (0.04)	0.74 *** (0.03)	0.66 *** (0.03)
Intercept	3.37 *** (0.39)	11.92 *** (3.28)	0.84 *** (0.21)	8.51 *** (1.99)
Num. obs.	764	764	764	764
Parameters	6	11	6	11
Log Likelihood	-1751.93	-1738.34	-1386.33	-1353.75
AIC (Linear model)	3639.27	3613.56	3163.54	3014.78
AIC (Spatial model)	3515.87	3498.68	2784.67	2729.49
LR test: statistic	125.40	116.89	380.88	287.28
LR test: p-value	0.00	0.00	0.00	0.00

\*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1

Standard errors in parentheses.

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