Who Benefits from Flood Adaptation? — Insights from Machine Learning

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Governments are racing to implement new climate change adaptation policies in order to prepare for the increasing damage and frequency of flooding events. In this rush, it is imperative to avoid implementing policies that perpetuate structural inequality and climate injustice. Policies must be evaluated not only for their effectiveness but also through a climate justice lens that considers the intersectionalities between climate and geo-demographics. In this work, we examine a nationwide US flood adaptation program, the FEMA National Flood Insurance Program Community Rating System (CRS), and evaluate how its impact on flood loss depends on the geo-demographics of a community. We conduct the first analysis of this kind by using a statistically powerful data set of 2.5 million flood insurance claims and a Machine Learning based approach with neural density estimation to overcome quantitative challenges that prevented such analyses in the past. We find strong evidence that the CRS is effective at reducing flood losses overall. Moreover, we show that the efficacy of the CRS flood adaption activities depends significantly on geo-demographic characteristics, such as income, flood proneness, and population. For instance, we find that lower income communities benefit the most from the flood adaptation measures, although the benefits are mostly seen by communities with larger populations and moderate to low flood risks. This work provides key insights for crafting and tailoring future flood adaptation policies to make them more effective and to ensure that their implementation advances climate justice.

Climate Justice | Flood Planning | Machine Learning | Equity | Social Construction of Risk

Flooding constitutes nearly a third of all losses from natural disasters worldwide (1). Underserved sectors of the population bear the brunt of this loss (2–4). As communities seek flood adaptation policies to combat sea level rises and extreme weather events (5–7), they run the risk of implementing policies that replicate historic discrimination (8, 9) and targeted environmental harm (10). In this paper, we aim to guide flood adaptation policies by evaluating not only whether they are effective but also *for whom.*

We investigate whether climate adaption actions consider the intersectionalities between climate and geo-demographic characteristics using a US wide data set on flood insurance payments. In the US, flooding causes more damage than any other severe weather related event, with losses averaging over \$5 billion annually (11). In response, the Federal Emergency Management Agency (FEMA) initiated the National Flood Insurance Program (NFIP) Community Rating System (CRS) in 1990 to improve community flood adaptation and resilience. The CRS is based on a set of prescriptive flood adaptation practices that are recognized as being conducive to flood risk reduction. To join the CRS, communities must implement a series of flood management and adaptation activities: *e.g.* floodplain mapping, open space preservation, storm water management activities, or public information and participation programs. In exchange, residents of the community receive a discount on their flood insurance premium rates. More than 1,500 out of roughly 20,000 communities in the NFIP are currently part of the CRS program (12).

In 2019, FEMA released the NFIP Redacted Claims data set that contains roughly 2.5 million flood insurance claims. The data set contains claims from communities participating in the CRS. It also includes claims from communities, who did not participate in the CRS but were eligible for insurance coverage because they complied with minimum requirements on regulating development in their floodplains. Thus, the Redacted Claims data set provides an ideal quasi-experimental setup. Insurance claims losses, which we use as a proxy for flood loss, can be compared between CRS participants and non-participants to quantitatively assess the effectiveness of the CRS flood management activities. We can also examine how that effectiveness is tied to the geo-demographic characteristics of a community.

Capitalizing on this quasi-experimental set up, past literature examined whether the CRS led to a reduction of flood claims (13–16). Despite some studies finding the contrary (17), the overall consensus is that flood losses are reduced by participating in the CRS. There has been, however, little investigation on how different sectors of the population benefit from the program. (18) found that purchasing the first \$60,000 of coverage costs more per dollar than higher amounts, which favors higher income claimants. Other studies have shown that communities are more likely to implement CRS activities when they have larger tax revenues and lower levels

Significance Statement

Evidence indicates that when it comes to climate extremes, underserved sectors of the population bear the brunt of losses. But could they benefit from flood adaptation interventions? Using data on flood insurance payments, we assess who benefited from the implementation of a multidecade US flood adaptation effort nationwide. Our findings show that lower income communities saw their losses reduced the most. These benefits are however absent for households living in less populated areas or on high flood risk zones. Our findings underline the urgent need to assess the effects of climate adaptation policies considering not only if they work but also for whom and tailoring them to further equitable resilience.

Please provide details of author contributions here.

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of crime and unemployment (19, 20). No studies have yet directly investigated the effectiveness of the CRS for different geo-demographic characteristics of the population.

One major challenge to answering this question is the limitations in quantitative methodologies. Examining the causal relations between flood losses and community characteristics requires accurately modeling their complex and correlated relationship — without making the strong implicit assumptions of many standard methods. In this work, we take a data-driven approach that exploits the statistical power of the NFIP data set and the latest advancements in Machine Learning. With our method, we accurately examine the effectiveness of the CRS in relation to community geo-demographic characteristics such as income, flood proneness, and population. The paper conclusively assesses the effectiveness of the CRS flood adaptation activities and sheds light on who benefits the most from it and under which circumstances. Our results aim to help communities tailor flood management interventions and re-envision flood adaptation activities through a climate justice lens.

Methods

One of the main goals of causal inference is to measure the treatment effect of some policy, like the CRS. For heterogeneous treatments, the effect is quantified using the conditional average treatment effect (CATE), the ATE as a function of covariates. By revealing the dependence of the treatment effect on covariates, CATE provides a more detailed understanding of the causal path. Given outcome Y, covariates X, and variable T that indicates the control ($T = 0$) or treatment ($T = 1$) groups, CATE is estimated as:

$$\mathrm{CATE} = E[\, Y \,|\, X, T = 1 \,] - E[\, Y \,|\, X, T = 0 \,]. \qquad [1]$$

$E[\, Y \,|\, X, T = 0, 1 \,]$ represents the expected value of Y given X for the control and treatment groups, respectively.

Typically, CATE is estimated using either matching or linear regression. In matching, samples in the treatment group are matched to ones in the control based on their X values. CATE is then estimated by comparing the outcomes of the matched samples. Even prevalent methods, such as synthetic control (21, 22) or propensity score matching (23), match samples based on some finite volume in covariate space, which can lead to incorrest estimates of the CATE.

The other approach is regression, most commonly with linear models (24, 25). A model of Y as a linear function of X is fit to the data and then used to estimate CATE. In many scenarios, assuming a linear model is incorrect. For instance, there is no reason to expect flood losses to depend linearly on its population, or median household income. Furthermore, there is often no a priori knowledge of the functional form that should be adopted for a model of Y.

CATE can instead be estimated using a data-driven approach without any of these assumptions. We can rewrite Eq. 1 as

$$\mathrm{CATE} = \int Y p(Y|X, T = 1)\,\mathrm{d}Y - \int Y p(Y|X, T = 0)\,\mathrm{d}Y, \qquad [2]$$

where $p(Y|X, T = 1)$ and $p(Y|X, T = 0)$ are the conditional probability distribution of Y given X for the treatment and control groups. If we can estimate $p(Y|X, T = 1) \approx q_T(Y|X)$ and $p(Y|X, T = 0) \approx q_C(Y|X)$ and sample from them, $Y'_{T,i} \sim q_T(Y|X)$ and $Y'_{C,j} \sim q_C(Y|X)$, we can estimate CATE using Monte Carlo integration:

$$\mathrm{CATE} = \frac{1}{N_T}\sum_{i=1}^{N_T} Y'_{T,i} - \frac{1}{N_C}\sum_{j=1}^{N_C} Y'_{C,j}. \qquad [3]$$

State-of-the-art methods in Machine Learning enable us to accurately estimate and sample from $p(Y|X, T = 0, 1)$. In this work, we utilize neural density estimators (NDEs) — deep neural networks trained to estimate density distributions. In particular, we use normalizing flow models (26, 27), which use a bijective transformation, $f : z \mapsto x$, that maps a complex target distribution, $p(x)$, to a simple base distribution, $\pi(z)$, in our case a multivariate Gaussian. f is defined to be invertible and to have a tractable Jacobian so that target distribution can be evaluated from the base distribution: $p(x) = \pi(z)|\det \frac{\partial f}{\partial x}^{-1}|$. A neural network is used for f to provide an extremely flexible mapping that can estimate complex distributions. NDEs have been used extensively in various fields spanning neuroscience (*e.g.* 28) to astrophysics (*e.g.* 29, 30).

Among recent normalizing flows, we use Masked Autoregressive Flow (MAF; 31) models implemented by (32, 33) to estimate $p(Y|X, T = 1)$ and $p(Y|X, T = 0)$. Our outcome, Y, is the total insurance claims dollar value per policy. The covariates, X, are: average precipitation in millimeters, FSF flood risk score, median household income, and number of residents. The treatment group consists of communities participating in the CRS, while the control group consists of those not participating. In the central panel of Figure 1, we mark the communities in the treated (orange) and control (blue) groups of our data set.

To train the models, we split each of the treated and control data sets into training, validation, and test sets with a 80/10/10 split. We then use the ADAM optimizer (34) to maximize the total log likelihood $\sum_i \log q(Y_i|X_i)$ over the training set, which is equivalent to minimizing the Kullback-Leibler divergence between q and p. We prevent over-fitting by evaluating the total log likelihood on the validation data at every epoch and stopping the training when the validation likelihood fails to increase after 20 epochs. After training, we verify that q_T and q_C accurately estimate $p(Y|X, T = 1)$ and $p(Y|X, T = 0)$ using the test set. Once trained, we can evaluate CATE at *any* given value of the covariates using q_T, q_C, and Eq. 3, as long as it is within the support of the covariates in the treatment and control data. Our NDE-based method relaxes many of the strong assumptions made in standard causal inference methods. It learns the detailed relationship between X and Y from the data to provide an accurate and robust estimate of the treatment effect.

Results

With our trained NDEs, we can now estimate the CATE of the CRS on the total flood insurance claims per policy for a set of community characteristics: average monthly precipitation, FSF flood risk score, median household income, and population. In the bottom panel of Fig. 1, we present the CATE for all of the communities in our data set, both treated and control, on a map of the US. The size of the marker represents

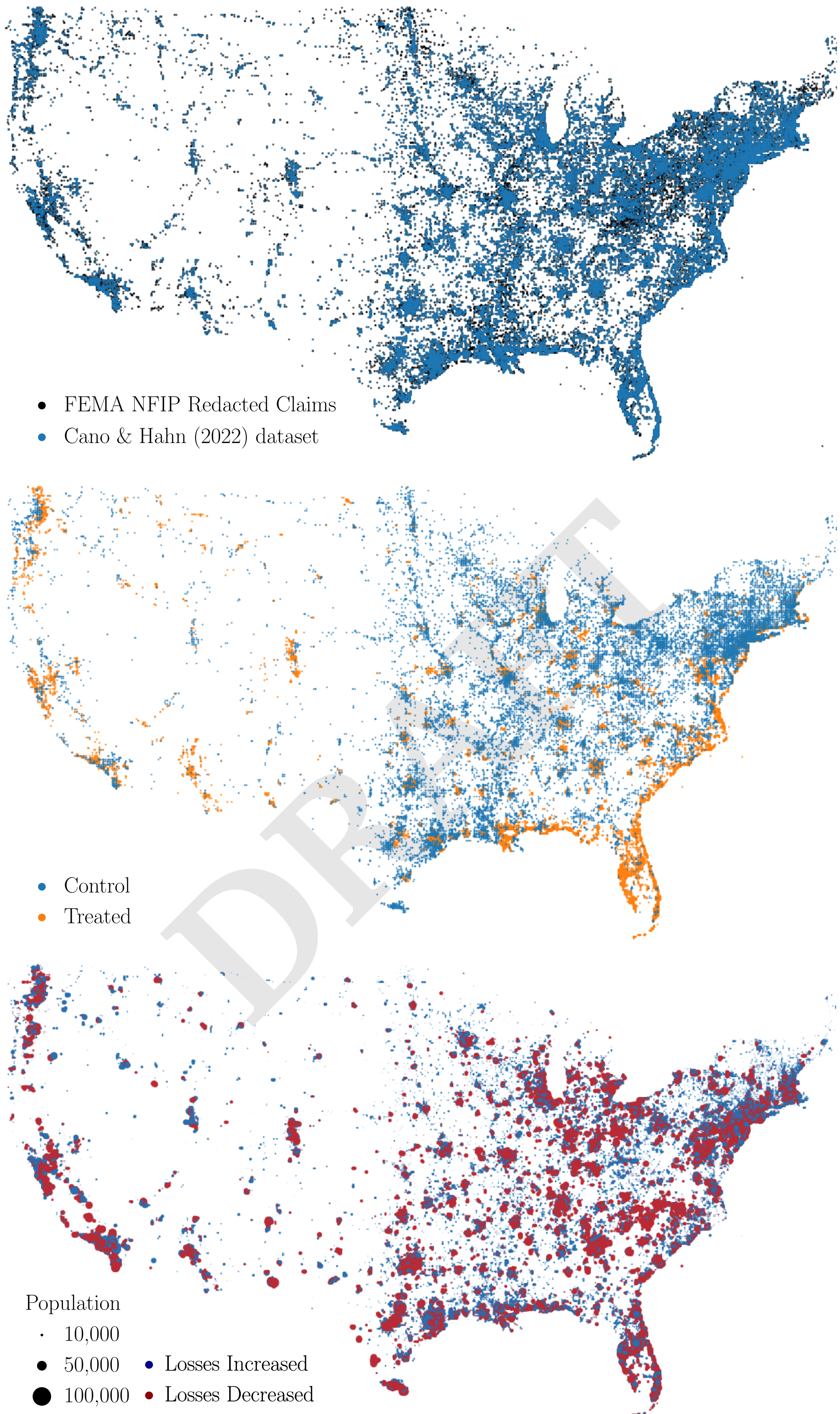

Fig. 1. *Top panel*: We compile our data set (blue) from the FEMA FIMA NFIP Redacted Claims data set (black) with additional information on community geo-demographic characteristics (precipitation, flood risk, income, and population) from other data sets. *Center panel*: We mark the communities that are within the treated (blue) and control (orange) groups. *Bottom panel*: We present the CATE evaluated using our NDE-based method for all of the communities in our data set. Communities whose total flood insurance claims per policy decrease from the CRS program (CATE < 0) are marked in red. The ones whose insurance claims increase (CATE > 0) are marked in blue. The size of the markers represents the population of the communities.

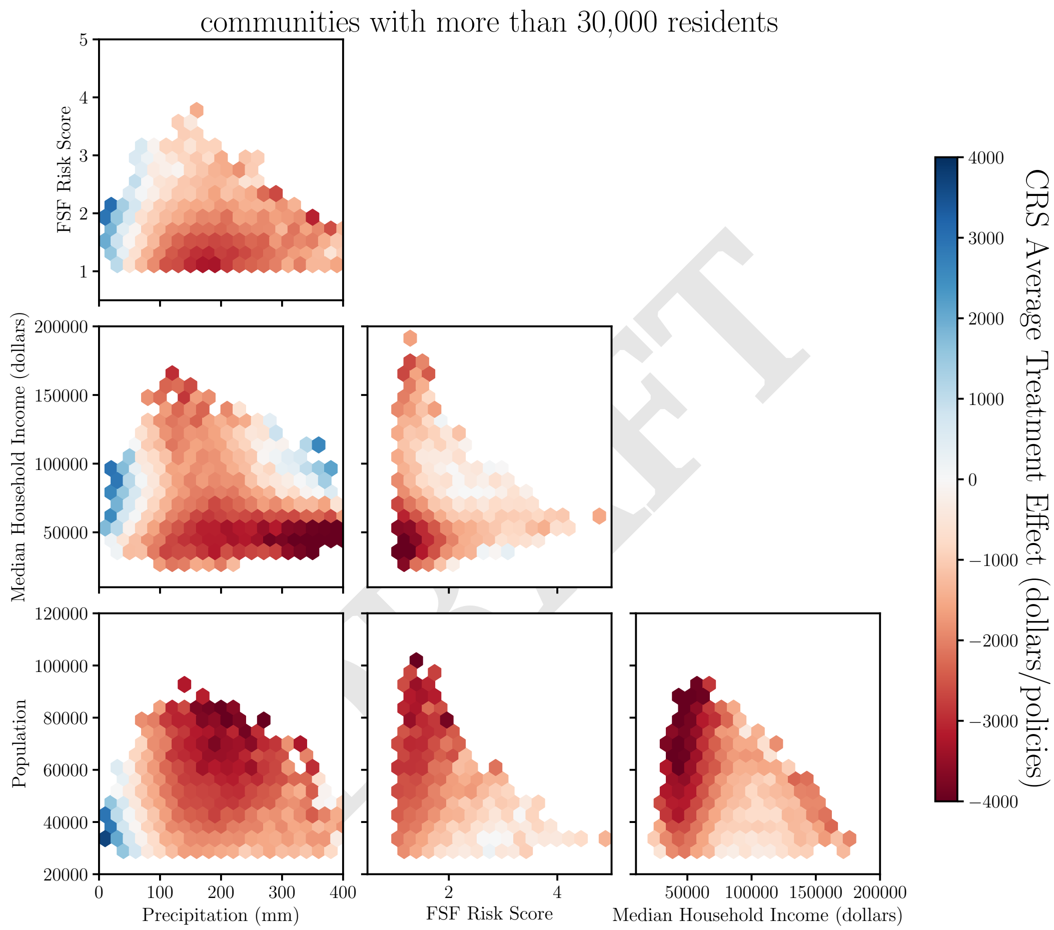

Fig. 2. The conditional average treatment effect (CATE) of the CRS as a function of average monthly precipitation, FSF flood risk score, median household income, and population for communities with more than 30,000 residents. Each panel presents the CATE as a function of two community characteristics. In each hexbin, the CATE is the average over all communities in the bin and marked using a red to blue color map. Red indicates a decrease in flood insurance claims per policy while blue indicates an increase.

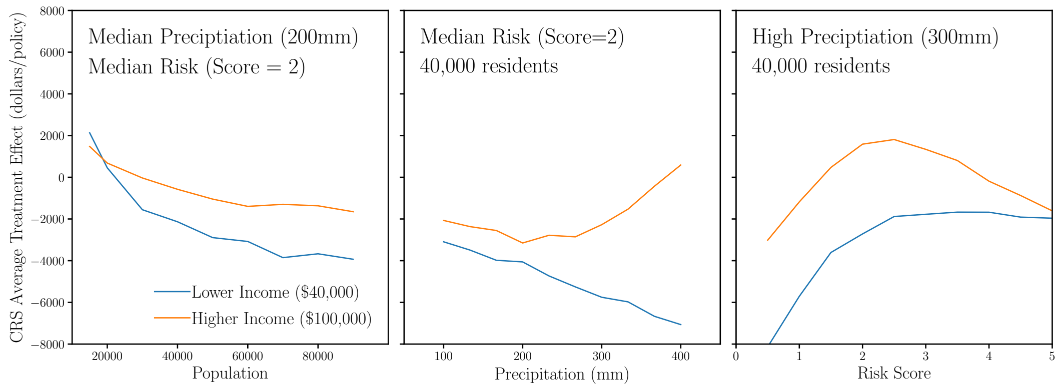

Fig. 3. The CATE of the CRS program as a function of precipitation (left), population (center), and flood risk (right panel) for lower (blue; $40,000) and higher (orange; $100,000) income communities with other properties fixed. In the left and center panels, we fix all other properties to the median values. Meanwhile, in the right panel, we examine communities with high precipitation (300mm), where we expect higher flood losses. We note that risk score <4 encompasses 90% of all communities in our data set. Our NDE-based method allows us to reveal the dependence of the CATE on any community characteristic.

the number of residents in the community. Furthermore, in Fig. 2, we present the CATE of this sample as a function of community characteristics. In both figures, we mark the communities for which the CRS decreases the total flood insurance claims per policy, CATE < 0, in red. If the CRS increases the flood insurance claim, CATE > 0, we mark it in blue. In Fig. 2, we focus solely on communities with more than 30,000 residents, which roughly corresponds to half of the communities in the CRS. We discuss this choice later in the text. Fig. 1 and 2 illustrate that the CRS significantly reduces the total flood insurance claims per policy for communities overall.

The CATE in Fig. 2 reveals some clear dependence on community characteristics. First, there is a significant population dependence: more populous communities benefit more from the CRS. Next, we find a significant dependence on the median household income. Communities with lower median household income (<$60,000) benefit more from flood adaptation measures, reducing their losses up to ∼$4000 per policy. The reduction of insurance claims for higher income communities (>$100,000) is significantly smaller: ∼$1000 per policy. Fig. 2 also suggests some dependence on monthly precipitation and flood risk. The benefits of the CRS are greater for communities with higher monthly precipitation and lower flood risks.

We can examine the CATE of the CRS in further detail. Our NDE-based method allows us to estimate the CATE for any set of community characteristics as long as they are within the support of the control and treatment samples. For instance, we can evaluate the CATE as a function of one characteristic while keeping all others fixed in order to examine the dependence of the CATE on just that characteristic. We do this in Fig. 3 and examine the CATE as a function of population, precipitation, and flood risk for lower ($40,000) and higher ($100,000) income communities with other properties fixed.

Despite reducing flood losses overall, the CRS flood adaptation activities are not equally effective for all communities. We find strong evidence that the decrease in flood losses is more significant for lower income communities. We find this gap for a wide range of population, precipitation, and risk score. The difference in the CATE between the lower and higher income communities is relatively consistent across population and flood risk, reducing flood damages by roughly $2000 per policy. In addition, we find that, the CRS is less effective for lower population communities regardless of income (left panel). The CRS is also less effective for higher risk communities (right panel). Finally, we find that losses are not significantly reduced for high income communities in the CRS that experienced high precipitation (center panel).

Discussion and Conclusion

Our findings lead to two key considerations for policy makers seeking to advance climate justice goals while improving flood adaptation. First, communities with fewer resources benefit from flood management interventions. Thus, these interventions will be crucial in curbing climate exacerbated inequalities. Second, climate justice goals may be hampered by a one-size-fits-all approach. Flood adaptation programs must consider community geo-demographic characteristics to ensure that resources are not captured by a small minority and to avoid imposing burdensome and ineffective requirements.

Flood adaptation activities decrease flood losses for lower income communities. In this work, we calculate the reduction in losses related to buildings and their contents. However, this reduction has positive implications beyond the dollar savings. Preventing damages to homes prevents further ripple effects in the livelihoods and well-being of communities. Exposure to flood damaged homes is linked to an increase in mental and health disorders (35), death and injury risk, disease outbreaks (*e.g.* gastroenteritis; 36), trauma, anxiety (37), and work disruption (38). These consequences are particularly severe for lower income households as they are often left to rely on economic resources that greatly exceed the compensation for the damages to a building or home. Hence, for every dollar reduction in loss we find in our results, we can expect a far larger reduction in the true loss. This makes flood adaptation activities even more necessary to mitigate the multiplicative negative effects of climate change on low income communities.

Beyond the income dependence of the CRS, our results also highlight the fact that the efficacy of flood adaption activities depends significantly on the specific geo-demographic characteristics of the community. For instance, among lower income communities, the effectiveness of the program depends significantly on their population (Fig. 3). This is consistent with evidence linking the adoption of CRS activities to highly populated communities as well as evidence showing that less populated communities struggle to implement some of the CRS required activities (20). For this reason, we focus on communities with more than 30,000 residents in this work. What is more, we find that the effectiveness of current CRS activities greatly diminishes for communities with high flood risk scores (right panel of Fig. 3). These communities may find greater benefit from spending their resources on flood adaptation activities currently not prescribed by the CRS.

The climate justice implications of the one-size-fits-all approach go further because performance on the CRS is tied to more affordable flood insurance. Communities may have to choose between investing in activities that do not effectively prevent losses solely to access more affordable insurance. However, communities should not be required to implement the same flood adaptation activities if there is no evidence that the activities are effective for their geo-demographic characteristics. Furthermore, if interventions are required for communities to access affordable flood insurance, that requirement should be accompanied by sufficient resources for the implementation.

Finally, policies need to be attentive to the distribution of resources in order to avoid elite capture. We find that the CRS is less effective at reducing flood losses for higher income communities, particularly with median income above $100,000, than in lower income communities with the same flood risk level, precipitation, and population. This is despite evidence that an increase in median household income is linked to better implementation of CRS activities (39). This signals potential resource and information asymmetries (40) when it comes to accessing the economic resources provided by insurance companies during recovery. Households with more economic resources are more likely to have the means to access the necessary information and file these claims. Field interviews support this possibility and have suggested that some households are taking advantage of the program to 'refurbish' their homes. Monitoring systems should be in place to understand this dynamic and to ensure an equitable allocation of resources.

Overall, our findings demonstrate that flood adaptation programs must be evaluated from a climate justice lens, examining not only whether they work but also for whom. Flood adaptation programs, like the CRS, have the potential to work towards a climate just future if they are tailored to the specific characteristics of communities. The CRS is already effective at diminishing losses for lower income communities. However, additional work is necessary to equitably distribute the limited flood adaptation resources and to effectively benefit all communities. Planning a climate just future will require undertaking actions that actively counteract pre-existing structures of inequality that originated climate vulnerability for many in the first place.

Data

For this work, we compile a data set based on the FEMA *FIMA NFIP Redacted Claims*[*] data with additional information on community geo-demographic characteristics. From the NFIP data set, we use data on CRS participation, the date of flood loss, and the total claims paid on building damages and content from the loss. We combine all the entries for a zipcode and calculate the total claims paid per policy.

For each zipcode, which we refer to as a community, we estimate its flood risk using risk scores compiled in the First Street Foundation data set[†]. The risk scores are computed based on factors including risk of flooding from high-intensity rainfall, overflowing rivers and streams, high tides, and coastal storm surges. We further supplement the data set with census data from the American Community Survey US Census Bureau[‡]. The census data is compiled in four year intervals: $2008-2012$, $2012-2016$, and $2016-2020$. We assign median income and number of residents of the communities based on their zipcode and date of loss. Lastly, we include average precipitation per month for each community. This data was extracted by splitting the PRISM climate group data[§] compiled by the Northwest Alliance for Computational Science and Engineering using US zipcode boundaries from 2020.

After cleaning the data set for problematic entries and missing data, our data set includes 14,729 unique communities. In the top panel of Fig. 1, we mark the communities that are included in our data set (blue) from the full FIMA data set (black) on a map of the US. Our final data set is publicly available at XXXXX.

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