The social correlates of flood risk: variation along the US rural–urban continuum

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Abstract
Compositional and contextual characteristics of a place capture the collective financial, physical, human, and social capital of an area and its ability to prevent, plan for, and recover from severe weather events. Research that examines the compositional and contextual characteristics of places with elevated flood risk is largely limited to urban-centric analyses and case studies. However, rural areas of the USA are not immune to flooding. In this paper, we integrate social and physical data to identify the social correlates of flood risk and determine if and how they vary across the rural–urban continuum for all census tracts in the coterminous USA. Our results show that risk of flooding is higher in rural tracts, in tracts with larger relative shares of socioeconomically vulnerable populations, and in tracts reliant on flood-vulnerable industries. We also show that compositional social correlates of flooding are not consistent across rural–urban areas. This work widens the scope of discourse on flooding to attend to the heterogeneity of social correlates and the implications for policy and future research.

Keywords Rural–urban · Disparities · Flooding · Social correlates

Introduction
As climate change ushers in increasing weather extremes, the devastating consequences of flooding from large events (e.g., hurricanes and storm surges) and smaller localized events will have major economic and health implications. In the
USA, flooding caused over $76 billion in costs,\(^1\) damaged or destroyed countless homes and businesses, and resulted in 259 deaths from 2000 to 2019 (NOAA, 2020). Given that most homeowner insurance policies do not cover flood damage and only about 10% of homeowners have flood insurance (Strochak et al., 2018), a flooding event can devastate the financial well-being of individuals and families, with potential residual impacts on broader health and well-being (Brody et al., 2011; Simpson-Houseley & De Man, 1989).

While climate change increases the risk of devastating flooding consequences for coastal urban areas via storm surges, hurricanes, and sea level rise, rural areas are not immune (Rhubart, 2020). Moreover, rural and urban communities vary in the compositional and contextual social characteristics that may exacerbate the impacts of flooding. These social characteristics capture the collective financial, physical, human, and social capital of an area and its ability to prevent, plan for, and recover from severe or chronic weather events. Demographic and socioeconomic characteristics (i.e., compositional characteristics) and social infrastructure and labor market structure (i.e., contextual characteristics) are all examples of potential social correlates that vary between rural and urban areas and that may influence flood risk and its impacts.

This research contributes to the growing literature on the impacts of climate change by integrating social and physical data to identify the social correlates of flood risk and determine if those correlates vary across the rural–urban continuum for the coterminous USA. We begin by discussing previous literature that suggests why we might expect to see disparities in compositional and contextual characteristics between places with different levels of flood risk and how that relationship might vary across the rural–urban continuum. We then present results of census tract–level analyses identifying the social correlates of flood risk – across compositional and contextual characteristics–and by rural–urban status. We close with suggestions for future research as well as recommendations for local and state leaders as they plan for and potentially mitigate such risks, with particular attention to the significant social correlates.

### Social correlates to flood risk

Following his work on the differential impacts of the 1995 Chicago heat wave, Eric Klinenberg argued that we must denaturalize disasters and extreme weather events to show how context shapes their impacts and how those events are experienced (Klinenberg, 1999). In the social sciences, denaturalizing is the process of exploring how the impacts of natural disasters are not solely the result of naturally occurring environmental processes, but also the product of how social processes have led to some groups of people being disproportionately impacted by such events compared to other groups of people. Denaturalizing flood risk requires determining if and how

\(^1\) This value only includes flooding events that accrued more than $1 billion in costs. Therefore, it is likely a gross underestimate of the total costs associated with flooding during this time period.
compositional and contextual characteristics vary across areas with different levels of flood risk. These characteristics – or the social correlates – tell us about the collective financial, physical, human, and social capital of an area to prevent, plan for, and recover from events that put livelihoods and well-being at risk (Kelly & Adger, 2000). Such forms of capital can yield tangible resources, such as financial capital, flood insurance, social safety nets, and disaster response systems as well as intangible assets such as social networks and support systems (Thomas et al., 2019; Cinner et al., 2018). Here we briefly review the literature that suggests why we might anticipate disparities in the compositional and contextual characteristics of places with different levels of flood risk and how they can mediate preparedness, mitigation, and recovery.

**Compositional characteristics**

Compositional characteristics related to socioeconomic status can mediate the impacts of flooding from the pre-impact stage through recovery and rebuilding stages (Emrich et al., 2020; Fothergill & Peek, 2004; Rufat et al., 2015). First, those in poverty have fewer relative resources to purchase flood insurance (Fothergill, 2004), evacuate under hurricane warnings (Gladwin & Peacock 1997), or recover following flooding. Moreover, in inland areas of the country, those in lower socioeconomic groups are more likely to live in flood-prone areas (Qiang, 2019). Floods can also be more devastating for low socioeconomic groups – the very groups who have the fewest resources to rebuild, relocate, or access mental health services following their loss (Garrison, 1985). Previous work has also shown that natural disasters result in increased poverty rates, potentially exacerbating socioeconomic challenges (Smiley et al., 2018). While public resources for flood assistance may be available, accessing those resources requires knowledge and connections to navigate their bureaucracies (Fothergill, 2004). This may be why higher income counties are more likely to administer voluntary buyout programs for flood-prone properties than low-income counties (Mach et al., 2019). Therefore, communities with larger shares of low-SES residents are not only collectively less able to prevent, plan for, and recover from flooding events, but may be less able to handle future disasters following a flooding event.

Place-level racial and ethnic composition can also be associated with fewer resources to prevent, plan for, and recover from flooding events – not because of the presence of historically marginalized populations, but because of the historical and contemporary policies and practices that have shaped residential patterns and limited access to financial, physical, and social capital (e.g., Chakraborty et al., 2019; Elliott et al., 2020). For example, previous work has documented altitudinal residential segregation patterns in the South whereby through historical processes, Blacks are clustered in low-lying and flood-prone areas (Chakraborty et al., 2019; Ueland & Warf, 2006). Indeed, recent flood risk analyses have pointed to a disproportionate share of Blacks living in flooding hotspots (Tate et al., 2021). Research on the impacts and aftermath of hurricanes and other flood-related events also points to the unique ways policies, recovery efforts, and buyout programs can bypass disenfranchised
communities of color and communities with low levels of English proficiency (e.g., Bullard & Wright, 2009; Drakes et al., 2021; Elliott et al., 2020; Emrich et al., 2020; Muñoz & Tate, 2016). Research examining relationships between flood risk and measures of place-level population composition also suggest that age composition may matter. For example, Rufat et al. (2015) found that risk to flooding varies across age, suggesting that places with larger relative shares of older adults may be less able to respond to (e.g., evacuate) and recover from a flood event. And in the USA, Qiang (2019) noted that disproportionate shares of older adults in flood-prone areas is most emblematic of coastal areas, not inland areas.

Finally, compositional characteristics vary substantially across the rural–urban continuum. In fact, the compositional characteristics of rural America make it more vulnerable to disasters in general. While rural areas are not monolithic, they have higher rates of poverty, population loss, and precarious employment and larger shares of older adults (Brown & Schafft, 2011; Jensen et al., 2020; McLaughlin & Coleman-Jensen, 2008). These factors often mean that on average there are fewer tax dollars and fewer appropriately skilled workers to mitigate risk, plan for, and assist with recovery from the impacts of a flooding event. Previous research on flooding has noted the compounding impacts of flooding for rural areas that are also more socially vulnerable (Drakes et al., 2021). Therefore, analyses that examine compositional social correlates ought to control for rurality/urbanicity.

**Contextual characteristics**

Here we use contextual characteristics to refer to the labor market structure and social infrastructure of a place. Labor markets shape the livelihoods and well-being of those within them. Sectors of the economy that are particularly vulnerable to flooding risk residual impacts on the well-being of that local economy and residents who rely on it. For example, flooding can have particularly negative consequences for communities that are more reliant on flood-vulnerable industries like farming, forestry, and mining – all of which are more common in rural areas. For example, flooding can damage crops, delay planting or harvesting, and increase agricultural production costs. Therefore, places that are dependent on agriculture may be more economically vulnerable in the wake of flooding. Forestry can also be sensitive to flooding by limiting loggers’ access to and from roads and suppliers’ access to rail lines and via lost product and productivity (South Carolina Forestry Commission, 2015). Some types of mining can also be particularly sensitive to flooding as well. For communities dependent on extractive industries, particularly coal and gas extraction, flooding can mobilize hazardous wastes associated with mining, further exacerbating hazardous exposures and public health concerns (Bell & York, 2010; Hendryx, 2013; Jackson et al., 2014; Wilke & Freeman, 2017). Mining activities can also increase the probability of flooding (Bell & York, 2010; Katpatal & Patil, 2010). Therefore, places that are dependent on extractive industries may be more at risk to environmental and public health impacts. On average, rural areas have traditionally been more likely to be dependent on industries like farming, forestry, and mining (Green, 2017). Therefore, we ought to examine whether dependence on
such flood-sensitive natural resource–dependent industries is more common across flood risk and across the rural–urban continuum.

The second contextual social characteristic of interest here is social infrastructure. There is a growing body of literature on the important role of social infrastructure in supporting the collective capacity of communities and reducing the deleterious effects of disasters (Klinenberg, 1999, 2018). While Eric Klinenberg (2018) defines social infrastructure as physical spaces that promote or facilitate sociality, we are specifically interested in the social infrastructure that can promote or facilitate direct or indirect support leading up to or following a disaster or extreme weather event. Types of social infrastructure that have played critical roles in supporting those impacted by flooding – as identified in previous research – include libraries, civic associations, religious groups, and social service organizations (Campbell, 2016; Tu-Keefner, 2016; Veil & Bishop, 2014; Shinn & Caretta, 2020). These outlets provide food, clothing, temporary shelter, volunteers and support accessing technology and Federal Emergency Management Agency (FEMA) (n.d.) recovery assistance. And in doing so, they help residents cope, recover, and rebuild. The role of social infrastructure in reducing flooding impacts may vary between rural and urban communities. Previous research shows that whereas economic capital drives disaster resilience in urban centers, community capital is most important in rural areas (Cutter et al., 2016). Therefore, determining whether social infrastructure capacity varies not only by level of flood risk, but also along the rural–urban continuum is essential for shedding light on challenges facing places with elevated flood risk.

**Study aims**

Based on the literature cited above, we have reason to believe that there may be compositional and contextual characteristics that could vary along flood risk (i.e., social correlates) and that these social correlates may vary across the rural–urban continuum. Therefore, we ask the following two research questions: (1) What are the social correlates of flood risk that may limit capacity to prevent, plan for, and recover from a flood event? (2) And do those social correlates vary across the rural–urban continuum? Understanding the social correlates of flood risk is essential for informing policies to prevent and mitigate the effects of flooding in vulnerable communities. We do this by integrating social and physical data to examine the census tract–level social correlates of flood risk across the rural–urban continuum for the coterminous USA.

**Data and analytic strategy**

We use census tracts as the unit of analysis because they better represent neighborhoods than other geographies (e.g., zip codes) and are more granular than counties in capturing risk and vulnerability.
Data

Flood risk measures

To determine tract-level flood risk, we use data from the First Street Foundation (FSF) Flood Lab (First Street Foundation, 2020a, 2020b). FSF data are the most comprehensive flooding-related data, because (1) they capture all four types of flooding (tidal, pluvial, fluvial, and surge) and their joint effects; (2) they cover all geographic areas, including remote rural areas; (3) they adjust for infrastructure and adaptation projects, including levees, pump stations, and wetland restoration; and (4) they include historical and present records and future climate change prediction models. Compared to FEMA data, FSF data are more recent and include more properties; FEMA contains only 8.7 million properties, whereas FSF covers 14.6 million properties (First Street Foundation, 2020a, 2020b). Finally, FSF data provide better flood risk estimates for rural areas that have previously been underestimated in FEMA data (National Research Council, 2009). A description of the data and model methodology can be found on the FSF website (First Street Foundation, 2020a, 2020b). Several manuscripts validating these measures have been recently published in Water Resources Research and Climate (Armal et al., 2020; Bates et al., 2020).

We use FSF data version 1.0, which was published in the spring of 2020. The data are based on property-level measures of flood risk from the coterminous USA aggregated into tract-level estimates for 71,273 tracts. We use the following variables: the percentage of properties identified at risk of flooding for 2020 and the average risk score of all properties in each tract. The percent of properties identified at risk for flooding refers to the percentage of total properties that might experience any depth of flooding to the building footprint in 2020. The tract-level percent of properties at risk ranged from 0.00 to 100.00. Each property is also assigned a risk score, ranging from 1 (low risk) to 10 (high risk). The score incorporates not only the likelihood of flooding, but also the severity (i.e., depth) of flooding should it occur. The average risk score refers to the average of all property risk scores in each tract. Tract-level average risk scores for the coterminous USA ranged from 1 to 10.

Both measures – percentage of properties at risk and average risk scores – are highly correlated (Pearson’s correlation coefficient = 0.920; \( p < 0.001 \)), but are both used in our analyses as they capture overlapping, but different measures. In addition, both measures are continuous measures that are positively skewed. This skewness violates the assumption of OLS regression. Therefore, we used the Box-Cox transformation (Box & Cox, 1964) to normalize the dependent variables, resulting in the use of the natural log for both variables.\(^2\)

\(^2\) The lambda of the standardized Box-Cox transformation for percent of properties at risk is 0.011, which means that the natural logarithm is the best transformation (Glen, 2015). Thus, we used the natural logarithm to transform percent of properties at risk. Because percent of properties at risk contains a 0 value, we added 1 to percent of properties at risk before the natural logarithm transformation. The lambda of the standardized Box-Cox transformation for average risk score was –1.000, which means that the reciprocal is the best transformation (Glen, 2015). However, the reciprocal reverses the magnitude of the average risk score, which might skew the associations. Thus, we still used the natural logarithm to transform the average risk score.
Social correlates

The social correlate variables are derived from the 2015 to 2019 5-year American Community Survey (ACS) and the National Neighborhood Data Archive (NaNDA). The ACS provides estimates of a wide variety of measures for all census tracts in the USA (US Census, 2020). All compositional characteristics and the labor market contextual characteristics are drawn from the ACS. These include percent under age 5, percent age 65 and older, percent racial/ethnic minority,\(^3\) percent unemployed, percent that experienced poverty in the last 12 months, percent with limited English proficiency, percent with no car, and percent of housing units that are renter occupied. The labor market structure variable included in the analyses was percent employed in agriculture, fishing, forestry, hunting, and mining. While we have no substantive rationale for inclusion of fishing and hunting, we were not able to obtain disaggregate measures at the tract level.

NaNDA data were used to construct the social infrastructure density variable. NaNDA data are from the University of Michigan’s Social Environment and Health Program. The data were created using the North American Industry Classification System (NAICS) to identify specific types of social infrastructure within the National Establishment Time Series (NETS) database. We retrieved the NaNDA data from the Inter-university Consortium for Political and Social Research (Finlay et al., 2020a, 2020b, 2020c). We drew specifically from the following NaNDA datasets: religious, civic, and social organizations; social services; and arts, entertainment, and recreation organization datasets. We included count data for libraries, civic organizations, religious organizations, and social service organizations for 2015. Social services include organizations serving children and youth, older adults and those with disabilities, individual and family services, community food services, emergency and other relief services, and vocational rehabilitation services. To examine social infrastructure density, we created spatial weighted items by calculating the spatial window sum in GeoDa for social infrastructure, which refers to the sum of the host tract and its neighboring tracts using a first-order Queens contiguity table. The spatial window sum feature includes the diagonal of the weights matrix in the calculation but does not use row standardization so that the final result is a total summed count. Our rationale is that during or following an extreme weather event, organizations and social services may mobilize resources and support to neighboring tracts. We then calculated a social infrastructure density measure by dividing the spatially lagged social infrastructure count (i.e., the spatial window sum) by the total host tract population and multiplying by 1000. Higher values indicate higher densities of social infrastructure, and lower values indicate lower densities of social infrastructure (i.e., more vulnerability).

\(^3\) The authors used percent racial/ethnic minority (i.e., percent not non-Hispanic white) because percent non-Hispanic Black and percent Hispanic were too highly correlated. While different racial/ethnic groups have different histories and experiences in the USA, tracts with larger relative shares of minorities are at greater risk of disenfranchisement and marginalization from decision-making processes related to flood mitigation and adaptation.
Finally, we are interested in whether flood risk varies across the rural–urban continuum as well as if the social correlates of flooding vary across the rural–urban continuum. To classify tracts, we use the 2010 Rural–Urban Commuting Area (RUCA) codes from the Economic Research Service (ERS). The RUCA codes rely on the Office of Management and Budget’s metropolitan/micropolitan delineations coupled with commuting flow data. The result is a series of 10 primary and 4 secondary designation combinations for census tracts based on primary and secondary commuting flows, respectively, resulting in 21 possible combinations for the 2010 edition. To make these 21 codes manageable and meaningful for our analyses, we relied on the Rural Health Research Center’s (n.d.) classification of RUCA codes into four categories:

- **Urban**: tracts in metro areas (RUCA 1–3) and micropolitan, small town, and isolated tracts with secondary commuter flows of 30–50% to an urbanized area (RUCA 4.1, 5.1, 6.1, 7.1, 8.1, 10.1)
- **Large rural**: tracts in micropolitan areas with secondary commuter flows of less than 30% to an urbanized area (RUCA 4.0, 5.0, 6.0)
- **Small rural**: tracts in small town areas and with secondary commuter flows of less than 30% to an urbanized area (RUCA 7.0, 8.0, and 9.0) or with secondary flows between 30 and 50% to an urban cluster (RUCA (7.2, 8.2)
- **Isolated**: tracts in rural areas with no primary commuter flows to an urbanized area or cluster and with secondary commuter flows of less than 30% to an urban area (RUCA 10.0, 10.2, 10.3)

This is the same delineation that has been recently re-published by NaNDA (Miller et al., 2021). Figure 1 shows this delineation of the RUCA codes for the coterminous USA. Urban tracts are predominantly in the eastern half of the map, and isolated and small rural tracts are predominantly in the inland western half of the map.

**Methods**

We use exploratory spatial data analysis (ESDA), exploratory data analysis (EDA), and fixed-effects linear regression to identify the social correlates of flood risk and determine if those correlates vary across the rural–urban continuum in the coterminous USA. All ESDA were conducted in the ArcMap 10.7 and GeoDa 1.14 software, and all EDA and regression analyses were conducted in Stata 16.

**ESDA and EDA**

We begin by presenting descriptive maps showing the spatial distribution of percent of properties at risk and average flood risk scores for tracts across the coterminous USA. We then present descriptive statistics of the dependent and independent variables across RUCA categories. For all ESDA and EDA, we use the original dependent variables – not their transformed versions.
Regression models

We use fixed-effects linear regression models to determine if flood risk is associated with the social correlates of interest. State-fixed effects are used because states play important roles in controlling flood-related activities (e.g., mitigation and recovery).

Fig. 1 Descriptive map of the RUCA code delineation as created by the Rural Health Research Center (n.d.) for the 2010 RUCA codes. Notes: Figure was created in ArcMap 10.7. The Economic Research Service does not create RUCA codes for tracts with zero population or for tracts with no rural–urban identifier information. These tracts are left white in the map

Fig. 2 Descriptive map of tract-level percent of properties at risk for the coterminous USA. Notes: Figure was created in ArcMap 10.7. Percent of properties at risk is categorized by quantiles
In each of these models, the dependent variables of interest are percent of properties at risk and average risk scores. The social correlates and rural–urban status are treated as independent variables – not as causal predictors but as characteristics that might vary by level of flood risk. We begin by presenting models for the entire coterminous USA ($N = 71,273$) in Table 2. For each dependent variable, we present the main-effect relationships and the full model. Table 3 presents the full models, again, but stratified by rural–urban status. All regression analyses are weighted by the log of the total number of properties in each tract. Because of the dependent variable transformation, coefficients cannot be directly interpreted. We have also included in the Appendix the same models using the original (untransformed) dependent variables showing similar results. This provides more straightforward interpretations about the magnitude of the coefficients. No issues with multicollinearity were determined based on vif/tol measures. We use an adjusted R-square to measure fit and the Akaike information criterion (AIC) and Bayesian information criterion (BIC) to specify models. While the final AICs and BICs are reported in the tables, they should not be used to compare across models presented here.

**Results**

**ESDA and EDA**

Figures 2 and 3 present descriptive maps of the spatial distribution of tract-level percent of properties at risk and average risk scores (both untransformed). The maps show that tracts with larger shares of percent of properties at risk and higher average risk scores are clustered along eastern and northwestern coastlines, the Mountain
Northwest, and Appalachia. Additional smaller clusters are present in New England, the Delta states, and parts of the Midwest (i.e., Wisconsin, Iowa). It is important to note here that because of the small size of some census tracts – particularly in urban areas – some tracts with high flood risk may not be visible in the map we have presented, but these places would be captured in the subsequent analyses. Moreover, simply because a tract with high risk is not clustered with other tracts with high risk

| Table 1 | Means and 95% confidence limits for model variables by rural–urban group for census tracts |
|---------|------------------------------------------------------------------------------------------|
| Variable | Urban \((N=59,251)\) | Large rural \((N=6094)\) | Small rural \((N=3036)\) | Isolated \((N=2892)\) |
| Dependent variables | | | | |
| Percent of properties at risk | 10.37 \((10.25, 10.49)\) | 12.65 \((12.31–12.99)\) | 13.08 \((12.67–13.49)\) | 15.07 \((14.64–15.49)\) |
| Average risk score | 1.82 \((1.81, 1.83)\) | 1.95 \((1.93–1.98)\) | 1.98 \((1.94–2.01)\) | 2.14 \((2.10–2.17)\) |
| Compositional characteristics | | | | |
| Percent under age 5 | 6.00 \((5.98–6.02)\) | 5.85 \((5.79–5.91)\) | 5.69 \((5.61–5.77)\) | 5.37 \((5.29–5.45)\) |
| Percent age 65+ | 15.75 \((15.68–15.81)\) | 18.37 \((18.20–18.54)\) | 19.89 \((19.67–20.10)\) | 22.36 \((22.09–22.63)\) |
| Percent minority | 41.95 \((41.71–42.19)\) | 24.02 \((23.43–24.60)\) | 21.60 \((20.82–22.38)\) | 16.41 \((15.66–17.15)\) |
| Percent poverty | 14.24 \((14.14–14.33)\) | 17.13 \((16.86–17.40)\) | 16.76 \((16.45–17.07)\) | 14.74 \((14.45–15.04)\) |
| Percent unemployed | 5.79 \((5.76–5.83)\) | 5.93 \((5.83–6.03)\) | 5.74 \((5.60–5.88)\) | 5.22 \((5.06–5.37)\) |
| Percent renter-occupied housing units | 38.04 \((37.85–38.24)\) | 32.18 \((31.75–32.61)\) | 29.28 \((28.79–29.76)\) | 23.46 \((23.08–23.84)\) |
| Percent of households with no car | 9.82 \((9.71, 9.92)\) | 7.04 \((6.89–7.19)\) | 7.05 \((6.85–7.24)\) | 5.43 \((5.25–5.61)\) |
| Percent with limited English | 8.45 \((8.36–8.54)\) | 3.15 \((2.99–3.31)\) | 2.42 \((2.24–2.59)\) | 2.16 \((1.98–2.34)\) |
| Contextual characteristics | | | | |
| Percent employed in agri., fishing, forestry, hunting, or mining | 0.99 \((0.97–1.01)\) | 3.81 \((3.67–3.95)\) | 5.34 \((5.12–5.57)\) | 9.55 \((9.22–9.89)\) |
| Social infrastructure density – per 1000 residents (lagged) | 758.79 \((659.26–858.32)\) | 30.62 \((29.41–31.83)\) | 16.16 \((15.52–16.81)\) | 107.97 \((29.51–186.43)\) |
| Number of properties | 1794.40 \((1782.87–1806.05)\) | 2617.79 \((2571.35–2664.22)\) | 3005.37 \((2932.47–3078.27)\) | 3707.15 \((3604.81–3809.49)\) |

\(N=71,273\)
Table 2  Linear regression model results examining social correlates of flood risk using transformed versions of the dependent variables and with state-level fixed effects

|                           | Percent of properties at risk (SE) | Average risk score (SE) |
|---------------------------|-----------------------------------|-------------------------|
|                           | Main effects | Full model      | Main effects | Full model      |
| (Intercept)               |             | 2.567*** (0.035) |             | 0.590*** (0.015) |
| Compositional characteristics |          |                |             |          |
| Percent under age 5       | −0.032*** (0.001) | −0.008*** (0.001) | −0.011*** (0.001) | −0.004*** (0.001) |
| Percent age 65+           | 0.020*** (0.000) | 0.011*** (0.001) | 0.007*** (0.000) | 0.005*** (0.000) |
| Percent minority          | −0.007*** (0.000) | −0.004*** (0.000) | −0.002*** (0.000) | −0.002*** (0.000) |
| Percent poverty           | −0.002*** (0.000) | 0.011*** (0.000) | 0.001*** (0.000) | 0.004*** (0.000) |
| Percent unemployed        | −0.002* (0.001) | 0.009*** (0.001) | 0.003*** (0.000) | 0.005*** (0.000) |
| Percent renter-occupied housing units | −0.006*** (0.000) | −0.001*** (0.000) | −0.001*** (0.000) | 0.000*** (0.000) |
| Percent of households with no car | −0.012*** (0.000) | −0.011*** (0.000) | −0.001*** (0.000) | −0.001*** (0.000) |
| Percent with limited English | −0.012*** (0.000) | 0.000 | −0.002*** (0.000) | 0.002*** (0.000) |
| Contextual characteristics |          |                |             |          |
| Percent employed in agriculture, forestry, hunting, or mining | 0.032*** (0.001) | 0.016*** (0.001) | 0.011*** (0.000) | 0.006*** (0.000) |
| Social infrastructure density – per 1000 residents (lagged) | 0.000*** (0.000) | 0.000 | 0.000 | 0.000 |
| Rural–urban status (ref.: isolated) |          |                |             |          |
| Small rural              | −0.209*** (0.023) | −0.094*** (0.022) | −0.095*** (0.009) | −0.055*** (0.009) |
| Large rural              | −0.292*** (0.020) | −0.127*** (0.020) | −0.117*** (0.008) | −0.058*** (0.008) |
| Urban                    | −0.666*** (0.017) | −0.321*** (0.018) | −0.232*** (0.007) | −0.110*** (0.008) |
| Adjusted R²              |             | 0.201 |             | 0.177 |
| AIC                      |             | 182,248.00 |             | 58,911.75 |
| BIC                      |             | 182,816.80 |             | 59,480.55 |

N = 71,273. Analyses are weighted for the log of the total number of properties in the census tract
*p < 0.05; **p < 0.01; ***p < 0.001

does not imply that their risk is less. Therefore, it is important to acknowledge the spatial heterogeneity that is also present in these maps.

Table 1 presents means and 95% confidence limits for the model variables by RUCA group. For both dependent variables, urban tracts have – on average – smaller
shares of properties at risk of flooding and lower average risk scores compared to all three rural groups. And isolated census tracts have – on average – larger shares of properties at risk of flooding and higher average risk scores compared to urban, large rural, and small rural census tracts. For compositional characteristics, urban
tracts have – on average – larger shares of residents under the age of 5 and larger shares of residents who are not non-Hispanic white, but smaller shares of residents 65 years and older when compared to the three rural groups. For social factors, poverty appears to be – on average – higher in large rural and small rural tracts, when compared to urban and isolated tracts. Unemployment is slightly lower in isolated tracts when compared to the other three rural–urban groups. Finally, rentership, share of households without a car, and percent with limited English are all highest in urban tracts. For contextual characteristics, percent employed in agriculture, fishing, forestry, hunting, and mining increases significantly with each category increase in rurality. And social infrastructure density is – on average – highest in urban and isolated tracts and lowest in large rural and small rural tracts. Lastly, the number of properties in census tracts varies – on average – across rural–urban groups, with urban tracts having the smallest number of properties and isolated tracts having the largest number of properties.

**Linear regression models**

Table 2 presents the results of the state-level fixed-effects linear regression models examining the tract-level relationships between flood risk – as measured by the transformed versions of percent of properties at risk and average risk scores – and compositional and contextual characteristics in order to identify the social correlates of flood risk. For compositional characteristics, tracts with larger relative shares of residents under age five had significantly smaller shares of properties at risk and lower average risk scores while tracts with larger relative shares of adults age 65 and older had significantly larger shares of properties at risk and higher average risk scores. Tracts with larger relative shares of racial/ethnic minorities also had smaller shares of properties at risk and lower average risk scores. Tract-level poverty and unemployment were associated with larger shares of properties at risk and higher average risk scores, and tract-level rates of rentership were associated with smaller shares of properties at risk but higher average risk scores. Percent of households with no car was associated with smaller shares of properties at risk and lower average risk scores. And percent with limited English was only associated with higher tract-level average risk scores.

For the contextual characteristics, percent employed in agriculture, fishing, forestry, hunting, or mining is associated with larger shares of properties at risk of flooding and higher average risk scores. The social infrastructure density variable was not significantly associated with percent of properties at risk or average risk scores. Finally, compared to isolated tracts, small rural, large rural, and urban tracts have – on average – significantly smaller shares of properties at risk and lower average risk scores. For both dependent variables, the coefficients increase in size with each incremental increase in rurality. Finally, the adjusted R-square shows that compositional and contextual characteristics explain more than 20% of the variation in tract-level percent of properties at risk and almost 18% of the variation in average risk scores.
Table 3 presents the results of the state-level fixed-effects linear regression models examining the tract-level relationships between flood risk – as measured by the transformed version of percent of properties at risk and average risk scores – and the independent variables, but stratified by rural–urban status. Models for rural tracts include rural status variables. For compositional characteristics, tracts with larger relative shares of residents under age 5 had significantly smaller shares of properties at risk and lower average risk scores while tracts with larger relative shares of adults age 65 and older had significantly larger shares of properties at risk and higher average risk scores. Tracts with larger relative shares of racial/ethnic minorities also had smaller shares of properties at risk and lower average risk scores. Tract-level poverty and unemployment rates are associated with larger shares of properties at risk and higher average risk scores. All of these compositional characteristic findings up to this point were consistent in the rural and the urban models.

Percent of households without a car was associated with smaller shares of properties at risk and lower average risk scores, but only in urban areas. In rural areas, percent without a car is associated with larger shares of properties at risk. Rural tracts with large shares of rentership have smaller shares of properties at risk and lower average risk scores, while the opposite is true for urban tracts – where higher rates of rentership are associated with higher average risk scores. And finally, tracts with larger relative shares of residents with limited English have higher average risk scores in both rural and urban tracts, but smaller shares of properties at risk in rural areas.

For the contextual characteristics in Table 3, percent employed in agriculture, fishing, forestry, hunting, or mining is associated with larger shares of properties at risk of flooding and higher average risk scores. This remained true in the rural and the urban models. The social infrastructure density variable is not significant in any of the models. Finally, compared to isolated tracts, small rural and large rural tracts have – on average – significantly smaller shares of properties at risk and lower average risk scores. Finally, the adjusted R-square shows that compositional and contextual characteristics explain approximately 17 to 18% of the variation in tract-level percent of properties at risk and average risk scores across all models in this table.

Discussion

Understanding the social correlates of flood risk and how those social correlates vary across the rural–urban continuum provides important insight for researchers, policymakers, and community leaders as they navigate the impacts of increasingly more common flooding. By integrating multiple novel physical and social datasets, we sought to answer two research questions: (1) what are the census tract–level social correlates of flood risk that may limit their capacity to prevent, plan for, and recover from flooding? And (2) do those social correlates vary across the rural–urban continuum? We have shown both the unique strengths and vulnerabilities facing tracts with elevated flood risk as well as how those social correlates vary between rural and urban areas. In this section, we discuss these findings in the context of the literature.
First, we found that flood risk is – on average – higher in rural tracts. This remained true even after controlling for all other covariates in the full models and weighting for the log of the total number of properties at risk, though the reduction in coefficient size suggest that a large share of the effect of rurality is explained by disparities in compositional and contextual characteristics across the rural–urban continuum. And even in the rural models, greater rurality was positively associated with flood risk. These findings are likely driven by the high levels of flood risk in Appalachia and the Northwest, which have a large share of rural tracts. In the case of Appalachia, this is concerning because of persistently high levels of poverty and unemployment that plague this region (Greenberg, 2017, 2018; Lobao et al., 2016; Tallichet, 2014). Moreover, rural flood risk is also problematic because in nonmetro areas people are more dispersed, which can slow coordination and limit the per capita impact of flood mitigation efforts (Prelog & Miller, 2013). Finally, while recent research using more updated flood estimates has noted higher risks of flooding in rural areas (e.g., Tate et al., 2021), this is one of the first papers – to the authors’ knowledge – that stratify flood risk models by rural–urban status to examine if and how social correlates vary.

Second, our findings point to a number of compositional and contextual characteristics in the models that were significant and can rightfully be referred to as social correlates of flood risk. Some of these are consistent across rural and urban landscapes, and others show rural–urban heterogeneity. We will first discuss the social correlates that were consistent. Tracts with higher flood risk have – on average – larger relative shares of older adults and smaller relative shares of minorities. This remained true in both the rural and urban models. The older adult finding is consistent with previous work generally showing larger shares of older adults in rural areas (Smith & Trevelyan, 2019) (areas with high flood risk) and more specifically in coastal urban flooding hotspots (Qiang, 2019). While this remained true in the rural and urban models, the risk of isolation for older adults during flooding events may be higher in rural areas as dispersed populations are more easily geographically cut off from each other. The findings related to minorities is inconsistent with some earlier research, which has found higher clustering of minorities (specifically Blacks) in flood hotspots (Chakraborty et al., 2019; Tate et al., 2021). This may reflect our measurement as we relied on percent racial/ethnic minority (i.e., percent not non-Hispanic white) given that percent Hispanic and percent non-Hispanic Black were too highly correlated with other model variables for inclusion.

In addition, we found that higher flood risk is associated with higher poverty rates and unemployment rates, which remained true in the rural–urban stratified models. This leaves these tracts with fewer economic resources to prevent, cope with, and recover from flooding. This includes purchasing flood insurance, evacuating under storm warnings, and navigating the bureaucracies of state and federal flood assistance programs (Fothergill, 2004; Gladwin and Peacock 1997; Tyler et al., 2019). These findings are consistent with previous studies noting that those in lower socioeconomic status categories are more at risk to flooding (Chakraborty et al., 2019; Qiang, 2019).
We have also identified heterogeneity in the types of social correlates of flood risk between rural and urban areas. Two compositional characteristics from this study were in fact significant social correlates of flood risk, but in different directions across the rural–urban models. Rentership was associated with higher average risk scores in urban areas, but smaller shares of properties at risk and lower average risk scores in rural areas. And percent of households with no car was associated with lower levels of flood risk in urban areas, but higher risk of flooding in rural areas. These heterogeneous findings are concerning in their own unique contexts. Rural areas have significantly less access to public transportation. Therefore, in the event of flooding, rural residents without vehicles may be less able to prepare, seek shelter elsewhere, or access the resources for recovery. And urban areas with large shares of rentership may face disproportionate shares of residents needing public assistance following potential displacement from their rental properties, especially given that only 41% of renters have insurance (Rental Housing Journal, 2018) – compared to 85% of homeowners (Croll, 2021) – and that most renter insurance policies do not have flood provisions. Finally, findings related to the percent with limited English point best to the differences in our two measures of flood risk. We found that tracts with larger relative shares of adults with limited English had – on average – higher average risk scores (but in rural areas, smaller shares of properties at risk). This likely reflects clustering of recent immigrant populations in areas facing high depths of flood risk (e.g., coastal cities, flood-prone agricultural areas that rely on immigrant workers).

Our results from the contextual social correlates also show that flood risk is higher in tracts with larger shares of residents employed in agriculture, fishing, forestry, hunting, or mining – industries that can be vulnerable to flood-related events (South Carolina Forestry Commission, 2015; Anderson et al., 2021). These findings remained true in the rural–urban stratified models. This indicates that the economic resources and the public health of those tracts may be at a greater risk should flooding occur. The elevated risk of economic insecurity caused by flooding not only puts at risk local livelihoods, but in the case of mining the elevated risk of public health crisis could further burden local health systems (Hendryx, 2013; Wilke & Freeman, 2017).

Finally, this is the first study to use data for the entire USA to examine whether social infrastructure is a social correlate of flood risk. We included social infrastructure density because previous work has shown that libraries, religious organizations, civic associations, and social services can play an important role in the recovery process from flooding and other disasters (Veil & Bishop, 2014; Shinn & Caretta, 2020; Campbell, 2016). We found that social infrastructure density was not significantly associated with flood risk. Given that previous work has shown that economic capital drives disaster resilience in urban centers and community capital is most important in rural areas (Cutter et al., 2016), we found no evidence to suggest that rural areas with high flood risk have greater access to such supports.

Findings should be interpreted within the context of several important limitations. Our analyses do not examine actual impacts of flooding. Rather, we examined the social correlates of flood risk that may make them less able to mitigate, cope with,
and respond to flood-related events. Further research is needed to validate these measures as predictors of such outcomes based on actual flooding events. Second, some of the social correlates used here are based on normative assumptions about what might make a place more vulnerable to disasters. Such normative ideas can be problematic and mask important paradoxes or contradictions (Hinkel, 2011). For example, while percent with limited English can capture communities with large shares of residents who may be less integrated into existing resources and networks, previous studies have found that strong bonding social capital in immigrant communities can greatly reduce vulnerability (Vu & VanLandingham, 2012). Finally, while census tracts do provide one of the most granular levels of analysis available – at least with regard to linking to compositional and contextual data – they too have their limitations. In particular, the FSF estimates can be easily skewed for large rural tracts or for tracts with few but large numbers of properties. While this would bias the findings from the figures and descriptive work in this paper, our weighting of the models by the log of the number of properties in tracts should provide some confidence that such tracts are not skewing the results.

Our findings have several important policy implications. First, while we provide a national-level analysis, the relationships examined in our models may vary across regions or sub-regions. Local and state leaders should pay particularly close attention to the characteristics of those facing elevated flood risk in their communities. In addition, given our finding that tracts with larger shares of residents with limited English face – on average – higher flood risk, leaders should develop outreach strategies that are culturally and linguistically appropriate for immigrant populations and tap into existing networks within immigrant populations. In addition, given that tracts with larger shares of low-SES residents face greater flood risk, assistance with enrolling in federally subsidized flood insurance programs as well as policies and recovery efforts should be designed to specifically target low-income populations to ensure that they are included in such efforts. Finally, efforts should be made to work closely with both the employers and workers in vulnerable industries (e.g., farming, forestry, and mining) to develop flood mitigation strategies and implement protocols to safeguard environmental health in the case of mining Tables 4 and 5.

Based on our findings, future research related to the social correlates or social vulnerabilities to flood risk should account for the potential heterogeneity of these relationships across the rural–urban continuum. This should include analysis of actual impacted communities and what factors mediate vulnerability. For example, does a higher density of social infrastructure help socioeconomically vulnerable populations better cope with and recover from floods? And given the findings of this study, future research should examine if and how disproportionate shares of rentership and not having a car shape the impacts of flooding in urban and rural areas, respectively. Additional work should also examine how predominantly rural industries are responding to flooding and the implications their responses have or will have on those communities. In addition, research is needed to examine the relationship between health and flooding, including both acute flooding disasters and chronic flooding, on physical, mental, and social health. As the body of literature that examines the capacities of communities to respond to weather-related disasters grows, this study provides an assessment of the unique social correlates of flooding in the coterminous USA and how those correlates vary across the rural–urban continuum.
## Appendix

### Table 4
Linear regression model results examining social correlates of flood risk using original versions of the dependent variables and with state-level fixed effects

|                                | Percent of properties at risk | Average risk score |
|--------------------------------|-----------------------------|--------------------|
|                                | Main effects (SE)           | Full model (SE)    |
|                                | (Intercept)                 |                    |
| Compositional characteristics  |                             |                    |
| Percent under age 5            | −0.373***                   | −0.152***          |
|                                | (0.021)                     | (0.023)            |
| Percent age 65+                | 0.239***                    | 0.207***           |
|                                | (0.007)                     | (0.008)            |
| Percent minority               | −0.042***                   | −0.053***          |
|                                | (0.002)                     | (0.003)            |
| Percent of properties at risk  | 10.736***                   | 1.726***           |
|                                | (0.553)                     | (0.040)            |
| Compositional characteristics  |                             |                    |
| Percent poverty                | 0.042***                    | 0.087***           |
|                                | (0.005)                     | (0.007)            |
| Percent age 65+                | 0.081***                    | 0.117***           |
|                                | (0.013)                     | (0.016)            |
| Percent of properties at risk  | 10.736***                   | 1.726***           |
|                                | (0.553)                     | (0.040)            |
| Contextual characteristics     |                             |                    |
| Percent unemployed             | 0.013                       | 0.025***           |
|                                | (0.002)                     | (0.004)            |
| Percent of properties at risk  | 10.736***                   | 1.726***           |
|                                | (0.553)                     | (0.040)            |
| Percent of properties at risk  | 10.736***                   | 1.726***           |
|                                | (0.553)                     | (0.040)            |
| Percent of properties at risk  | 10.736***                   | 1.726***           |
|                                | (0.553)                     | (0.040)            |
| Percent of properties at risk  | 10.736***                   | 1.726***           |
|                                | (0.553)                     | (0.040)            |
| Percent of properties at risk  | 10.736***                   | 1.726***           |
|                                | (0.553)                     | (0.040)            |
| Percent of properties at risk  | 10.736***                   | 1.726***           |
|                                | (0.553)                     | (0.040)            |
| Percent of properties at risk  | 10.736***                   | 1.726***           |
|                                | (0.553)                     | (0.040)            |
| Percent of properties at risk  | 10.736***                   | 1.726***           |
|                                | (0.553)                     | (0.040)            |
| Percent of properties at risk  | 10.736***                   | 1.726***           |
|                                | (0.553)                     | (0.040)            |
| Percent of properties at risk  | 10.736***                   | 1.726***           |
|                                | (0.553)                     | (0.040)            |
| Percent of properties at risk  | 10.736***                   | 1.726***           |
|                                | (0.553)                     | (0.040)            |
| Percent of properties at risk  | 10.736***                   | 1.726***           |
|                                | (0.553)                     | (0.040)            |
| Percent of properties at risk  | 10.736***                   | 1.726***           |
|                                | (0.553)                     | (0.040)            |
| Percent of properties at risk  | 10.736***                   | 1.726***           |
| Adjusted R²                    | 0.278***                    | 0.164***           |
|                                | (0.012)                     | (0.014)            |
| Percent of properties at risk  | 10.736***                   | 1.726***           |
| Social infrastructure density  | 0.000                       | 0.000              |
| per 1000 residents (lagged)    | (0.000)                     | (0.000)            |
| Rural–urban status (ref.:      | 0.000                       | 0.000              |
| isolated)                      | (0.000)                     | (0.000)            |
| Small rural                    | −2.414***                   | −1.273***          |
|                                | (0.347)                     | (0.347)            |
| Large rural                    | −2.641***                   | −0.932***          |
|                                | (0.304)                     | (0.310)            |
| Urban                          | −5.591***                   | −2.133***          |
|                                | (0.262)                     | (0.286)            |
| Adjusted R²                    | 0.135                       | 0.158              |
| AIC                            | 574,049.50                  | 201,262.30         |
| BIC                            | 574,618.30                  | 201,831.10         |

*N = 71,273*. Analyses are weighted for the log of the total number of properties in the census tract  

* *p < 0.05; **p < 0.01; ***p < 0.001*
| Compositional characteristics | Percent of properties at risk | Average risk score |
|-------------------------------|-----------------------------|--------------------|
|                               | Rural full model (SE)       | Urban full model (SE) | Rural full model (SE) | Urban full model (SE) |
| (Intercept)                   | 13.960***                   | 8.749***           | 2.089***              | 1.548***              |
|                               | (1.003)                     | (0.541)            | (0.077)               | (0.039)               |
| Percent under age 5           | −0.357***                   | −0.119***          | −0.027***             | −0.008***             |
|                               | (0.052)                     | (0.025)            | (0.004)               | (0.002)               |
| Percent age 65+               | 0.071***                    | 0.221***           | 0.006***              | 0.017***              |
|                               | (0.020)                     | (0.009)            | (0.002)               | (0.001)               |
| Percent minority              | −0.066***                   | −0.049***          | −0.006***             | −0.004***             |
|                               | (0.008)                     | (0.003)            | (0.001)               | (0.000)               |
| Percent poverty               | 0.059***                    | 0.088***           | 0.005***              | 0.006***              |
|                               | (0.017)                     | (0.008)            | (0.001)               | (0.001)               |
| Percent unemployed            | 0.138***                    | 0.100***           | 0.010***              | 0.010***              |
|                               | (0.033)                     | (0.018)            | (0.002)               | (0.001)               |
| Percent renter-occupied housing units | −0.015                   | 0.029***          | −0.001                | 0.003***              |
|                               | (0.010)                     | (0.004)            | (0.001)               | (0.000)               |
| Percent of households with no car | 0.066*                     | −0.026***         | 0.003                 | −0.001*               |
|                               | (0.026)                     | (0.008)            | (0.002)               | (0.001)               |
| Percent with limited English  | 0.100***                    | 0.062***           | 0.009***              | 0.005***              |
|                               | (0.026)                     | (0.008)            | (0.002)               | (0.001)               |
| Contextual characteristics    |                             |                    |                      |                      |
| Percent employed in agriculture, fishing, forestry, hunting, or mining | 0.088***                   | 0.247***           | 0.006***              | 0.019***              |
|                               | (0.018)                     | (0.020)            | (0.001)               | (0.001)               |
| Social infrastructure density – per 1000 residents (lagged) | 0.000*                     | 0.000              | 0.000**               | 0.000                 |
|                               | (0.000)                     | (0.000)            | (0.000)               | (0.000)               |
| Rural–urban status (ref.: isolated) |                       |                    |                      |                      |
Table 5 (continued)

|                      | Percent of properties at risk |                     | Average risk score |                     |
|----------------------|-------------------------------|---------------------|--------------------|---------------------|
|                      | Rural full model (SE)         | Urban full model (SE) | Rural full model (SE) | Urban full model (SE) |
| Small rural          | −1.424*** (0.309)             | −0.120*** (0.024)    | −1.632*** (0.292)   | −0.128*** (0.022)    |
| Large rural          | −1.632*** (0.292)             | 0.141               | 0.154              | 0.168               |
| Adjusted R²          | 0.131 (0.292)                 | 0.141               | 0.154              | 0.168               |
| AIC                  | 92,526.10                     | 480,276.00          | 30,725.56          | 169,371.30          |
| BIC                  | 92,969.77                     | 480,806.40          | 31,169.23          | 169,901.70          |

Rural N = 12,022; urban N = 59,251. Analyses are weighted for the log of the total number of properties in the census tract.

*p < 0.05; **p < 0.01; ***p < 0.001
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Availability of data and material Data is available through the First Street Foundation.

Code availability Code available upon request to the corresponding author.

Declarations

Conflict of interest The authors declare no competing interests.

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