

**Differential flood insurance participation and housing market trajectories under future coastal
flooding in the United States: Supplementary information**

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Supplementary Note 1: SE modeling description

Flood risk results from hazards (e.g., storm surge and pluvial/riverine inundation), exposure of people and properties, and their vulnerability to flooding events¹. These components have non-linear effects on each other, and their long-term interactions have been studied with socio-environmental (SE) models²⁻⁶. The integration of empirical data in these models makes it possible to quantify flood risk characteristics of a community⁴. In this study, we applied an SE model² derived from prior formulations³ by incorporating a time variant housing market and multiple forms of flood hazard (i.e., storm surge and precipitation). The applied SE model (Fig. S1a,b) was used to predict how peak annual hazards would result in census tract-level NFIP claims (L), NFIP policies (A), flood preparedness (P), population densities (D), and median housing values/prices (HP). The SE models describe numerically how these state variables interact to inform future anticipated NFIP claims (L) (Fig. S1b).

A general flow diagram of the SE model calibration and simulation is presented in Figs. S1a and b. The SE model posits that flooding events above the threshold for flooding result in an immediate positive claim total (L). This causes abrupt increases in both flood awareness (A) and preparedness (P) and decreases in population density (D) and lagged decreases in median housing prices (HP). In contrast, during years with no loss event (L), A and P decay and D recovers (Figure S1 b).

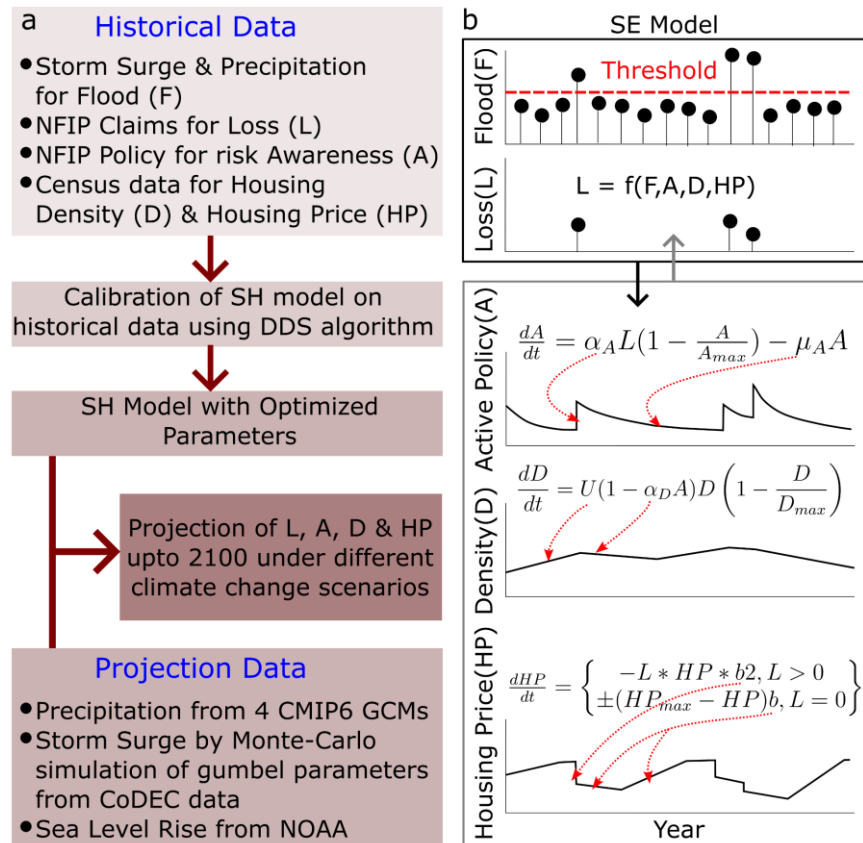


Figure S1: a) SE modeling workflow for forecasting future flood loss, flood insurance uptake, population density, and housing value under climate change scenarios b) Schematics of socio-environmental(SE) model illustrating two way dynamics between flooding events and societal responses (A, D, HP). Flooding exceeding a threshold causes loss (L), perturbing A , D , & HP , which

in turn feedback into the future flood losses. The equations show how these variables (L, A, D, HP) change over time, with red arrows indicating parameters responsible for perturbation during flood and non-flood years.

Supplementary Note 2: Historical datasets & SE model calibration approach

A full list of hazard and social datasets used for the calibration of the model is presented in Table S1. The study area with tidal gauging stations with at least 50 years of historical records where the hazard dataset is collected is presented in Figure S2. These gauges were then allocated to the corresponding census tracts based on geographical proximity, and gauging stations from one coast were not assigned to the other coast. The dataset that is used to evaluate the global Normalized Root Mean Square Error (NRMSE) objective function is noted as $NRMSE_{Loss}$, $NRMSE_{Policy}$, $NRMSE_{Density}$, & $NRMSE_{Housing\ price}$.

Table S1: Summary of hazard and social dataset used for model calibration.

Definition	Period	Data used	Source
Annual peak water surface elevation across tidal gauging stations of US (m)	1970-2021	Hydrological input to model	NOAA ⁷
Annual peak 24-hour precipitation across US coastal census tracts (cm/day)	1970-2021	Hydrological input to model	NOAA ⁸
NFIP Flood insurance claims across the US coastal census tracts (USD)	1979-2021	To calibrate simulated flood loss ($NRMSE_{Loss}$)	FEMA ⁹
NFIP Flood insurance policy held across the US coastal census tracts (number)	2009-2021	To calibrate simulated awareness/active policy ($NRMSE_{Policy}$)	FEMA ⁹
Housing density across the US coastal census tracts (number)	2010-2021	To calibrate simulated density ($NRMSE_{Density}$), and to normalize flood insurance policy	US Census ¹⁰
Aggregate housing value across the US coastal census	2010-2021	To normalize flood insurance claims	US Census ¹¹

tracts (USD)

Median housing
value across the US
coastal census
tracts (USD)

2010-2021

To calibrate
simulated housing
price
($\text{NRMSE}_{\text{Housing Price}}$)

US
Census
12

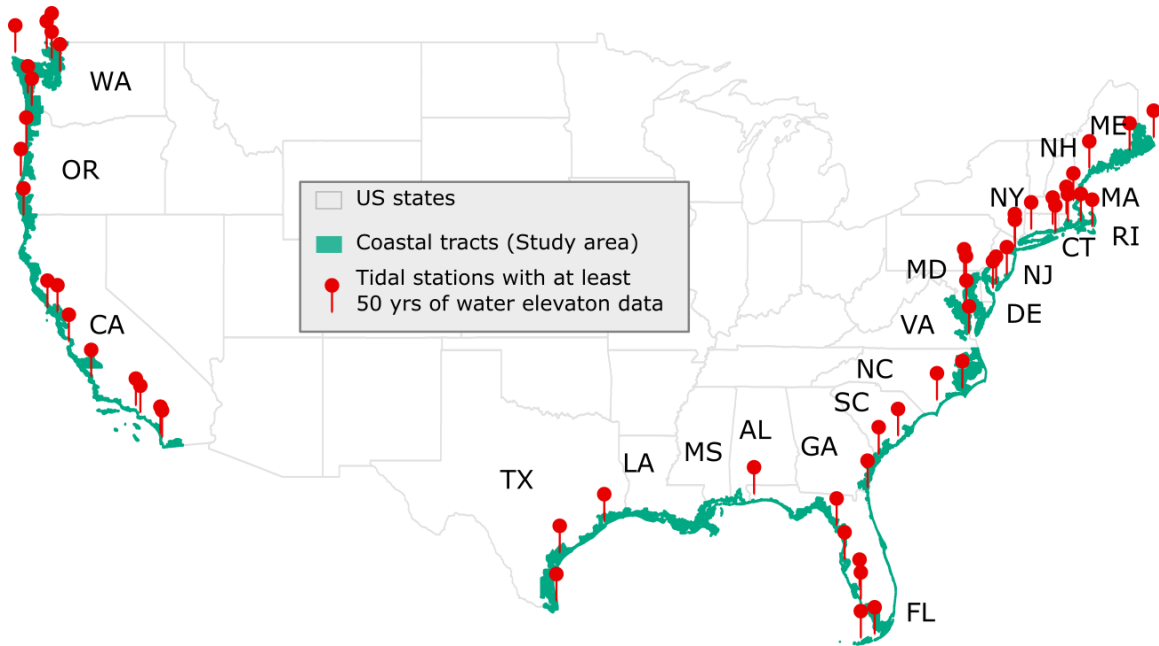


Figure S2: Map of study area showing the distribution of tidal gauging stations with at least 50 years of water surface elevation data used for this study.

All hazard inputs and model outputs are aggregated to the annual scale^{3,4}. Coastal hazards were input into the model as the peak annual water surface elevation (i.e., mean sea level taken relative to the land surface elevation + tides + surge). In the case of historical peak water surface elevations, all of these individual components are inherently captured in the observed water surface elevations. Hourly tidal elevation data was obtained from NOAA⁷ and then aggregated to peak annual water surface elevations.

The SE model parameter values with feasible ranges are presented in Table S2.

Table S2: SE model parameters and feasible ranges used for calibration of US coastal tracts.

Parameter	Description	Feasible range	Unit
S	Storm surge threshold	0, $S_{\max}$	m
R	Rainfall threshold	0, $R_{\max}$	m/day
POT S max	Maximum peak over threshold for storm surge	0, $S_{\max}$	m

POT R max	Maximum peak over threshold for rainfall	0, $R_{\max}$	m/day
A1	Initial awareness	0.001, 0.2	n_h/n_h
P1	Initial preparedness	0.001, 0.2	n_m/n_m
D1	Initial housing density	0.5, 1	m^2/m^2
HP1	Initial housing value	0.1, 0.5	USD/USD
α_d	Risk-taking attitude	0.001, 15	$1/(n_h/n_h)$
α_a	Anxiousness	0.001, 150	$1/(\text{USD}/\text{USD})$
α_p	Activeness	0.001, 100	$(n_m/n_m)/(n_h/n_h)$
α_r	Effectiveness of preparation	0.001, 1	$1/(n_m/n_m)$
β_r	Over threshold discharge to loss ratio	1	$(\text{USD}/m^2)/(\text{USD}/m^2)$
μ_a	Forgetfulness	0.001, 0.3	1/t
μ_p	Decay of precautionary measures	0.001, 1	1/t
U	Ambient population growth rate	0.001, 3	1/t
b1	Housing value rise rate during no- flood years	0.001, 0.3	1/t
b2	Immediate loss in housing value	0.001, 300	$1/(\text{USD}/\text{USD})$
b3	Sustained decline rate of housing value after flood loss	0.001, 5	1/t
d	Recovery duration	0.001, 15	t

Note: $S_{\max}$ and $R_{\max}$ indicate the feasible upper limit of peak annual water surface elevation and peak daily precipitation, respectively. n_h and n_m are the number of properties within the study area and the number of properties with precautionary measures, respectively. The model time step is t .

The SE model simulates all state variables (L , A , D , HP) on the interval 0 to 1. All data used in calibration therefore was normalized to match the model formulation. We normalized flood insurance claims (L) by estimated mean property values within the tract (i.e., reported as a fraction of total tract home values). Active insurance policies (A) were normalized by the mean number of individual properties within each tract (i.e., reported as the fraction of insured properties). The mean estimate of property value and the number of properties were calculated over the period for which corresponding data was available.

Annual median home values (HP) and housing density (D) data were first normalized relative to the median housing price and housing density for the entire US to remove national trends not related to flooding events (Fig. S3). The housing datasets were then scaled for each census tract such that peak year is 1 so that the variable would exist on the interval 0 to 1 (Figure S3).

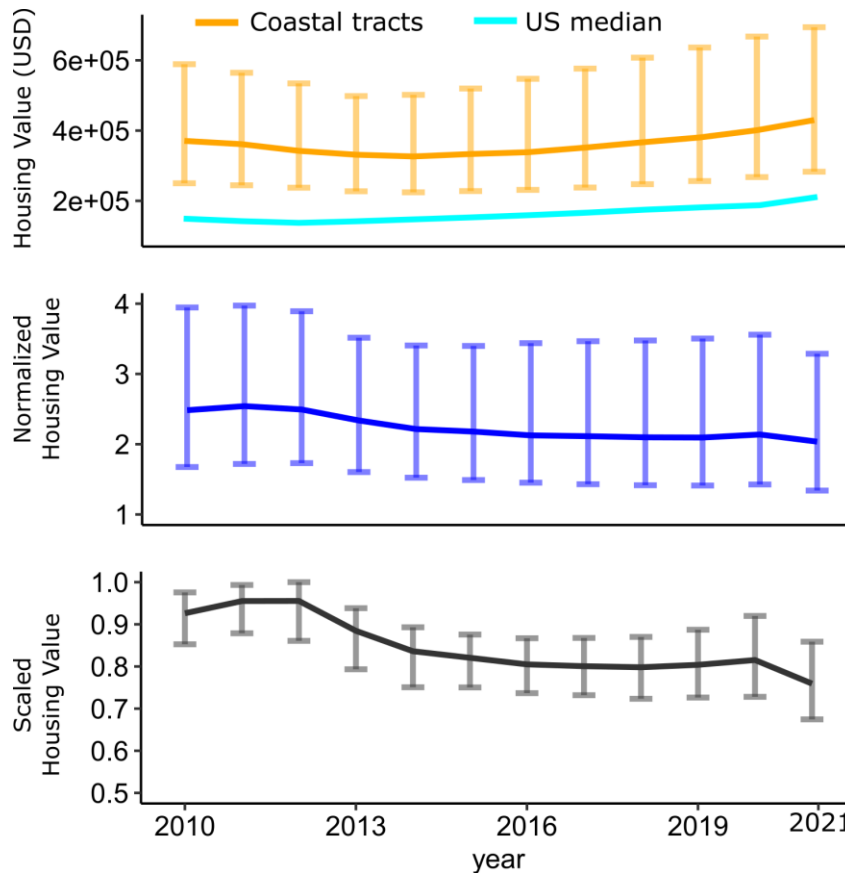


Figure S3: Preparation of housing value dataset for SE modeling. Solid lines are median values with error bars representing the 25th to 75th percentile distribution. Similar procedure is adopted for normalization and scaling of the housing density dataset as well.

Supplementary Note 3: SE model calibration results

The distribution of calibration metrics: $NRMSE_{Loss}$, $NRMSE_{Policy}$, $NRMSE_{Density}$, $NRMSE_{Housing\ price}$, & $NRMSE_{Total}$ is presented in Figure S4. $NRMSE_{Total}$ is the Euclidean distance of individual metrics

(Equation 1). To eliminate poorly calibrated tracts from further analysis, we first set an optimal cutoff threshold to $NRMSE_{Total}$. We used histogram distribution of $NRMSE_{Total}$ and systematically tested various cutoff values to choose the threshold that only retains census tracts that are capable of effectively reproducing observed data. This step identified an optimal cutoff threshold of 6 for $NRMSE_{Total}$, which served as the global calibration criterion for accepting or rejecting census tracts. However, even after filtering by global threshold, few tracts remained that exhibited good global calibration ($NRMSE_{Total} < 6$) but showed poor calibration for individual metrics (i.e., $NRMSE_{Loss}$, $NRMSE_{Policy}$, $NRMSE_{Density}$, $NRMSE_{Housing\ price}$). To address this, as a second filtering step, we also established thresholds for individual calibration metrics using the same procedure as for global threshold. We also confirmed that the combination of selected individual thresholds gives the Euclidean distance consistent with the chosen global threshold. This two-step filtering approach removed census tracts from our modeling analysis where the available datasets did not support a robust analysis of human-flood dynamics. The result was that we eliminated approximately 30% of all tracts from further consideration and only used the retained 1124 tracts that showed satisfactory performance across all evaluated metrics.

$$NRMSE_{Total} = \sqrt{NRMSE_{Loss}^2 + NRMSE_{Policy}^2 + NRMSE_{Density}^2 + NRMSE_{Housing\ Price}^2}$$

Equation (1)

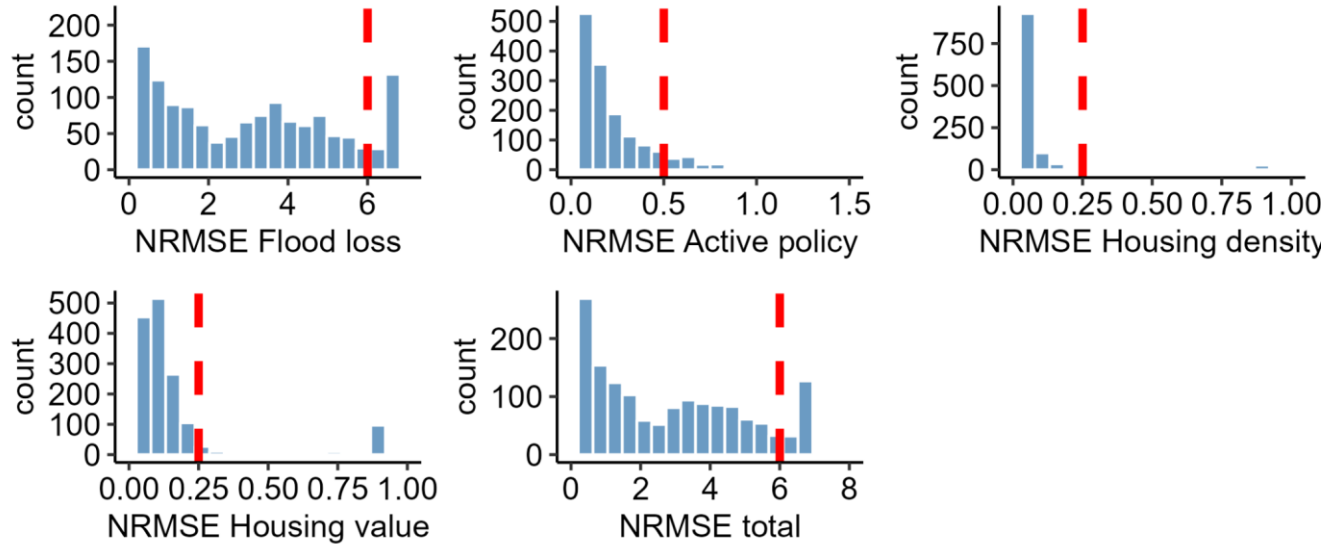


Figure S4: Distribution of Normalized Root Mean Square Error (NRMSE) values across study area. Dashed red line depicts the cutoff for each metric. The x-axis for the NRMSE Active policy has been limited to 1.5 for better visualization, but there are outliers going up to 6, as seen in Figure S5.

We compared the NRMSE metrics with corresponding validation data, observing significant negative correlations, suggesting that census tracts with frequent/larger flood losses, larger policy uptakes, and larger population exhibited better calibration (Figure S5). We also observed significant trade-offs between calibration metrics, demonstrating that the model does simultaneously optimize for all the validation data (Figure S6). This result is likely attributable to a combination of imperfect SE

model structure, imperfect forcing data (i.e., supplied surge and rainfall extremes), and inaccuracies in the underlying databases used for calibration.

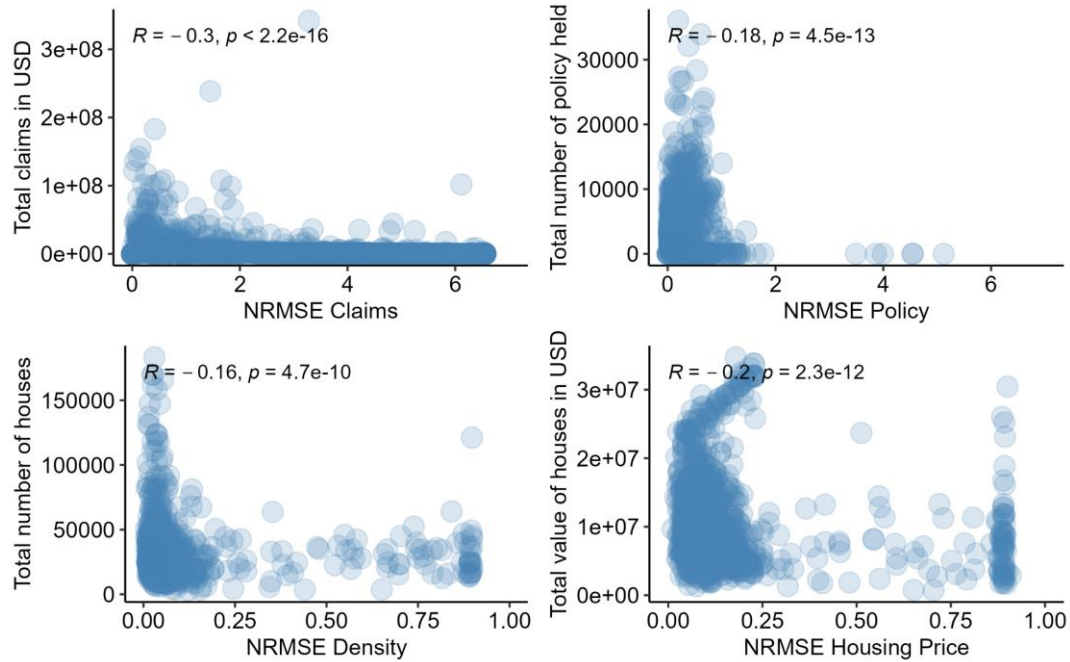


Figure S5: Scatter plot showing the correlation between Normalized Root Mean Squared Errors (NRMSE) objective function and corresponding calibration dataset. We find significant negative correlation across all cases suggesting that census tracts with frequent/larger flood losses, larger policy uptakes, and larger population calibrates better.

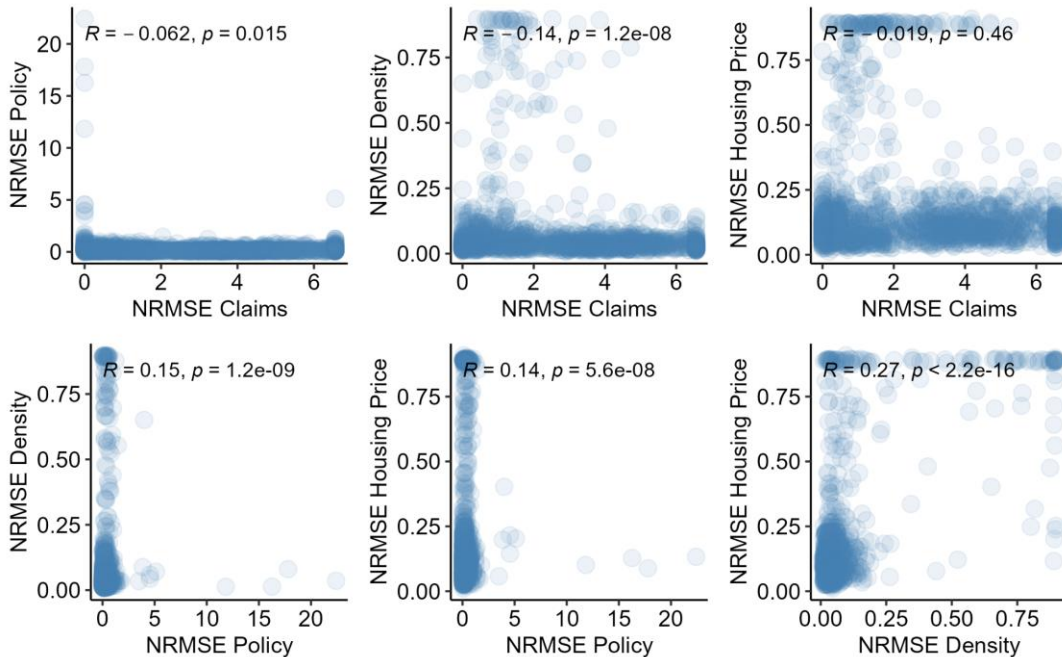


Figure S6: Scatter plot showing the correlation and tradeoff between Normalized Root Mean Squared Errors (NRMSE) objective functions. We observed significant negative correlation between NRMSE Claims and NRMSE Density suggesting a negative tradeoff between calibration of flood loss (claims) and housing density. Significant positive correlation of NRMSE policy with NRMSE Density and NRMSE Housing Price suggests a positive tradeoff in calibration of policy

data with housing data. Additionally, significant positive correlation between NRMSE Density and NRMSE Housing price suggest a positive tradeoff between calibration of housing density and housing values datasets.

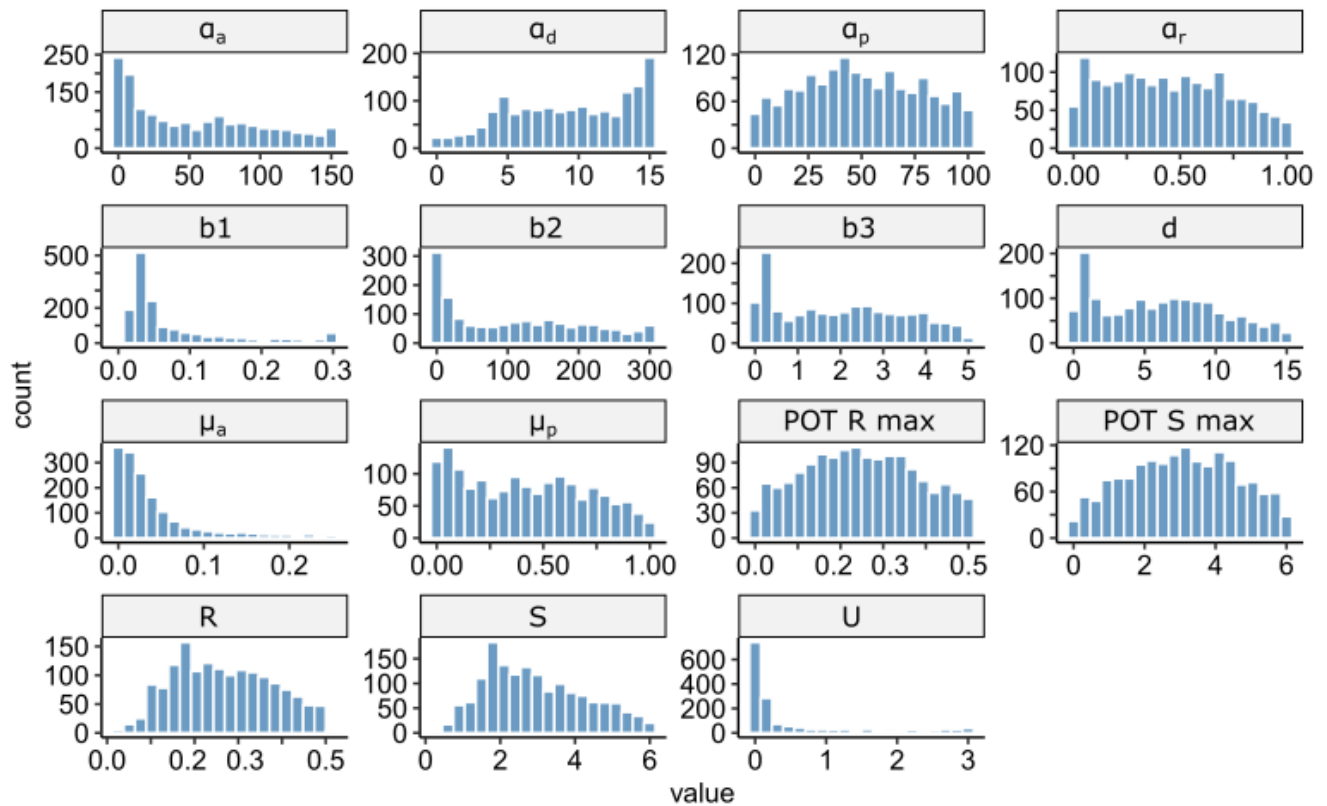


Figure S7: Distribution of calibrated model parameters value across study area.

Supplementary Note 4: Social vulnerability measures

The CDC/ATSDR¹³ uses 16 variables to determine the social vulnerability of a community. These variables were sourced from the US Census's American Community Survey (ACS). ACS only samples a subset of the US population thus the variables are provided with the margin of error (MOE) as an estimate of variation around the population value. To ensure a thorough analysis, we address these MOEs in the correlation test by using a Monte Carlo sampling approach. We resampled the census variables through 10,000 Monte Carlo simulations under the reported assumption of normally distributed residuals. We then performed Spearman's ranked correlation test of each sampled value against the SE parameters. Finally, we evaluate the statistical significance of the correlation test based on the median value of p-value distribution. Figure S8-14 shows the density plots for p-values of Monte Carlo sampled census variables against SE model parameters. Figure S15 shows the state-level correlation of social vulnerability measures with SE parameters.

CDC/ATSDR further uses these 16 variables to determine the overall social vulnerability of communities with values ranging from 0 to 1, higher values indicating greater vulnerability. Figure S16 shows the distribution of overall social vulnerability across the US coastal census tracts.

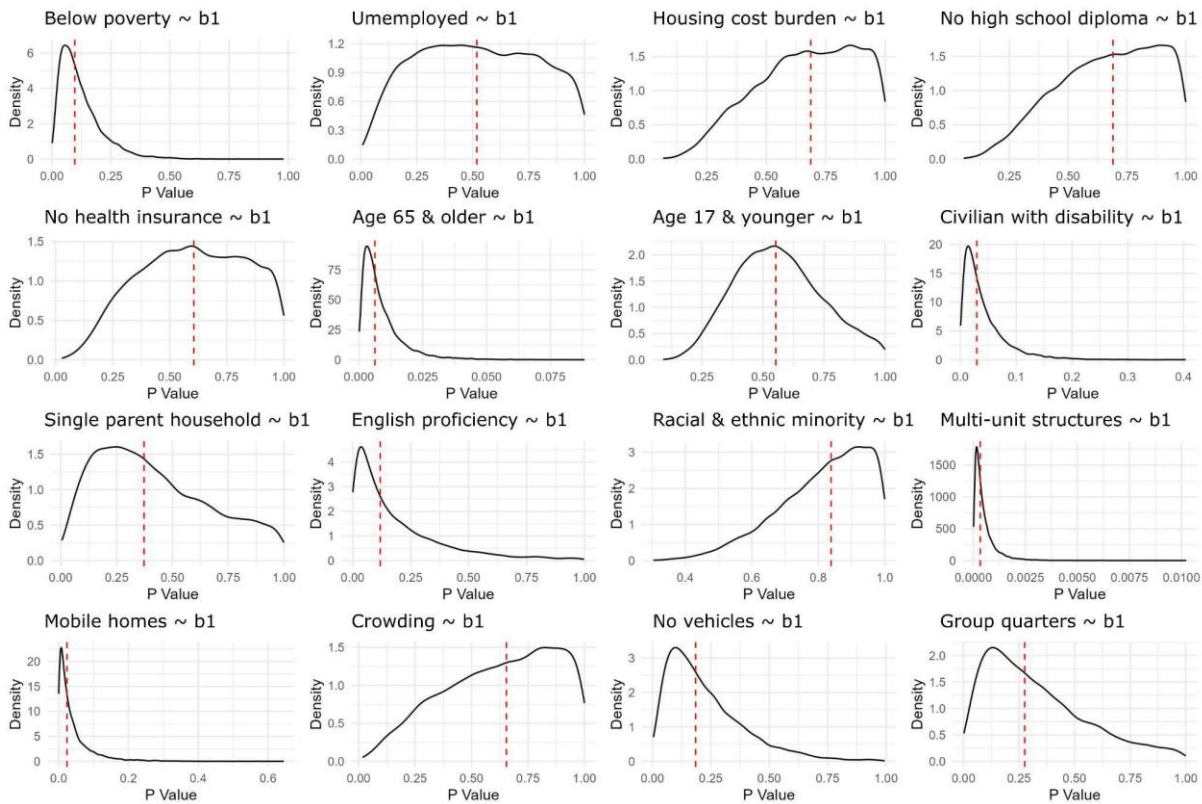


Figure S8: Density plot of Spearman's rank correlation p-values between census variables (10000 Monte Carlo Sampled) and b1 parameter. Red dashed line indicates the median value.

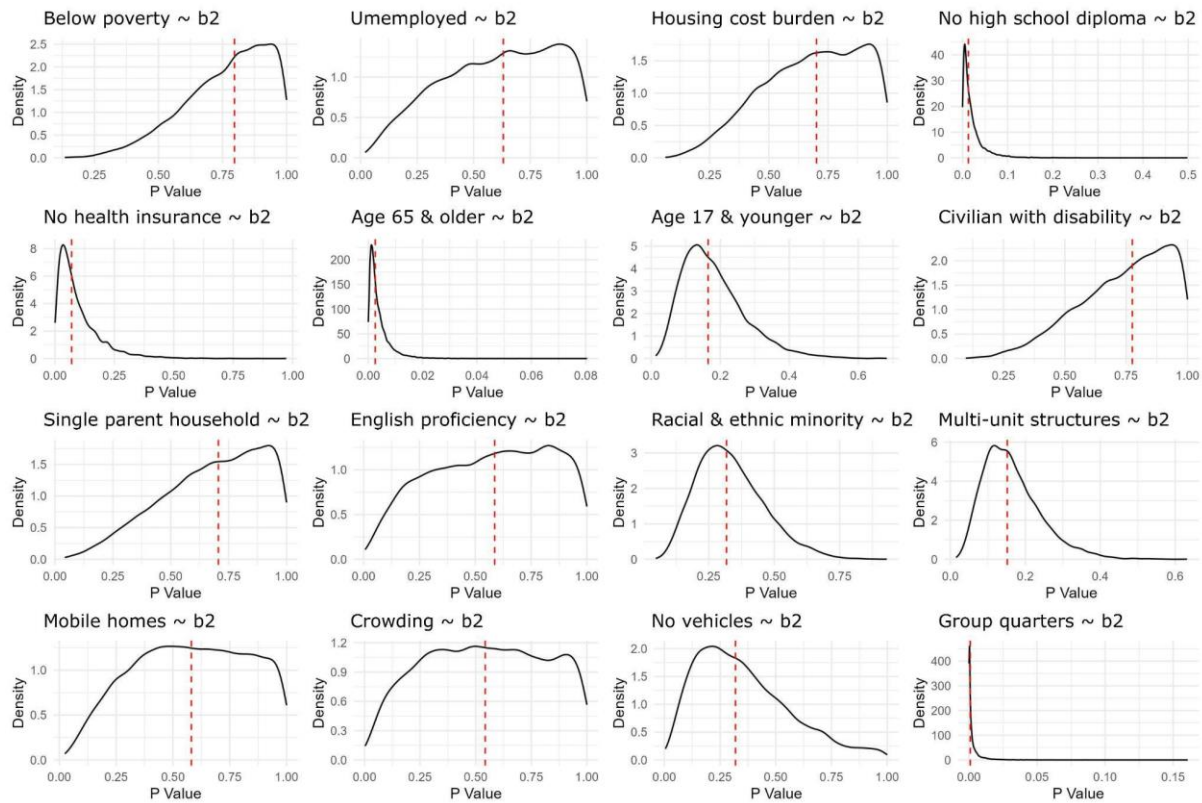


Figure S9: Density plot of Spearman's rank correlation p-values between census variables (10000 Monte Carlo Sampled) and b2 parameter. Red dashed line indicates the median value.

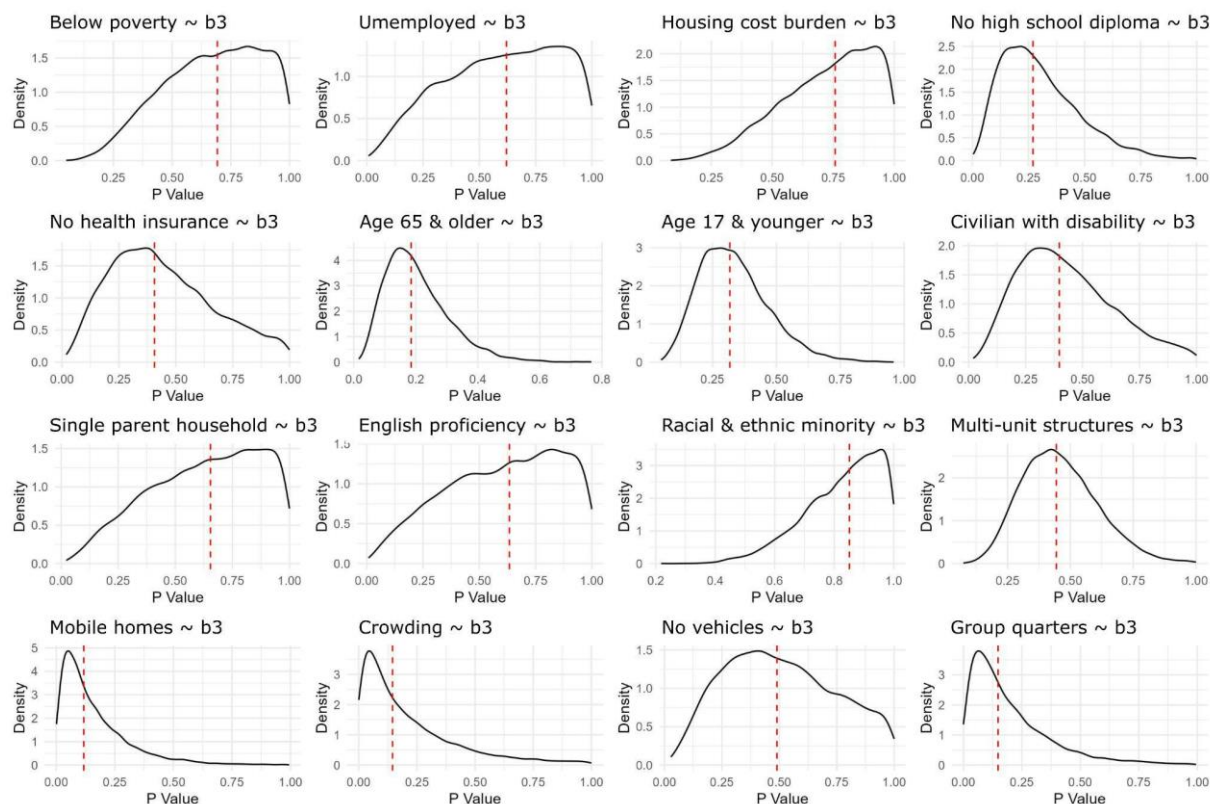


Figure S10: Density plot of Spearman's rank correlation p -values between census variables (10000 Monte Carlo Sampled) and b_3 parameter. Red dashed line indicates the median value.

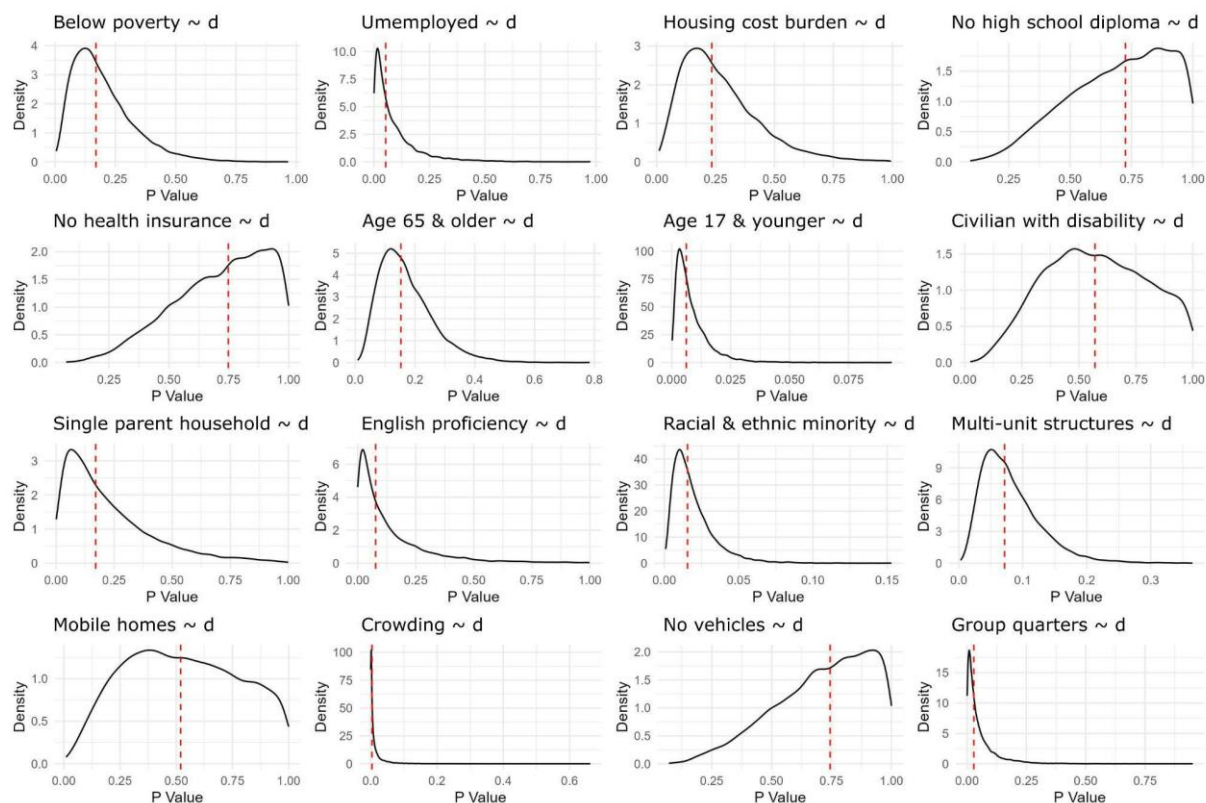


Figure S11: Density plot of Spearman's rank correlation p -values between census variables (10000 Monte Carlo Sampled) and d parameter. Red dashed line indicates the median value.

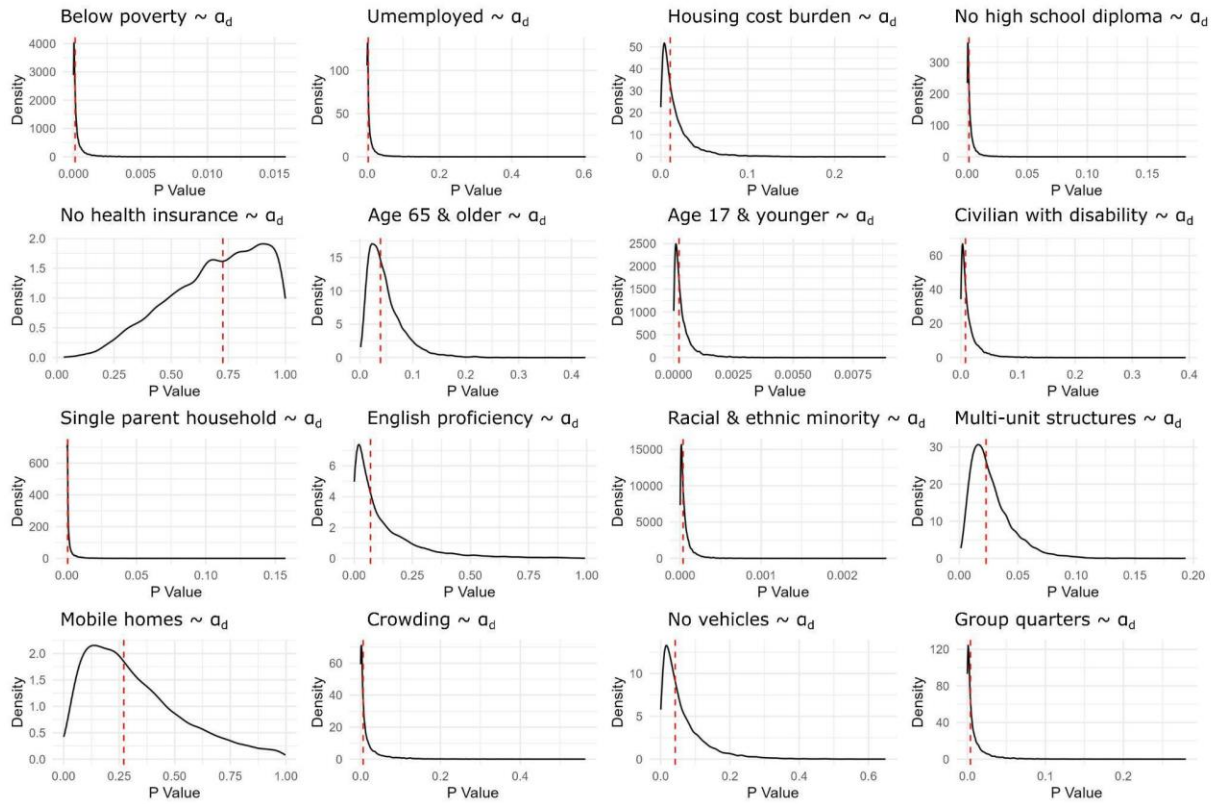


Figure S12: Density plot of Spearman's rank correlation p -values between census variables (10000 Monte Carlo Sampled) and α_d parameter. Red dashed line indicates the median value.

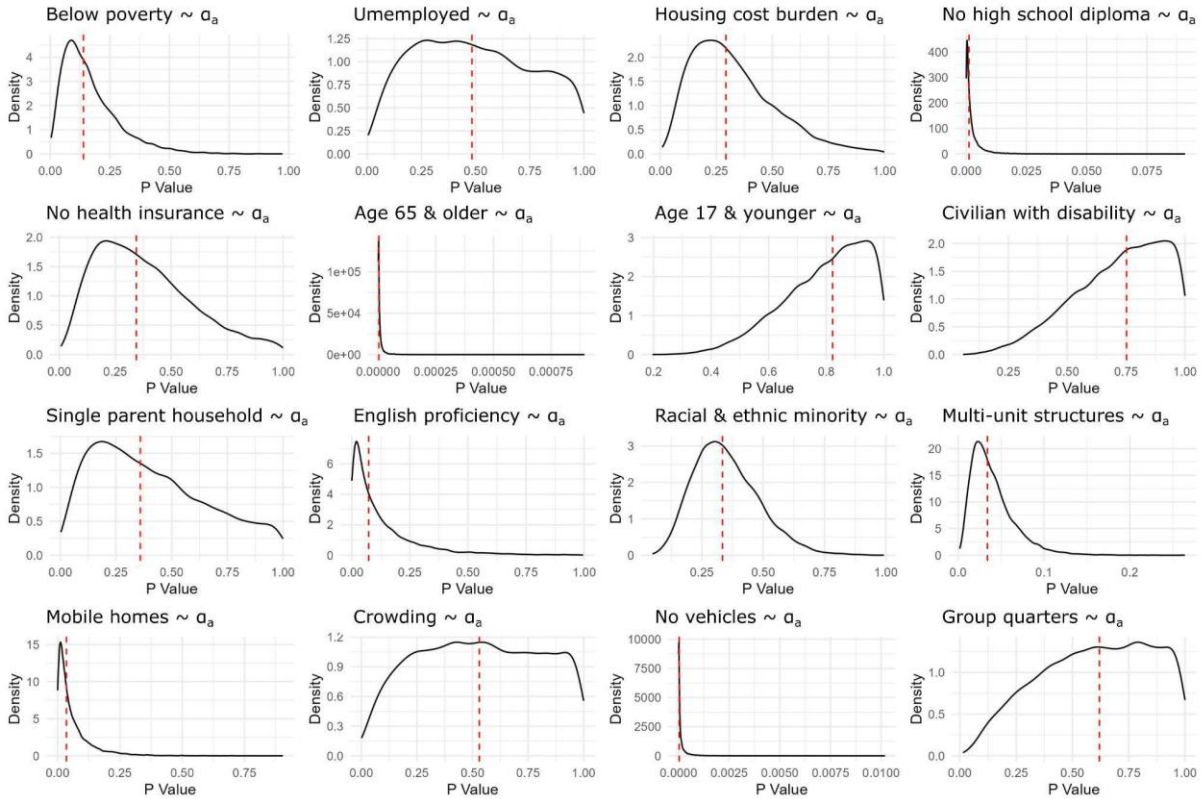


Figure S13: Density plot of Spearman's rank correlation p -values between census variables (10000 Monte Carlo Sampled) and α_a parameter. Red dashed line indicates the median value.

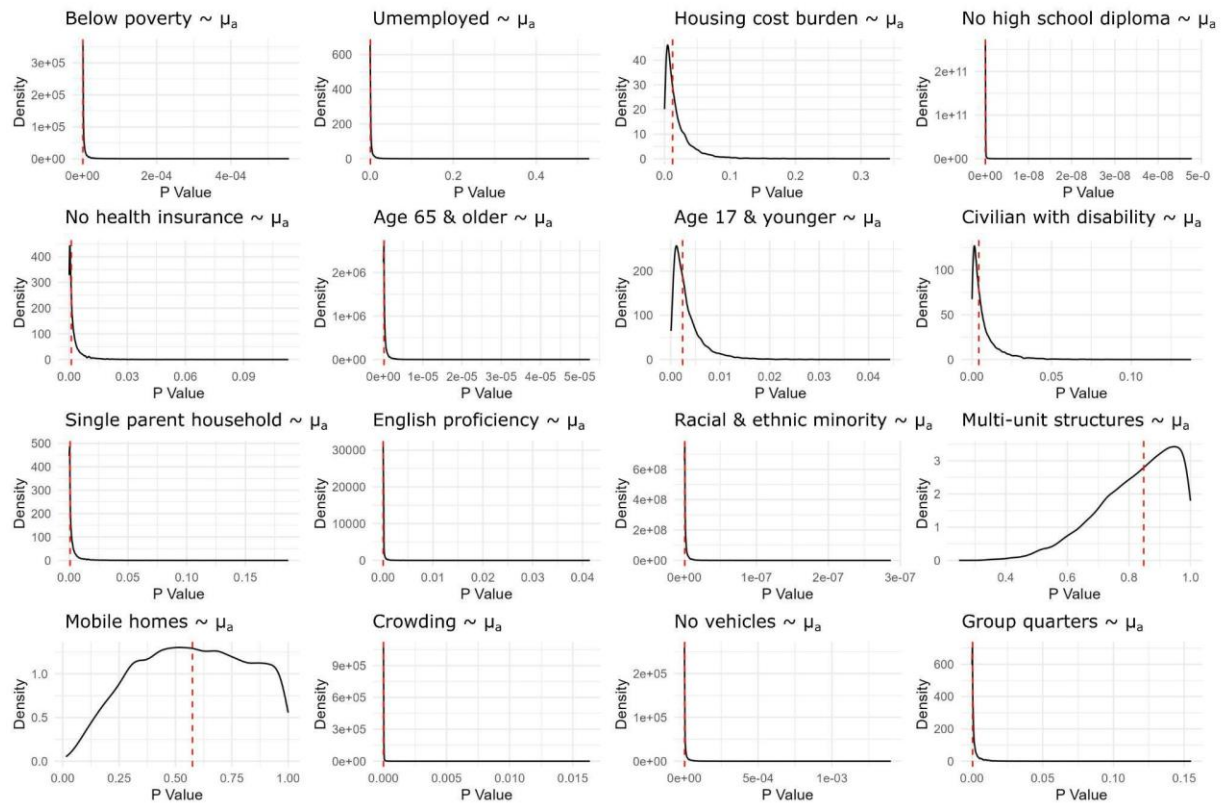


Figure S14: Density plot of Spearman's rank correlation p-values between census variables (10000 Monte Carlo Sampled) and μ_a parameter. Red dashed line indicates the median value.

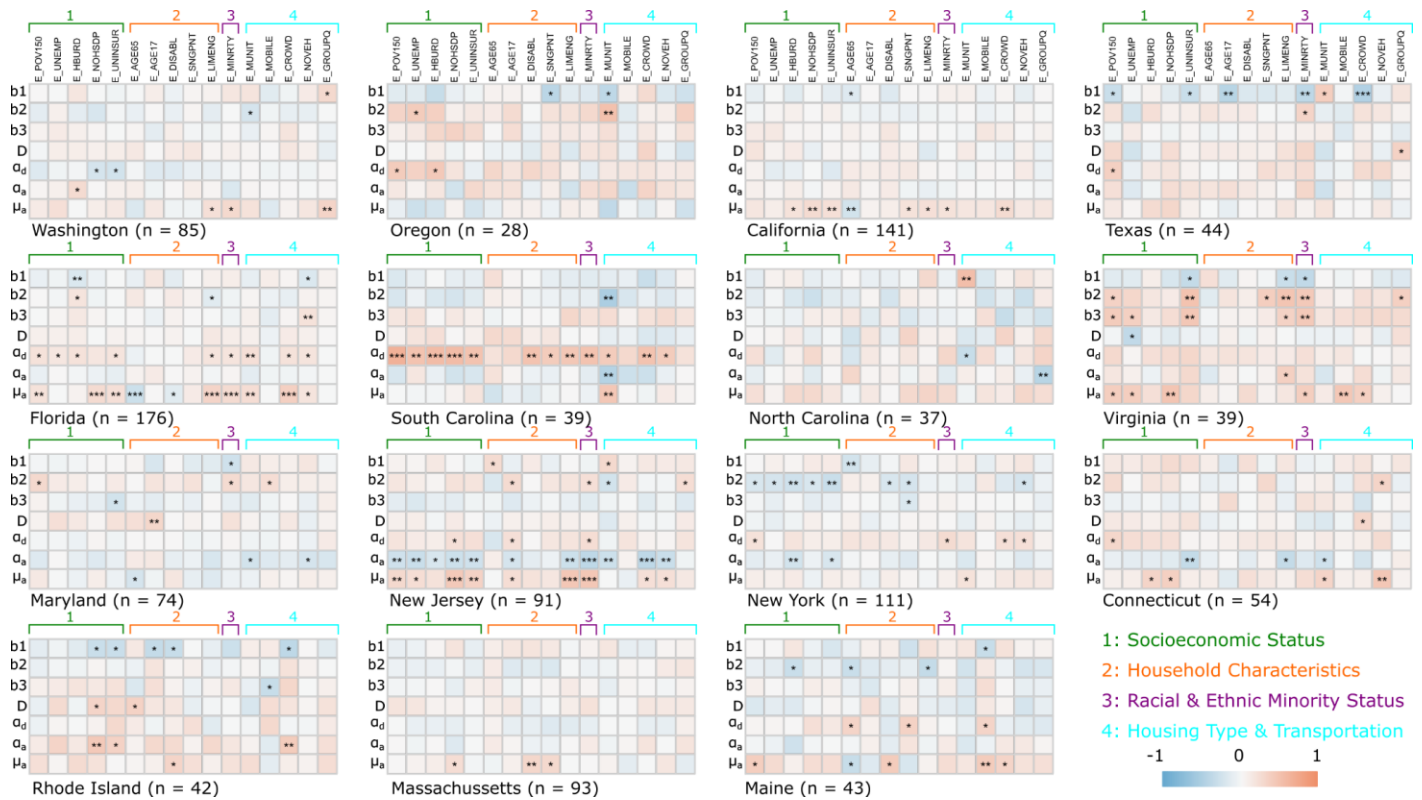


Figure S15: Correlation plot between SE model parameters and measures of social vulnerability across the coastal states. “n” indicates the number of census tracts that are calibrated well for each state. Significance level are measured at $P<0.05$ (*), $P<0.01$ (**), & $P<0.001$ (***)

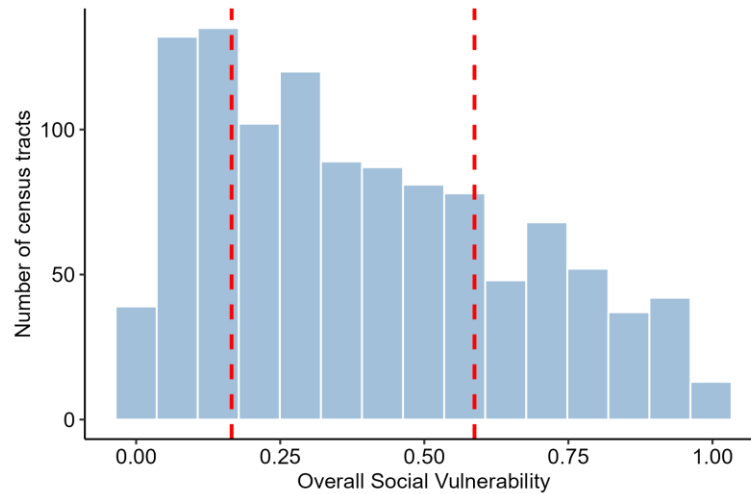


Figure S16: Histogram plot of measure of overall social vulnerability across the US coastal census tracts. Red dashed lines indicate position of 25th and 75th percentile. For this study, census tracts below the 25th percentile line are categorized as Low SVI, between the 25th and 75th percentile as Medium SVI, and above 75th percentile as High SVI.

Supplementary Note 5: SE model calibration results, climate projection datasets, and SE model forecasts

We projected future losses, awareness, population density, and home values from time series of annual projected coastal hazards (i.e., peak water surface elevations and precipitation intensity). A full list of climate projection datasets used for the forecasting of flood loss, active policy, housing density, and housing price to 2100 is presented in Table S3.

Peak annual daily precipitation estimates were obtained from an ensemble of CMIP6 LOCA downscaled models¹⁴. Peak water surface elevations were obtained by combining a dataset of annual sea level rise¹⁵ (i.e., MSL elevation adjusted for changes in both sea level rise and vertical land motion^{16,17}) with probability distributions of future tidal and surge heights taken relative to MSL¹⁸. We then obtained annual peak water surface elevation estimates by resampling the extreme value distributions to obtain tide + surge heights and then adding them to annual MSL projection. Resampling was performed 1000 times for each census tract.

In coastal regions, combinations of multiple climate drivers and hazards may lead to compound flooding events (i.e., high water surface elevations and intense rainfall)^{19,20}. To analyze whether the occurrence of high water elevations and intense rainfall events are independent, we tested for significant ranked correlation between peak water surface elevations and peak annual rainfall using Spearman's ρ . We demonstrate that only 5% of coastal locations exhibited a significant ranked correlation between peak annual water surface elevation and precipitation intensity (Fig. S17). Further, the most highly correlated site only exhibited $\rho = 0.45$. Assessing the role of individual flood drivers (e.g., surge, waves, tides, SLR) and their spatiotemporal variability potentially leading to compound flooding events^{19,21} is beyond the scope of this study and we therefore adopted the simplifying assumption based on Spearman's test that these two forms of hazard could be modeled independently.

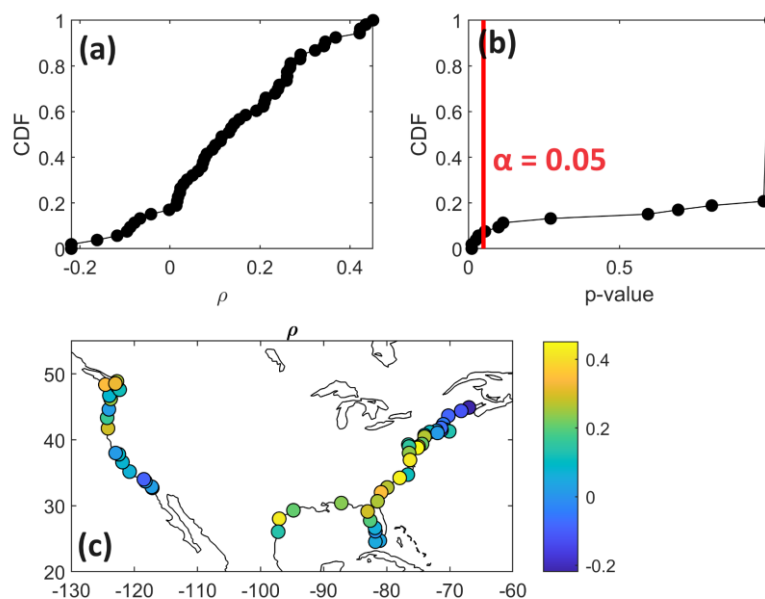


Figure S17: Cumulative distribution function (CDF) of a) Spearman's ρ , b) Spearman's ρ test p-values, and c) the spatial distribution of Spearman's ρ

Table S3: Summary of climate projection datasets used for model forecasting.

Definition	Time points	Source
CMIP6 Loca downscaled precipitation dataset across the US coast for shared socio-economic pathways; SSP245 & SSP585	2021-2100	CNRM-CM6-1, GFDL_ESM4, NorESM2-LM, & MIROC6 ¹⁴
Gumbel extreme value distributions of future tidal fluctuations and storm surge heights	2021-2100	Coastal Dataset for the Evaluation of Climate Impact (CoDEC) ¹⁸
Sea Level rise for shared socio-economic pathways; SSP245 & SSP585	2021-2100	2022 Sea Level Rise Technical Report ¹⁵

Time series of state-aggregated simulated, observed, and forecast NFIP claims, NFIP policies, population densities, and median home values is presented in Figs S18-21. We note that for all states, the model calibration resulted in strong reproductions of historical recorded NFIP claims, NFIP policies, and population densities. States that were substantially impacted by Hurricane Sandy show a strong reproduction of historical median home values. However, several states show a declining trend in median home values from 2012 through 2020 without experiencing significant surge or rain from Sandy. In these cases, the SE model does not provide a strong fit to historical median home values, as there was no associated forcing data (i.e., high water elevations, intense rainfall) to drive this change. Decreasing home values of neighboring Atlantic coast states where Hurricane Sandy resulted in proportionally fewer NFIP claims (e.g., ME, MA; Fig. S18) may be due to regional perceptions of coastal risk affecting the housing market beyond the immediate path of the storm. Similar trends for Pacific coast states may be related to the 2011 Fukushima tsunami and perceptions of exposure risk. More advanced SE model formulations than that employed in this research (Fig. S1) would be required to capture these processes.

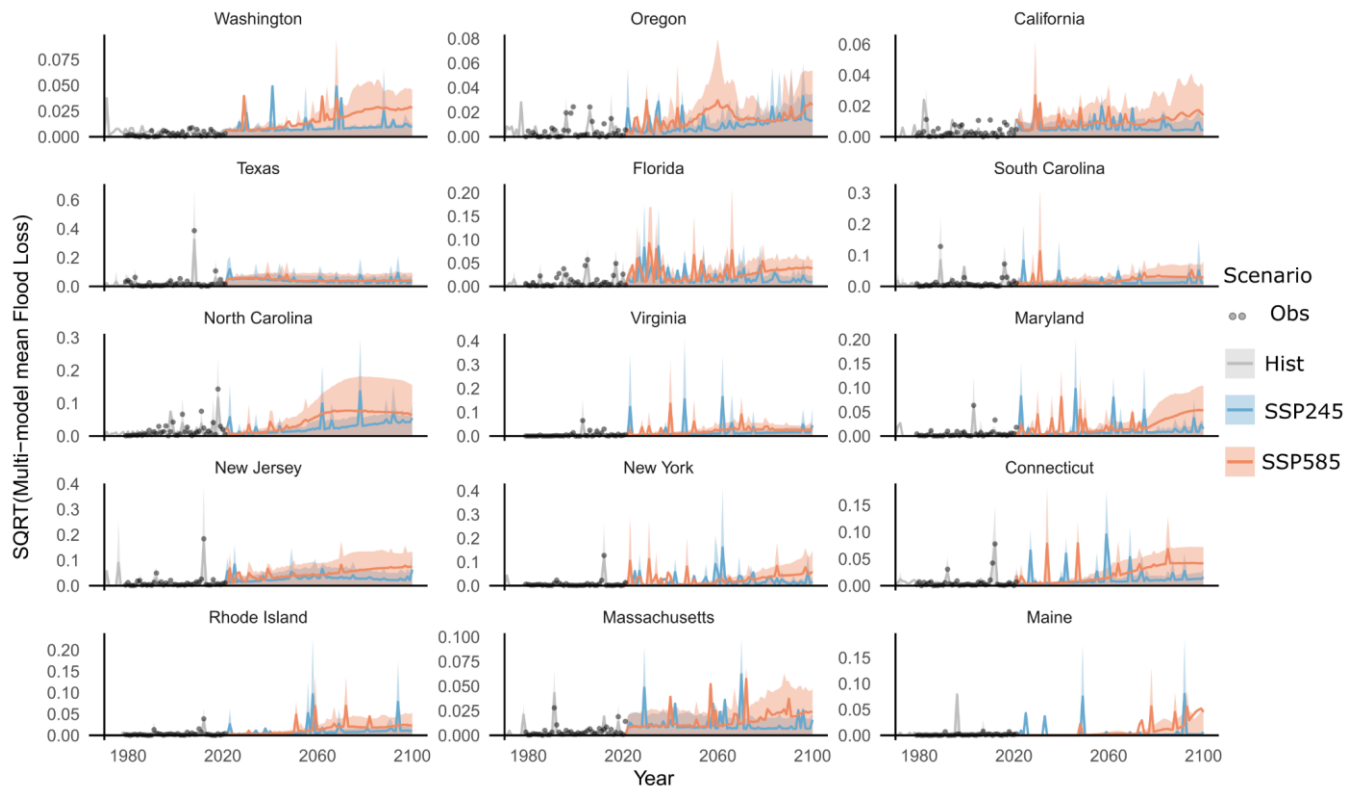


Figure S18: Historical(1970-2021) and projected(2021-2100) multi-model mean flood loss across US coastal states under climate projection scenario: SSP245 & SSP585. The uncertainty bound represents 5th to 95th percentile distribution across all models. Grey dot and line represent observed and simulated historical records. Red and blue lines represent projected results for high(SSP585) & low (SSP245) climate change emission scenarios.

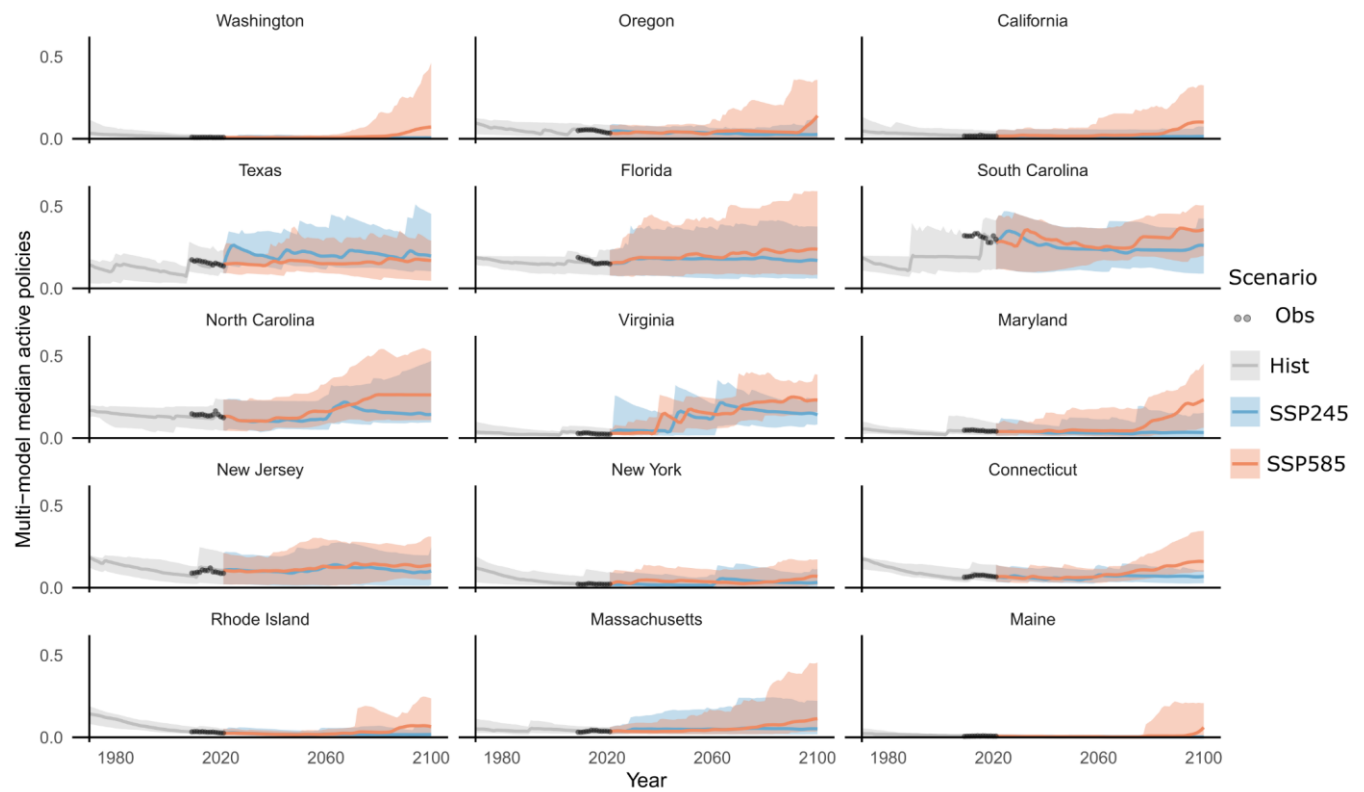


Figure S19: Historical(1970-2021) and projected(2021-2100) multi-model median active flood insurance policy purchased across US coastal states under climate projection scenario: SSP245 & SSP585. The uncertainty bound represents 25th to 75th percentile distribution across all models. Grey dot and line represent observed and simulated historical records. Red and blue lines represent projected results for high(SSP585) & low (SSP245) climate change emission scenarios.

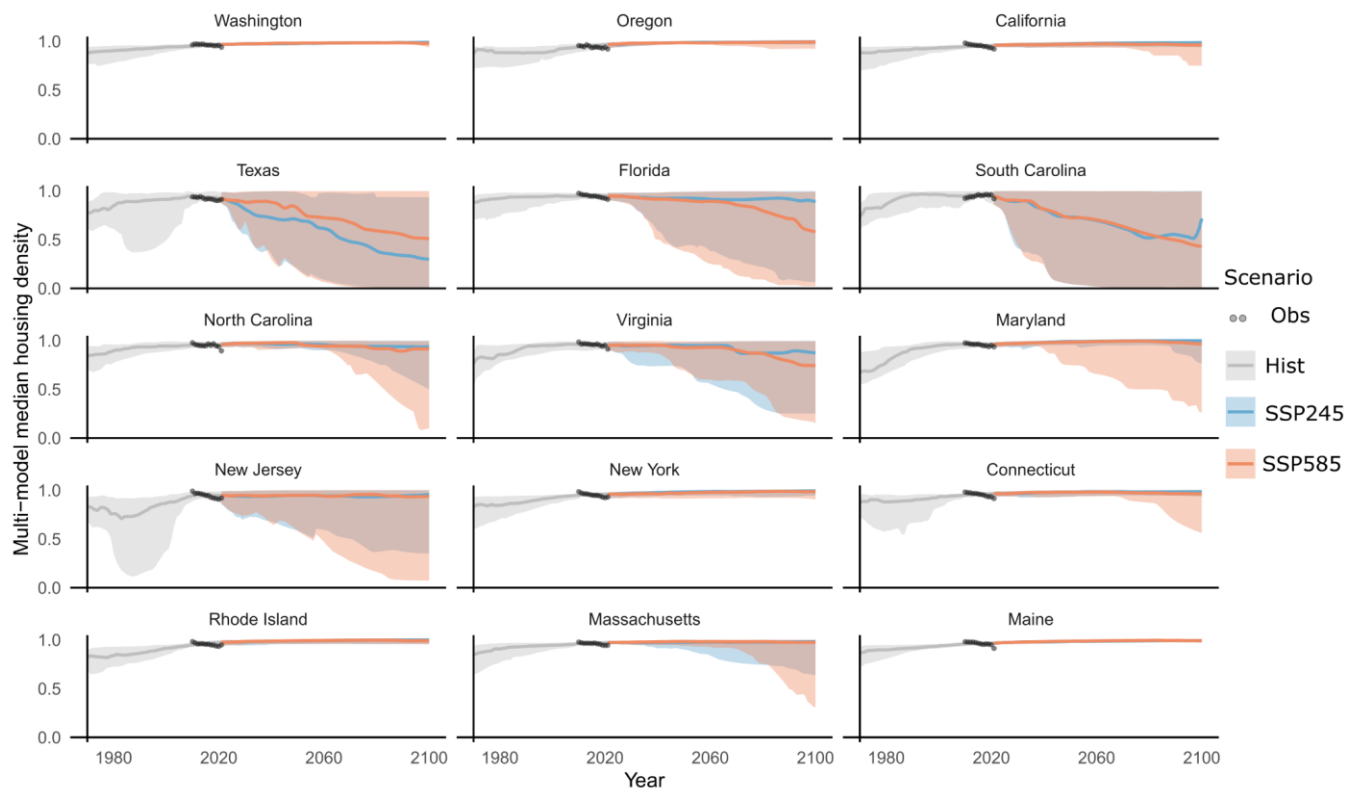


Figure S20: Historical(1970-2021) and projected(2021-2100) multi-model median housing density across US coastal states under climate projection scenario: SSP245 & SSP585. The uncertainty bound represents 25th to 75th percentile distribution across all models. Grey dot and line represent observed and simulated historical records. Red and blue lines represent projected results for high(SSP585) & low (SSP245) climate change emission scenarios.

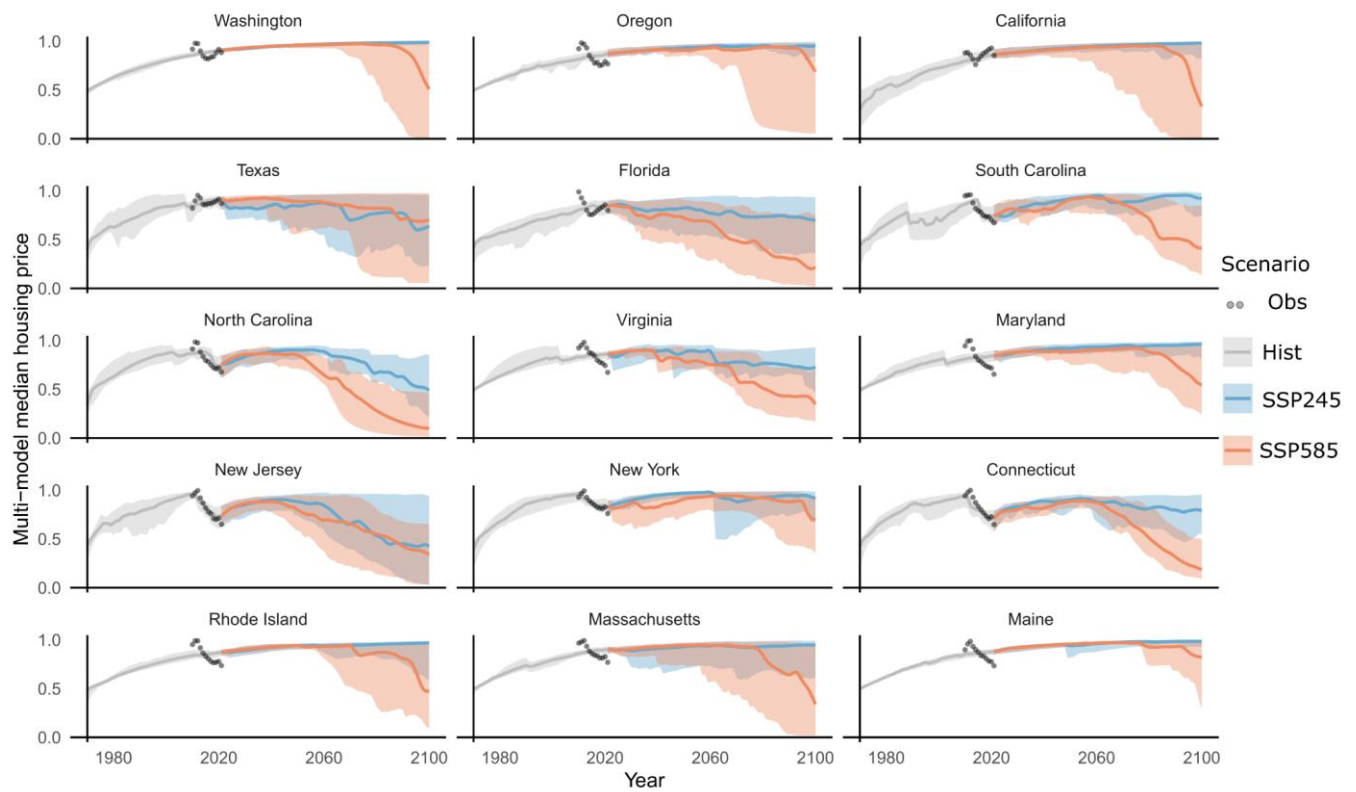


Figure S21: Historical(1970-2021) and projected(2021-2100) multi-model median housing values across US coastal states under climate projection scenario: SSP245 & SSP585. The uncertainty bound represents 25th to 75th percentile distribution across all models. Grey dot and line represent observed and simulated historical records. Red and blue lines represent projected results for high(SSP585) & low (SSP245) climate change emission scenarios.

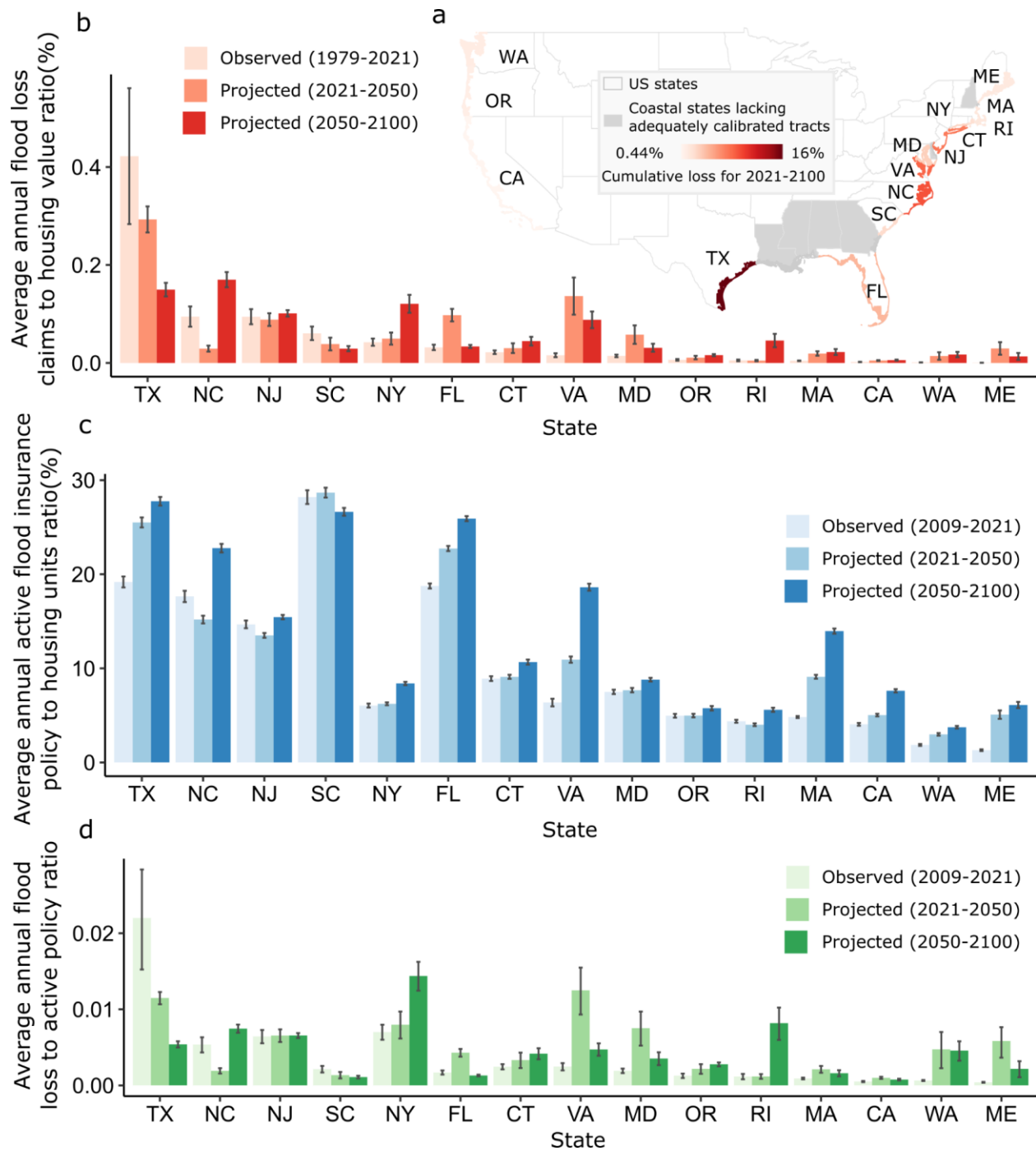


Figure S22: a) Map showing the projected cumulative flood loss for 2021-2100 across the coastal US under climate scenario SSP245. b) Average annual flood loss claims expressed as a percentage of housing value across the US coast for the observed period, projected under SSP245 until mid-century(2021-2050), and until the end of the century(2051- 2100). c) same as (b) for annual average flood insurance policy purchases expressed as a percentage of housing units d) ratio of (b) and (c). The error bar represents standard error.

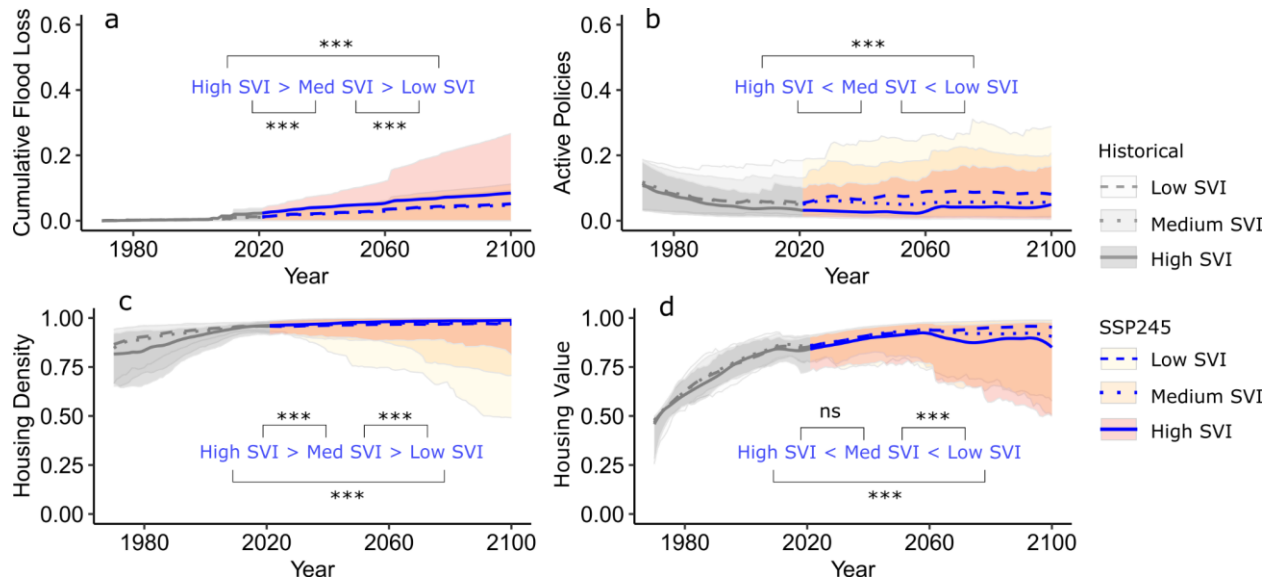


Figure S23: a) Cumulative average flood loss for three different social vulnerability groups (Low SVI, Med SVI, & High SVI) across coastal US under shared socio-economic pathway 245. Linetype; dashed, dotted, & solid depicts median values across Low SVI, Med SVI, & High SVI respectively. Line color; gray & blue represents historical and projected estimates respectively. Shading represents 5 to 95 percentile distribution for each social vulnerability group across all models. b) Same as (a) for median active policies with shading depicting 25 to 75 percentile distribution. c) same as (b) for housing density. d) same as (b) for housing price. The difference between the projected estimates for each vulnerability group is tested with Mann-Whitney U test. Significance level are measured at $P < 0.001$ (***), $P > 0.01$ (ns).

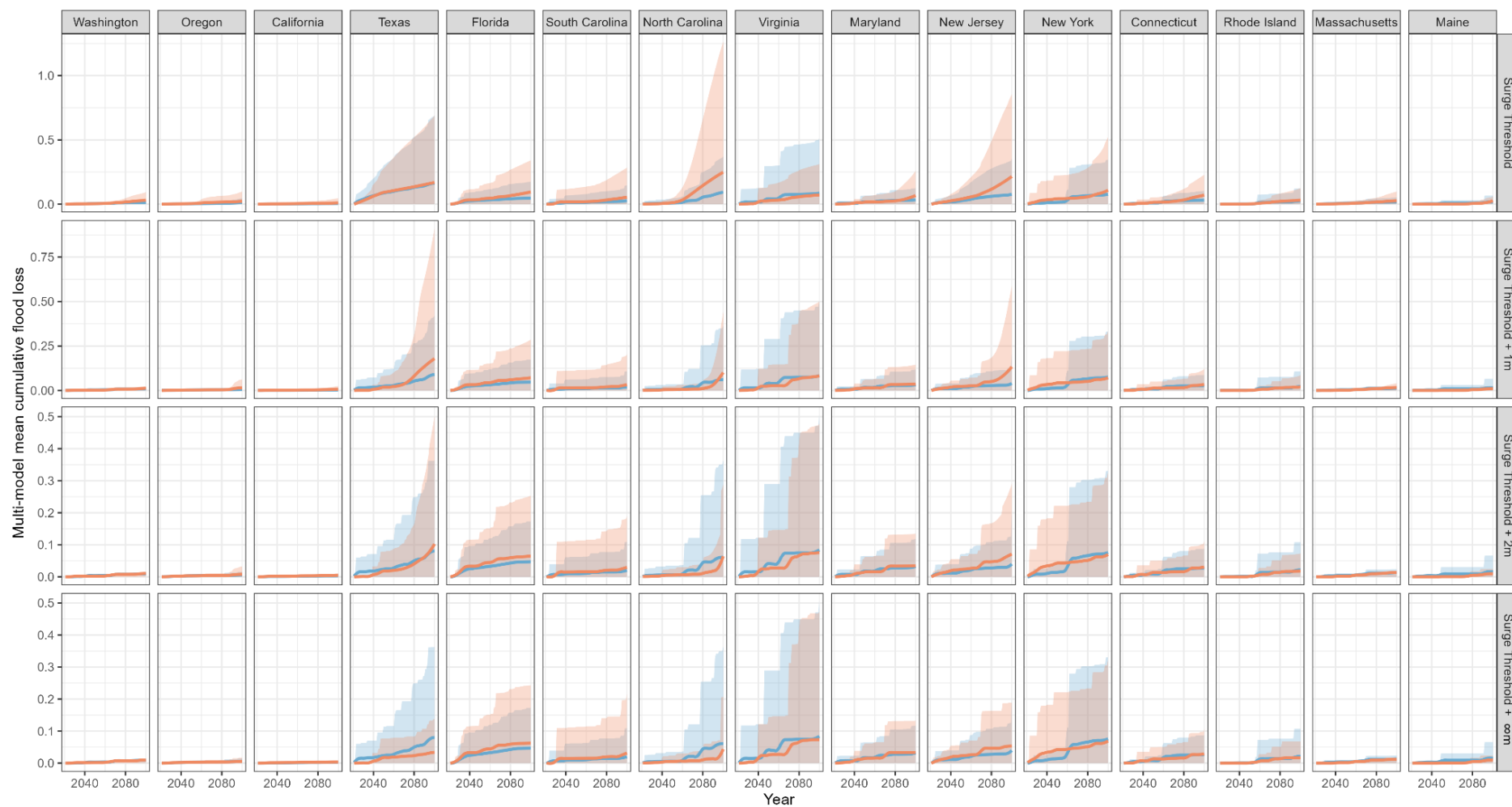


Figure S24: Projected cumulative flood loss for modeled (original) surge threshold and for surge threshold increased by 1m, 2m, & ∞ m respectively across the US coastal states.

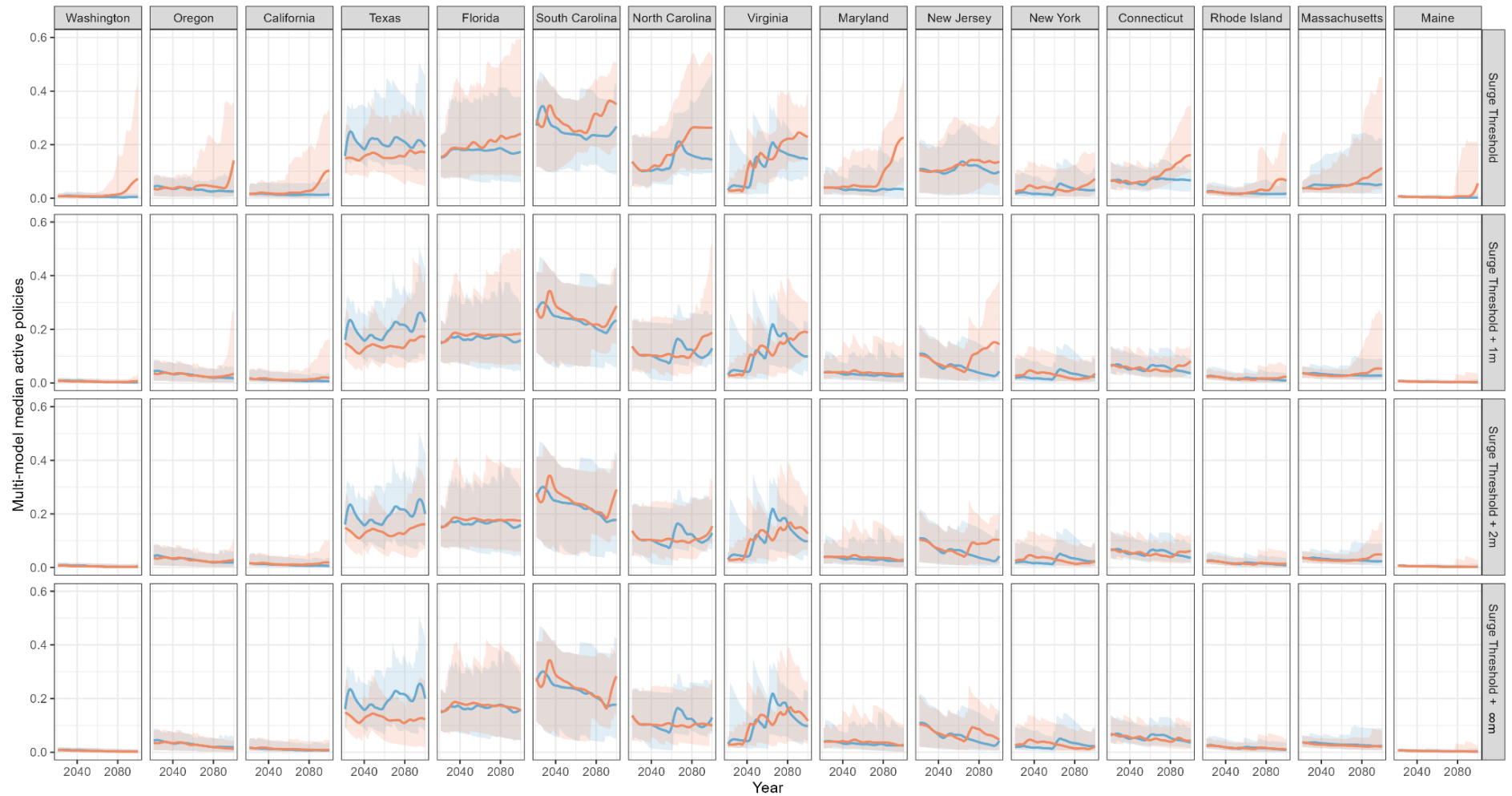


Figure S25: Projected active policies for modeled (original) surge threshold and for surge threshold increased by 1m, 2m, & ∞ m respectively across the US coastal states.

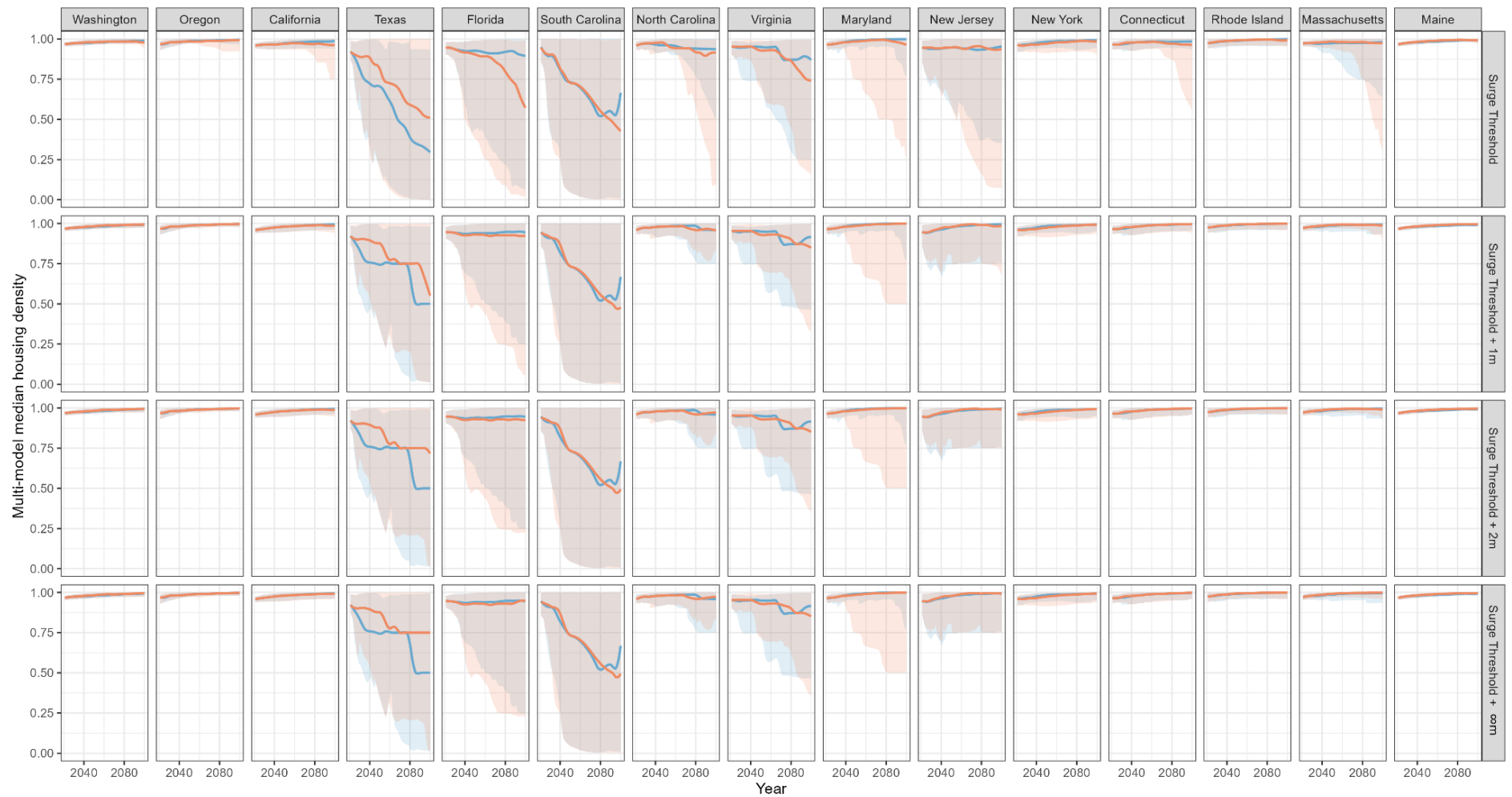


Figure S26: Projected housing density for modeled (original) surge threshold and for surge threshold increased by 1m, 2m, & ∞ m respectively across the US coastal states.

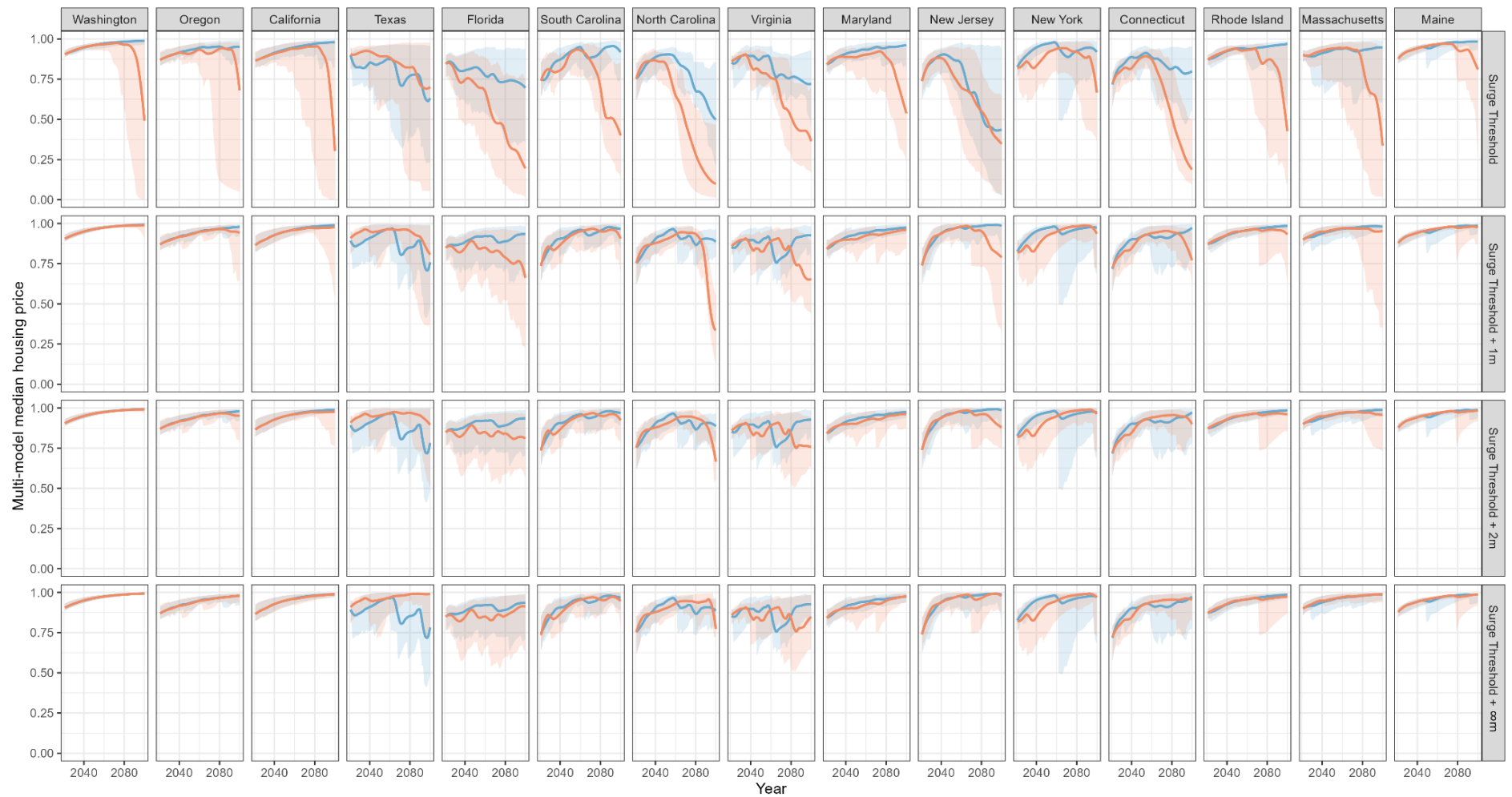


Figure S27: Projected housing values for modeled (original) surge threshold and for surge threshold increased by 1m, 2m, & ∞m respectively across the US coastal states.

5. Supplementary References

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