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Supplementary information

Inequitable patterns of US flood risk in the Anthropocene

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SUPPLEMENTARY INFORMATION

Inequitable patterns of US Flood Risk in the Anthropocene

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1. Correlation of location-level uncertainty

The handling of uncertainty in this analysis yields 100 samples of Average Annual Loss (AAL) for every building in the United States (see Methods). Here, we explore the sensitivity of national-level losses to three methods for aggregating the location-level AAL samples: (i) no correlation of uncertainty between locations; (ii) total correlation of uncertainty between locations within the same HUC10 unit (see Supplementary Fig. 2) and no correlation of uncertainty between HUC10 units; and (iii) total correlation of uncertainty between all locations nationwide. Method (i) and (iii) represent the extreme ends of possible national AAL distributions, where complete independence (i) involves location-level extremes cancelling each other out and complete dependence (iii) means extremes compound. From Supplementary Fig. 1, the 95% confidence range of US AALs is \$32.0 – \$32.2 with no correlation (i) or \$4.6 – 96.8 billion with total correlation (iii). The latter is a very unlikely scenario, since it conceptually involves an additional ~2 m of flood depths everywhere for the higher bound, or ~2 m lower depths everywhere for the lower bound. These effectively constitute impossible floodplain volumes, given physical reasoning. It is, however, also likely that errors do have some spatial coherence. Conceptually, if inaccurate boundary conditions, channel schematisation, defence information, or topography generate an erroneous water surface (and thus depth) at one location, it is likely to also be incorrect for neighbouring locations too.

To provide a reasonable compromise between the extreme methodologies of (i) and (iii), we use catchment-based correlations (ii) as our central estimate in this analysis. This method assumes locations within the same hydrological unit have correlated uncertainty. In practice, this involves generating a random number and holding it constant for all location samples in the same catchment and repeating this process for all catchments and nationwide samples. While the above criticisms could defensibly be levelled at this method too – correlations may extend beyond these relatively small catchment units, yet, equally, total within-catchment correlation may also be effectively physically implausible – we acknowledge that there is scant objective guidance for the aggregation of location-level uncertainties in a flood model of this scale and fidelity. Method (ii) represents a subjectively reasonable estimate of uncertainty aggregation – out of many possibilities – falling between the implausible extremes of (i) and (iii). As per Supplementary Fig. 1, we can see the 95% confidence bounds of US AAL are $30.5 – 33.8 billion under this assumption. Importantly, this also shows that the median estimate of national flood losses is invariant to the aggregation technique, with slight differences subject to sampling error. The impact on nationwide uncertainty bounds, however, is stark, illustrating the need for future research to identify objective methods for the consideration of uncertainty correlation.

2. Risk model validation

With previous literature comprehensively evidencing the validity of the hazard model (see Hazard model in Methods), an evaluation of its use in risk quantification remains. Ensuring that the estimates of risk output by a model are valid and reliable is a convoluted and complex endeavour. Indeed, the very reason models of flooding are required is because observations are too sparsely available to meaningfully understand risk. Understanding risk requires large samples of extreme, infrequent floods events, which thus requires a long observational record of flood losses to capture. Paradoxically, to ensure loss observations are relevant to today's risk, only the most recent observations collected in today's environmental and socio-economic contexts should be captured. This diametric opposition means we either question whether an observational record contains extreme enough flood events to understand risk, or whether historical building stock, their susceptibility to damage, and contemporary hydrologic conditions are relevant to the present-day. This insoluble challenge, however, does not diminish the need to evidence the validity of modelled losses, but it does require creativity to execute. Further, realistic expectations for how close a match between benchmark and model is desirable should be set, given the limited information content and likely error of observations in this context.

As such, we look to the recent release of OpenFEMA National Flood Insurance Program (NFIP) datasets to forge a meaningful comparison between the risk purported by the model presented here and a benchmark database of historical US flood risk. The underlying population of NFIP policyholders has not only changed in line with US development patterns, it is also a subset of contemporary populations (owing to low insurance penetration). As such, NFIP claims are not the only flood losses to have occurred historically; they are simply those filed under this particular insurance programme. In fact, in recent testimony to the US Congress, the FEMA Assistant Administrator for Risk Management estimated that flood risk has grown from an average annual damage total of ~$4 billion in the 1980s to ~$17 billion in the 2010s.[57] Those numbers, undoubtedly low relative to actual risk, can be further compared to the ~$2.8 billion paid out by the NFIP over that same period. To address the imbalance between the exposure and population of the NFIP compared to that which we have modelled (every present-day building), we compute the reported damages for each NFIP claim as a proportion of its full replacement value. This yields the average relative damage to buildings which have ever been flooded according to the NFIP. The analogous quantity from our model is the relative AAL (loss as a proportion of replacement cost) for any residential building that incurs non-zero loss. Given flood insurance is only mandatory in the high-hazard SFHAs delineated by FEMA, it may be that claims and policies are concentrated in more risky areas and thus, generally, have a higher flood risk than the whole population. To account for this, we reproduce an estimated risk profile of the NFIP in our model: a weighting of 73% for relative AALs within the SFHA and 27% for those outside of the SFHA. These weightings are based upon 27% of historical claims in the NFIP database occurring outside the SFHA. The NFIP-based value is 0.342% of replacement value, while that of our median model is 0.340%. This comparison demonstrates that there is close agreement between the average model response and observations in the general building-level damageability of floods.

The above comparison does not illustrate that the correct number (or proportion) of buildings are flooded; only, for those that are flooded, their damage response is generally in line with what observations suggest. To get an idea of whether the rate at which our model inundates US buildings is sensible, we compare the modelled average annual number of flooded buildings to the average annual number of claims filed under the NFIP. To, again, normalise the differing underlying populations these two quantities are drawn from, they are divided by the total number of buildings and the total number of NFIP policies in force, respectively. The median modelled relative average annual building exposure is 1.68% (a 73:27 weighting of 2.26% within the

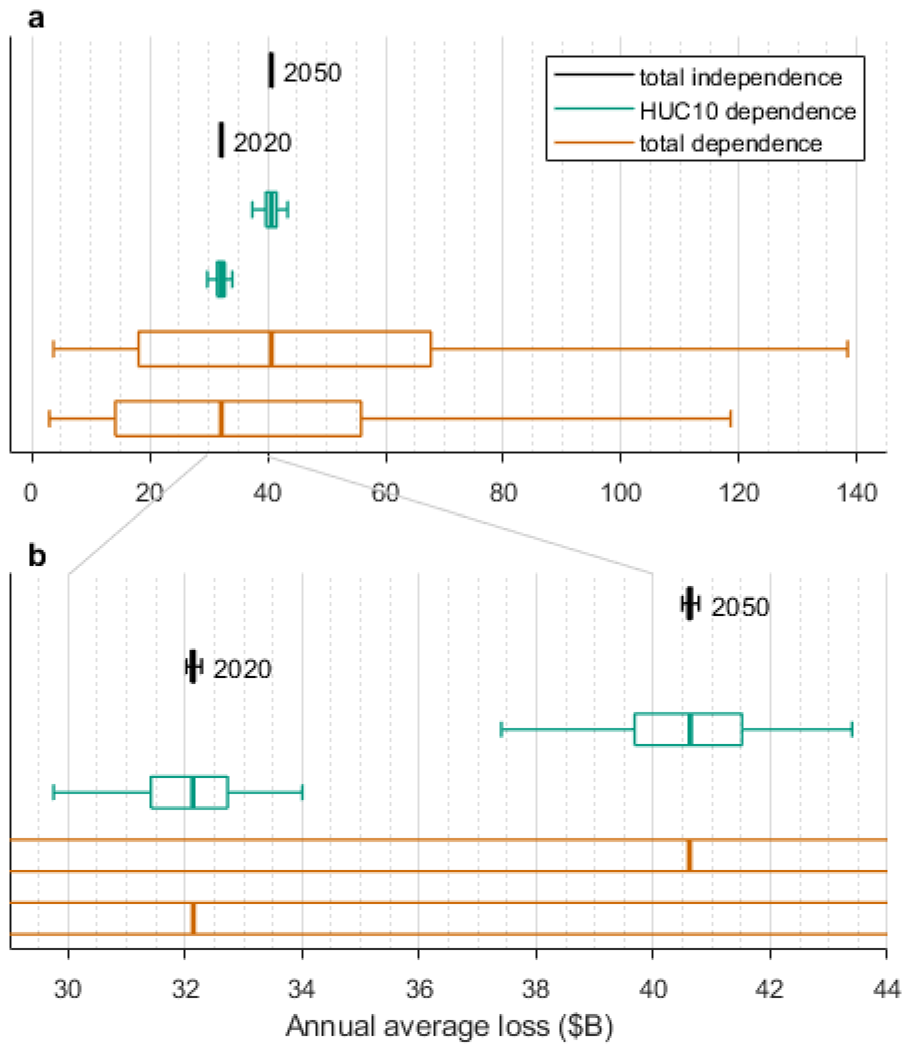
SFHA and 0.12% outside of it), while that purported by the NFIP is 1.18%. The risk profile of policies is slightly different to those of claims, with only 57% of policies insuring properties within the SFHA. With a 57:43 weighting, the median modelled value falls to 1.33%.

We also sum the replacement value of building structure and contents for every NFIP policy in each year. Policy records with no entries for replacement value (~10-15% of the data used) were assigned the average value from the given year. With average annual damage as a proportion of total exposure (as opposed to just the value of flooded buildings, calculated above), the mean NFIP-derived figure comes to 0.082%. The median modelled equivalent for residential buildings is 0.080%: a 57:43 weighting of 0.114% within the SFHA and 0.034% outside of it.

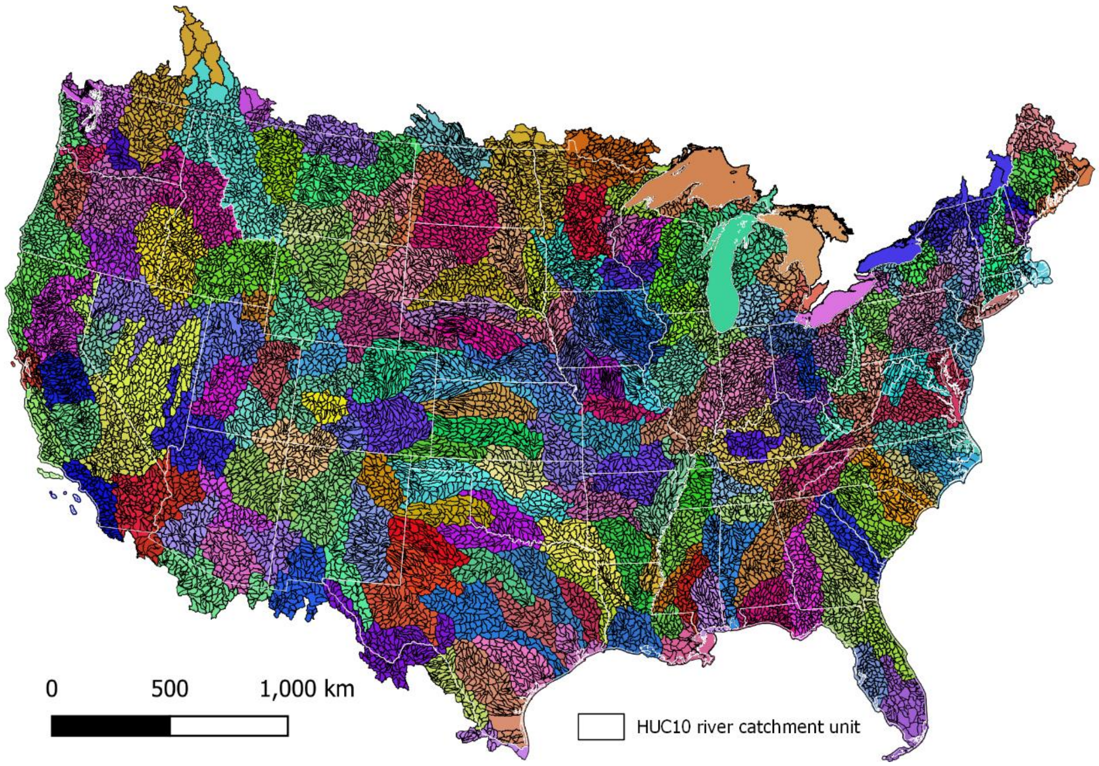
While exposure differences have been controlled for as much as is possible, the validity of these comparisons is partly predicated on the assumption that flood frequencies and building vulnerability have remained static across the period of the NFIP (1968–present). Embedded amongst these assumptions employed to control for the temporal and spatial discrepancies between model and observations is the unknown accuracy of the assessed damages and replacement costs in the OpenFEMA claims and policies databases. Considering these limitations, the comparison outlined here has exhausted the utility of the validation data available; finding a largely indistinguishable view of national-scale flood risk between model and observations. We are thus unable to source any evidence contradicting the view that the model presented here provides a reliable estimate of national-scale flood risk. Supplementary Table 1 summarises the results of this exercise.

Comparison scenario	NFIP (%)	Model (%)
NFIP: Average relative damage to all flooded buildings in the NFIP. ***Model:*** Average annual relative damage to all residential buildings that ever incur damage (weighted to NFIP claims risk profile).	0.342	0.340
NFIP: Average annual number of NFIP claims per policy in force. ***Model:*** Average annual number of US residential buildings inundated as a proportion of all buildings (weighted to NFIP policies risk profile).	1.18	1.33
NFIP: Average recorded yearly damages as a proportion of the yearly total value of NFIP policies. ***Model:*** Average annual relative damage to all residential buildings inclusive of non-flooded buildings (weighted to NFIP policies risk profile).	0.082	0.080

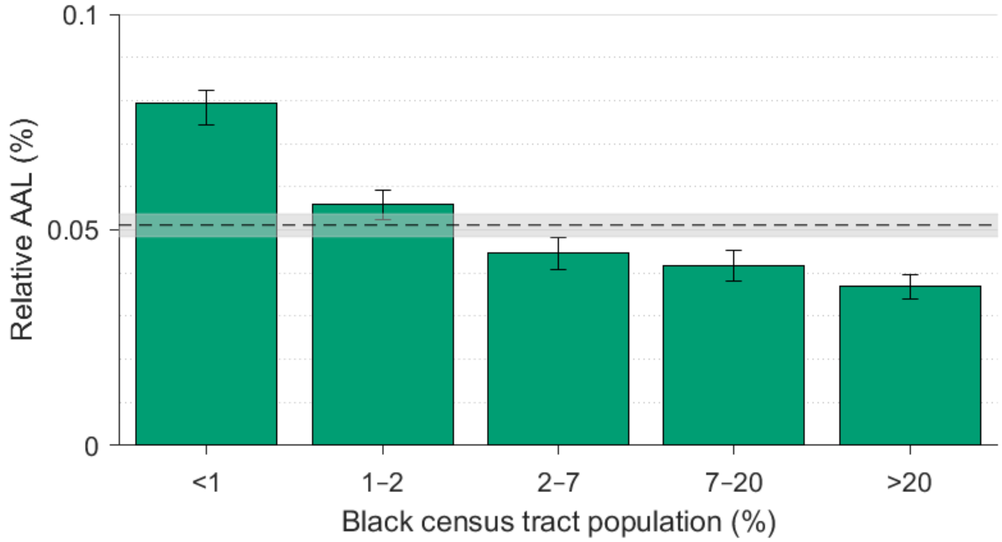
Supplementary Table 1. Summary of the key metrics in the comparison of observed and modelled US flood risk.



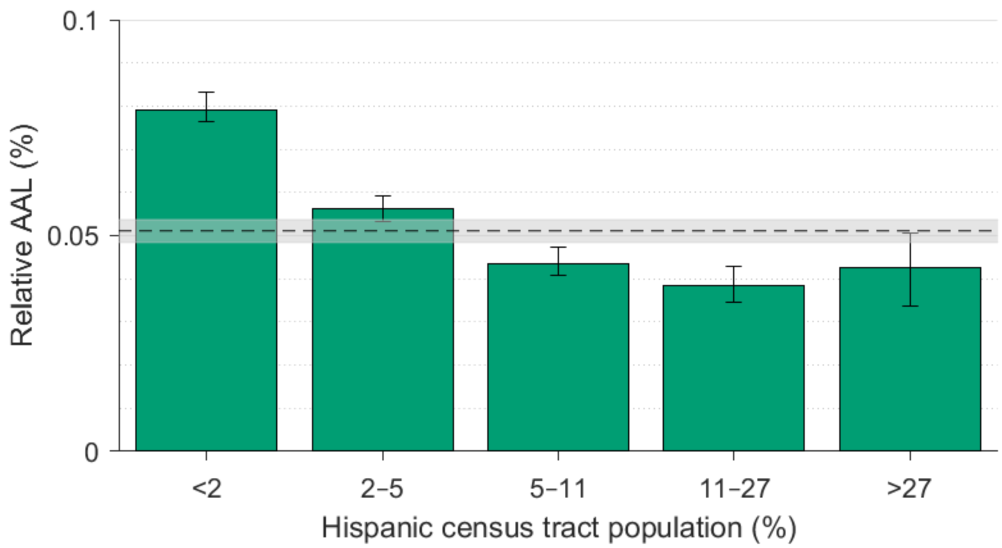
Supplementary Figure 1. The effect of three different uncertainty correlation methods on the distribution of US AALs: no correlation of uncertainty between locations (black); total correlation of uncertainty between locations within the same HUC10 unit (see Supplementary Fig. 2) and no correlation of uncertainty between HUC10 units (aquamarine); total correlation of uncertainty between all locations nationwide (vermilion). Panel **b** is the same as panel **a** but with a smaller *x* scale. Boxplots of AALs in 2050 lie above those in 2020 for each correlation group. Boxes are bounded by the upper and lower quartiles, with the median at the centre, and minima and maxima at the end of each whisker.



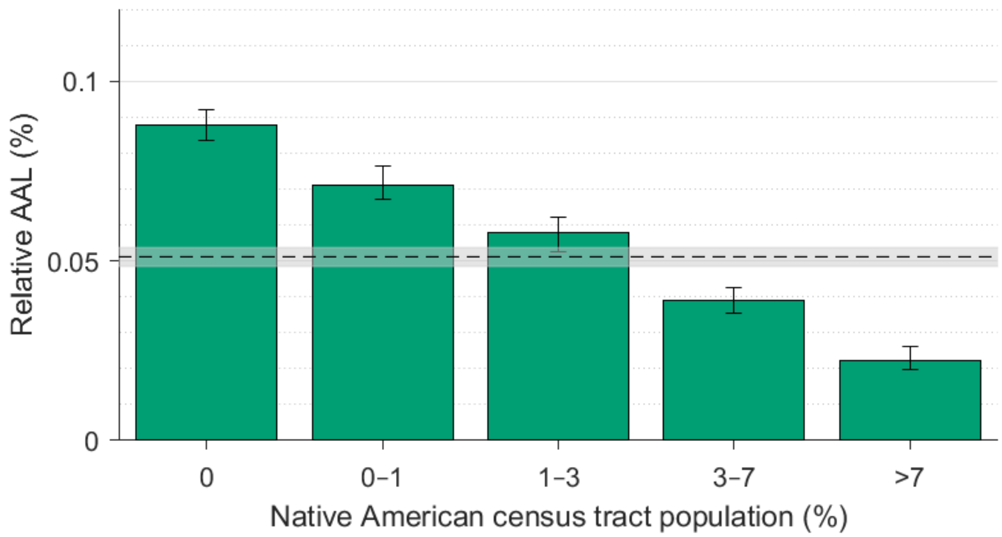
Supplementary Figure 2. The US Geological Survey HUC10 river catchments units within which this analysis assumes total correlation of uncertainty.



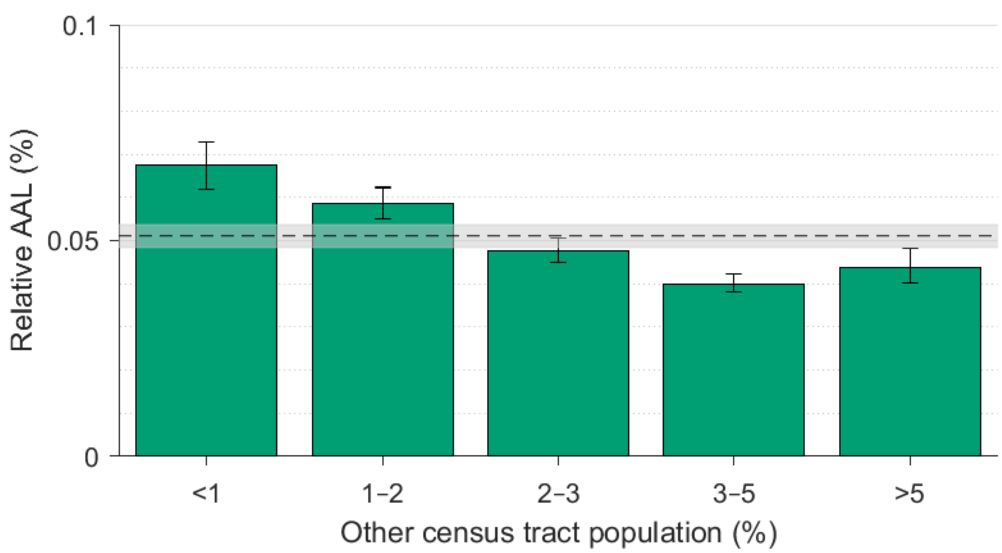
Supplementary Figure 3. Relative average annual loss in 2020 by census tract quintile of Black population proportion. Error bars (quintiles) and grey shading (national average) represent the 95% confidence interval.



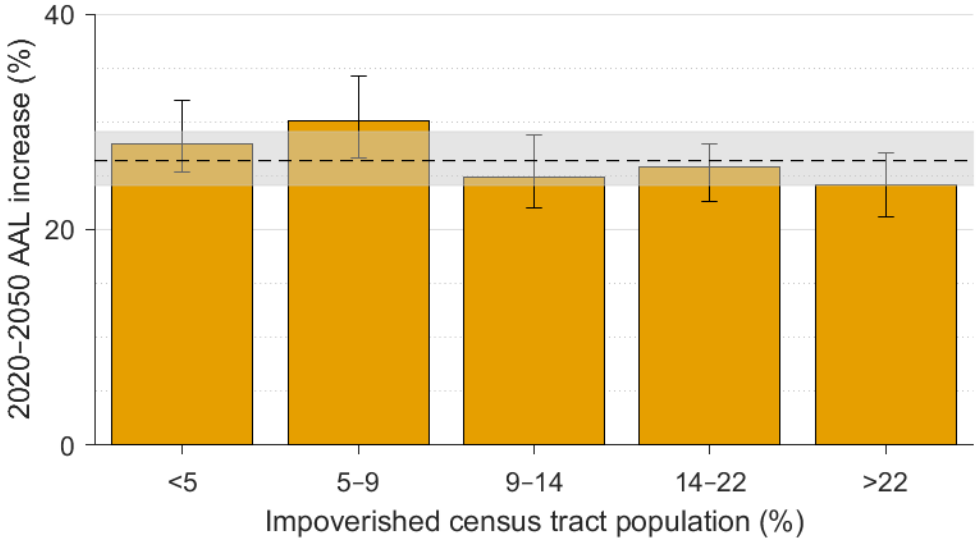
Supplementary Figure 4. Relative average annual loss in 2020 by census tract quintile of Hispanic population proportion. Error bars (quintiles) and grey shading (national average) represent the 95% confidence interval.



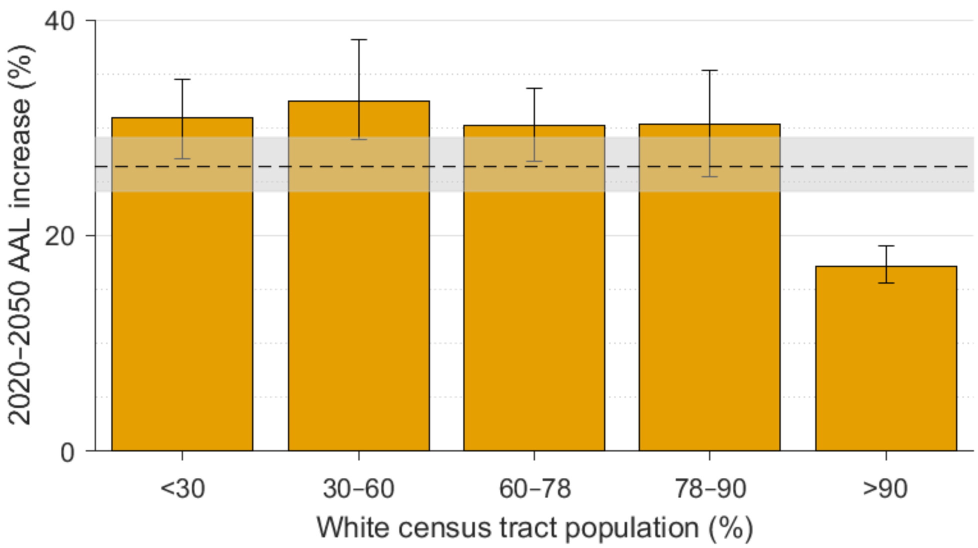
Supplementary Figure 5. Relative average annual loss in 2020 by census tract quintile of Native American population proportion. Error bars (quintiles) and grey shading (national average) represent the 95% confidence interval.



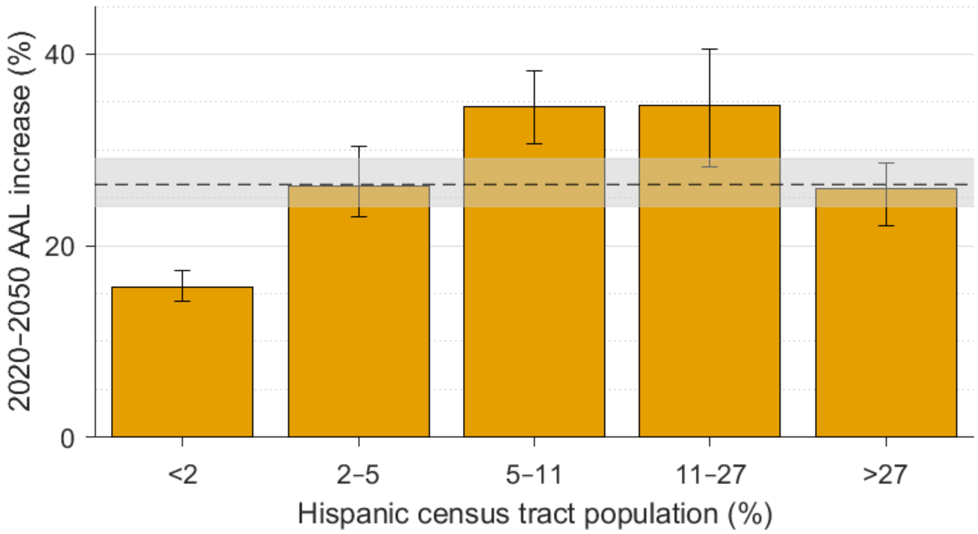
Supplementary Figure 6. Relative average annual loss in 2020 by census tract quintile of other racial groups (not White, Black, Hispanic, or Native American) population proportion. Error bars (quintiles) and grey shading (national average) represent the 95% confidence interval.



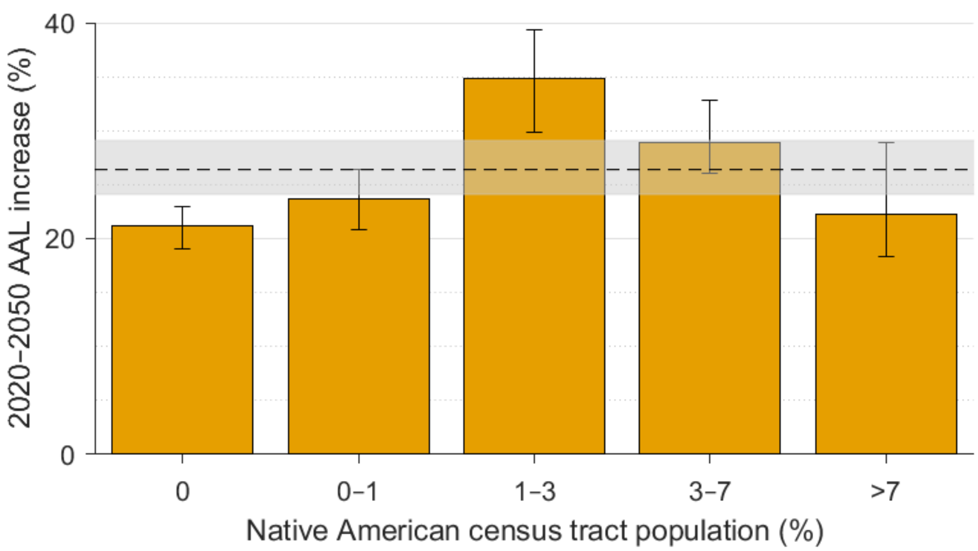
Supplementary Figure 7. Average annual loss increase from 2020 to 2050 for census tract quintile bins of proportion of population in poverty. Error bars (quintiles) and grey shading (national average) represent the 95% confidence interval.



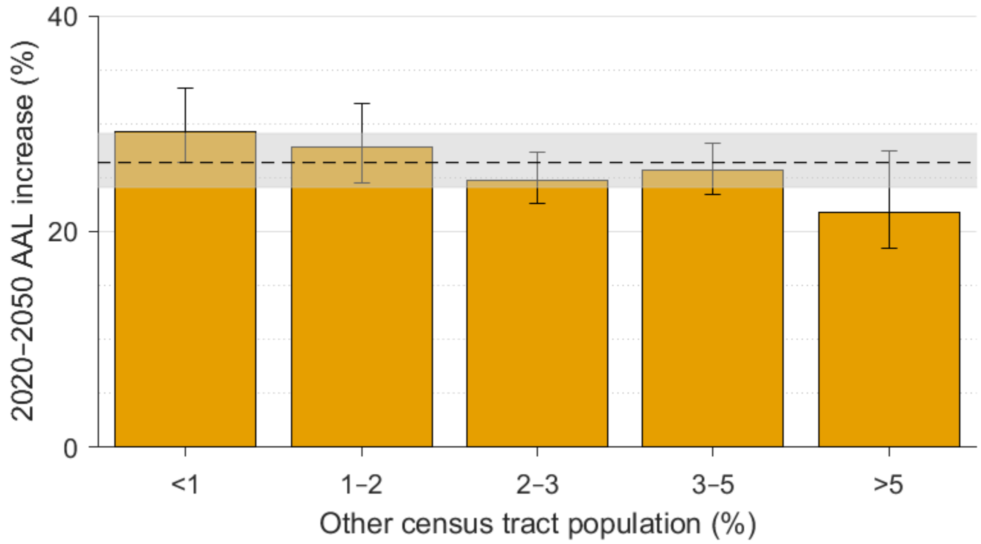
Supplementary Figure 8. Average annual loss increase from 2020 to 2050 for census tract quintile bins of White population proportion. Error bars (quintiles) and grey shading (national average) represent the 95% confidence interval.



Supplementary Figure 9. Average annual loss increase from 2020 to 2050 for census tract quintile bins of Hispanic population proportion. Error bars (quintiles) and grey shading (national average) represent the 95% confidence interval.



Supplementary Figure 10. Average annual loss increase from 2020 to 2050 for census tract quintile bins of Native American population proportion. Error bars (quintiles) and grey shading (national average) represent the 95% confidence interval.



Supplementary Figure 11. Average annual loss increase from 2020 to 2050 for census tract quintile bins of other racial groups (not White, Black, Hispanic, or Native American) population proportion. Error bars (quintiles) and grey shading (national average) represent the 95% confidence interval.

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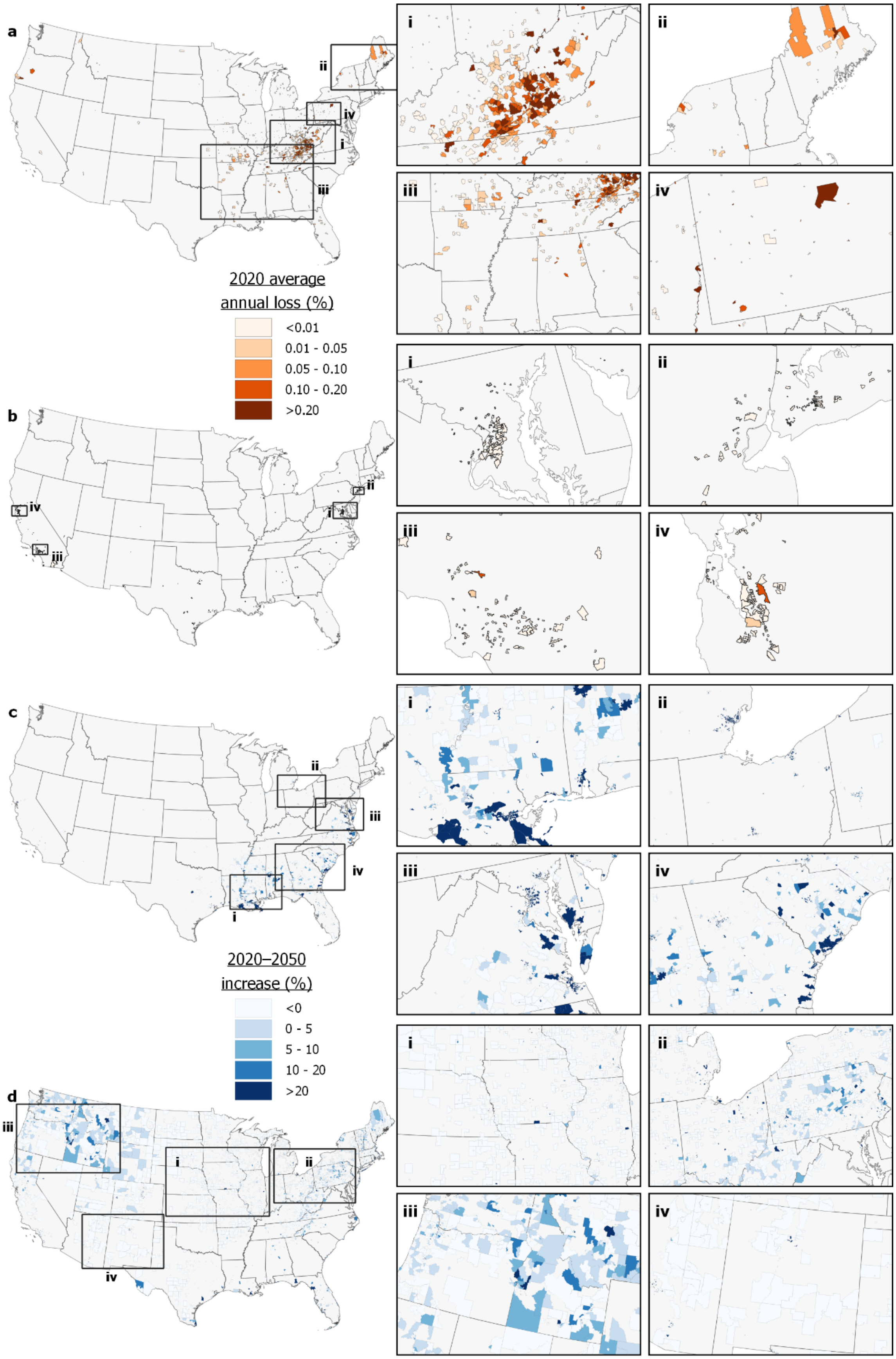
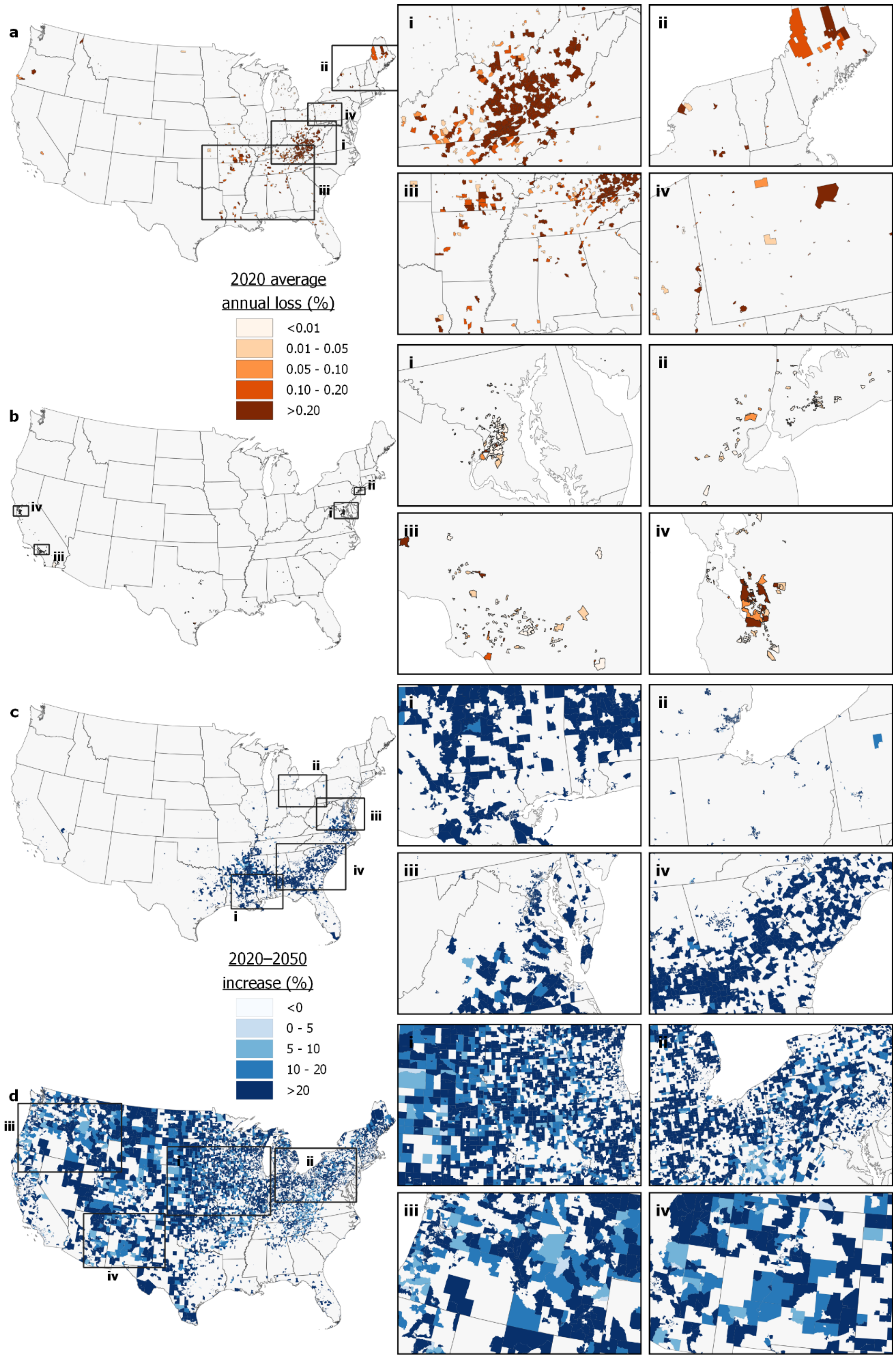

a
b
c
d
i
ii
iii
iv
2020 average
annual loss (%)
<0.01
0.01 - 0.05
0.05 - 0.10
0.10 - 0.20
>0.20
2020–2050
increase (%)
<0
0 - 5
5 - 10
10 - 20
>20

Supplementary Figure 12. Present and future spatial distribution of flood risk amongst select demographic groups; the lower bound of the 95% confidence interval of the data shown in Fig. 3 of the main text. **a** $Q_{2.5}$ relative flood risk of census tracts which fall into the top 20% White population proportion and top 20% poverty rate. **b** $Q_{2.5}$ relative flood risk of census tracts which fall into the bottom 20% White population proportion and bottom 20% poverty rate. **c** $Q_{2.5}$ relative flood risk increase to 2050 of census tracts in the top 20% Black population proportion. **d** $Q_{2.5}$ relative flood risk increase to 2050 of census tracts in the bottom 20% Black population proportion. Panels **i-iv** highlight selected areas for each panel **a-d**.


a
b
c
d
i
ii
iii
iv
2020 average
annual loss (%)
<0.01
0.01 - 0.05
0.05 - 0.10
0.10 - 0.20
>0.20
2020–2050
increase (%)
<0
0 - 5
5 - 10
10 - 20
>20

180

Supplementary Figure 13. Present and future spatial distribution of flood risk amongst select demographic groups; the upper bound of the 95% confidence interval of the data shown in Fig. 3 of the main text. **a** $Q_{97.5}$ relative flood risk of census tracts which fall into the top 20% White population proportion and top 20% poverty rate. **b** $Q_{97.5}$ relative flood risk of census tracts which fall into the bottom 20% White population proportion and bottom 20% poverty rate. **c** $Q_{97.5}$ relative flood risk increase to 2050 of census tracts in the top 20% Black population proportion. **d** $Q_{97.5}$ relative flood risk increase to 2050 of census tracts in the bottom 20% Black population proportion. Panels **i-iv** highlight selected areas for each panel **a-d**.

Supplementary References

57. FEMA. *Testimony of Michael Grimm before the Committee on Science Space, and Technology* (available from: https://science.house.gov/imo/media/doc/Grimm%20Testimony.pdf, 2020)