1. Introduction

The Midwest flood of 2019 was a significant hydrological event affecting the Missouri and Mississippi River basins during the winter and spring of 2019. While the contributing weather phenomena were typical for a Midwest spring, the magnitude of precipitation was uncharacteristically high. According to the National Oceanic and Atmospheric Administration (NOAA), June 2018–May 2019 was the second wettest year on record (NWS 2019b). In March 2019, heavy rain fell on still-frozen soil and snowpack across South Dakota, Nebraska, and Iowa. With the soil unable to store the excess water, runoff quickly overwhelmed nearby streams and rivers (Flanagan et al. 2020). Concerningly, the frequency of these major flood events has been increasing in recent decades and is projected to become even more common in the future (Mallakpour and Villarini 2015; Neri et al. 2019). As the effects of climate change intensify, warmer temperatures will allow more moisture to be held in the atmosphere, resulting in greater amounts of precipitation in some regions of the U.S. Midwest, particularly during spring (Cook et al. 2008; Fowler et al. 2021; Villarini et al. 2013). Residential damages due to flood events will likely increase, and having an economic disaster recovery plan will be necessary for homeowners and renters alike (Merz et al. 2021).

Nine states (Illinois, Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota, and Wisconsin; Fig. 1) across the Midwest were impacted by the 2019 Midwest flood, causing widespread utility outages, property damage, and residential evacuations. Communities in Iowa and Nebraska were particularly hard hit; Governor Reynolds of Iowa stated that damages topped $1.6 billion (Pitt 2019), while Nebraska had more than $1.3 billion in infrastructure and property damage (Hollingsworth 2019), comparable to damages from the 2008 (FEMA 2009) and 1993 (Schwartz 2005) Midwest floods. Total estimated damages for this event (including some states not analyzed in this study) were approximately $10.7 billion (NCEI 2022). While these figures provide rough estimates of damage to public property, there is limited information about the direct economic impacts of the 2019 flood on households and individuals.

Given the strong connection between flooding conditions and significant economic losses, we evaluate the damages incurred during the 2019 flood by combining analysis from both hydrologic and socioeconomic perspectives. Previous analyses of the 2019 Midwest flood event focused solely on the economic impacts of crop loss or public sector (English et al. 2021; Shirzaei et al. 2021) but neglected the impacts to individuals and households. Studies of past flooding events in the Midwest region consider the hydrologic or economic perspectives separately and focus either on contributing hydrological and climatological conditions (Junker et al. 1999; Villarini et al. 2011) or disaster recovery resource distribution (Muñoz and Tate 2016). In contrast, this work seeks to describe the hydrologic conditions of the 2019 Midwest flood in tandem with the economic impacts on individuals and households. We first analyze the hydrological characteristics such as flood magnitude and duration across the study area, then we determine the likelihood of recurrence by estimating the annual exceedance probability (AEP) of the flood. We then evaluate the financial impact of flooding on households by investigating...
residential demographics and location of the Federal Emergency Management Agency (FEMA) National Flood Insurance Program (NFIP) claims and Individual and Households Program (IHP) grant applications. Last, we develop spatial regression models for selected watersheds to evaluate the Program (NFIP) claims and Individual and Households Management Agency (FEMA) National Flood Insurance resident demographics and location of the Federal Emergency Management Agency (FEMA) National Flood Insurance Program (NFIP) claims and Individual and Households Program (IHP) grant applications. Last, we develop spatial regression models for selected watersheds to evaluate the relationship between hydrologic and socioeconomic factors and NFIP insurance claims. Understanding the magnitude of damage and financial assistance necessary for disaster recovery of this event is necessary to address the vulnerability of communities and the economic toll of future flooding events.

2. Data and methods

Analysis of the 2019 flood concentrated on the hydrologic and socioeconomic factors between 1 March 2019 and 31 May 2019. We sourced hydrological data related to annual and instantaneous peak discharge through the U.S. Geological Survey (USGS) National Water Information System (USGS 2021) for 717 stream gauges across the affected region between 1980 and 2019. We then extracted maximum daily peak discharge for each site. We retained only gauges with at least 30 years of records and for which the Mann–Kendall test did not detect significant changes at the 5% level, reducing the sample size from 717 to 543.

The magnitude of flooding was evaluated by determining the flood stage of the maximum discharge for each available gauge station during the 2019 flood. The NWS defines flood stages in four categories: action, minor, moderate, and major. In general, action stage is gauge height at which emergency managers employ mitigation techniques in preparation for future flooding. The other flood stages correspond to flooding conditions of increasing severity, for example, minor flooding may not result in any infrastructure damage, whereas major flooding likely means resident evacuations are necessary (NWS 2016). Using maximum daily peak-discharge records, we determined the level of flood severity for 213 USGS gauges where discharge designations were available (NWS 2019a). While there are typically four flood stages associated with discharge levels, some stations do not have discharge designations for each stage. Additionally, we evaluated flood duration for each of the gauges: sites with long-term inundation may indicate significant flood damage, as discharge magnitude and flood duration are often related. In this case, we characterize duration by the number of days a station had a daily discharge value above each exceedance threshold.

To provide a regional perspective on the flood hazard, rather than just at the stream gauge locations, we first calculate the flood ratio to determine the magnitude of the flooding at each gauge station in relation to discharge quantities as

\[
\text{flood ratio} = \frac{Q_1}{Q_2},
\]

where \(Q_1\) is the peak instantaneous discharge recorded at the gauge during the event and \(Q_2\) is the discharge associated with the median peak discharge value during 2008–19 (Czajkowski et al. 2017). We considered \(Q_2\) as the reference as it is indicative of water out of the banks; hence, it is a proxy for flooding (e.g., Czajkowski et al. 2017; Ghaedi et al. 2022). The advantage of using the flood ratio is that it allows us to account for the discharge dependence on catchment size, providing a regional view of flooding across the study area. We then spatially interpolated across the study area the flood ratio calculated at each USGS stream gauge, using inverse-distance weighting to infer the magnitude of flooding in regions without a stream gauge.

We estimated the AEP of maximum peak discharges at 540 USGS gauge locations across the study area. The AEP represents the annual probability of a flood event occurring each year. The PeakFQ software by USGS is used to characterize flood magnitude and frequency and fits a log-Pearson type-III (P-III) distribution using the methods described in the Bulletin 17C (England et al. 2019). We estimated the mean, standard deviation, and skewness coefficient using an estimated moments algorithm (EMA) method, which is based on the method-of-moments parameter estimation procedure. In this case, we estimated the skewness coefficient for each USGS station rather than applying a constant regional skew coefficient across the study area to better represent any spatial heterogeneity among gauges. The EMA additionally adjusts for potentially influential low floods (Cohn et al. 2013), missing data, or nonflood years that may affect the dataset fit of the P-III distribution (England et al. 2019).

FEMA manages two natural disaster assistance and recovery programs for households: the NFIP and the IHP. The NFIP, established under the National Flood Insurance Act of 1968 (FEMA 1997), offers federally backed flood insurance to homeowners, renters, and business owners in regions that enact flood mitigation strategies. Policies cover building damage for home and business owners, with coverage amounts up to $250,000 and $500,000, respectively, and $100,000 in building-content damage to all parties (FEMA 2022d). Conversely, the IHP provides financial assistance grants to under- or uninsured
households following a natural disaster. Grant funds can be applied to temporary housing, building and content repair or replacement, and other disaster recovery needs (FEMA 2022g). To receive an IHP grant, applicants are first referred for housing assistance (HA), other needs assistance (ONA), or both. Applicants are then required to verify their identity, flood insurance status, and ownership or occupancy of the damaged home (FEMA 2022a). However, this process often disproportionately excludes low-income households (Texas Low-Income Housing Information Service 2018) and results in an inequitable distribution of disaster relief funds across socioeconomic groups (Emrich et al. 2022). Furthermore, IHP grants are only available in areas where a presidential disaster declaration has been issued. Additionally, IHP grants are not intended to return homes to predisaster state but rather restore homes to a sanitary and functional condition (FEMA 2022g). As a result, grant allocations are often significantly less than claim payouts from flood insurance policies (Butler et al. 2020). In a report to Congress (U.S. Department of Homeland Security 2018), FEMA states that low-income households are less likely to hold NFIP policies yet are more likely to live in high-risk [i.e., special flood hazard areas (SFHAs)]. Therefore, many low-income families without flood insurance rely on IHP disaster recovery grants yet are likely to receive insufficient financial assistance.

To quantify the economic impact of flooding on individuals and households, we used NFIP claim data sourced through the FEMA NFIP Redacted Claims v1 dataset via OpenFEMA (FEMA 2019a). This dataset provides information about the location, residence type, flood zone, and claim amount of the damaged structure. For individual privacy reasons, claim data are anonymized to county, census tract, zip code, and 0.1 decimal degree of latitude and longitude coordinates (FEMA 2019a). We obtained IHP claim data through the Individuals and Households Program Valid Registrations v1 dataset via OpenFEMA (FEMA 2019b). The IHP dataset provides a more comprehensive view of registrant demographics, such as household composition, age of the primary applicant and household occupants, and income range (FEMA 2022e). In addition, county, zip code, residence type, and financial grant amount data are available. Unlike the NFIP dataset, FEMA does not collect information on census tract, coordinates, or flood zone of the damaged building for the IHP. Therefore, it is difficult to directly compare NFIP and IHP application characteristics. While it is possible to compare the location of NFIP claims and IHP applications, we are unable to provide any evaluation of applicant demographics between programs.

We compiled NFIP claim data for our study region from 1 March to 31 May 2019 (these dates were selected from approximately the beginning of flooding to the date when maximum inundation had already occurred across the region). Two states (Nebraska and Iowa) issued Presidential Disaster Declarations for the 2019 flood event, meaning that IHP grants were only available to residents within those two states. Each claim (NFIP) or application (IHP) is aggregated to evaluate damage costs and policyholder demographics at the county level. Although the NFIP provides limited information on policyholder demographics, we analyze specific IHP applicant demographics to determine the vulnerable populations most affected by flood damage. To identify key differences between applicants with and without flood insurance policies, we first stratify insurance claims by NFIP policyholder status before investigating residence type, gross income, aid eligibility, and type of financial aid.

In addition, we investigate the flood zone designation of the NFIP residence locations. Flood zones are set by FEMA and determine the level of flood risk associated with a property’s location (FEMA 2020). These designations help set flood insurance rates for a specific property. Flood zone categories are generally designated as high, moderate, or low flood risk. High-risk flood zones have multiple labels that provide additional risk information, but for brevity we will refer to them as zone A, in accordance with FEMA’s flood zone naming convention. High-risk flood zones or SFHAs are areas with a 1% annual chance of flooding. Due to significant flood risk, properties in SFHAs with government-backed mortgages are legally required to have flood insurance. Moderate flood hazard areas are typically labeled as zone B and represent areas with an annual flood chance between 0.2% and 1%. Low-risk zones are labeled as zone C or zone X and are designated areas of minimal flood hazard with an annual chance of flooding of less than 0.2%; however, zone C may also indicate an area with minor local drainage problems that do not warrant additional study (FEMA 2020).

To demonstrate the relationship between the previously described hydrologic and socioeconomic aspects of the 2019 flood and NFIP insurance claim locations, we develop spatial regression models at the census-tract level for five hydrologic unit code (HUC) 8 watersheds that reported at least 150 claims during this event and cumulatively represent approximately half of all NFIP insurance claims reported for the 2019 event. HUC 8 represents the subbasin level that captures medium-size river basins (EPA 2016), and the locations of these watersheds are shown in Fig. 2. We utilize zero-inflated negative binomial (ZINB) regression models for each HUC as the dependent variable (number of NFIP insurance claims) is nonnegative and discrete. A ZINB model accounts for potential overdispersion due to the large number of zeroes (i.e., census tracts with no claims) in the data. To counteract this, the excess zeroes are modeled separately from the count values (University of California, Los Angeles 2011). This method has been used previously to predict flood damages (Ghaedi et al. 2022) and flood insurance claims related to tropical cyclones (Czajkowski et al. 2017).

The predictors considered for each model capture both hydrologic and socioeconomic factors unique to each HUC. For the count model, we included census data, sourced through the American Community Survey (ACS) 5-year estimates, such as populations identifying as White and non-Hispanic, Hispanic, and Black (U.S. Census Bureau 2022). Additionally, we used the number of occupied housing units within a census tract, also sourced through ACS, to calculate policy density. Policy density is defined as the number of active policies within a census tract during the 2019 event divided by the number of housing units. While we are unable to stratify the
number of housing units by type (e.g., apartments, single-family and multifamily homes), this variable gives insight into the proportion of insured housing units. For hydrologic variables, we calculate the maximum flood ratio within each census tract to give indication of flooding severity. The predictors for the excess zeroes model were the maximum flood ratio and the policy density at each census tract. We performed model selection based on the lowest Akaike information criterion (AIC). Additionally, we evaluated each model for potential spatial autocorrelation by applying the Moran’s I test to the residuals of each HUC model. The Moran’s I statistic can indicate evidence of correlation among neighboring census tracts. Each HUC had a p value greater than 0.05, indicating that no significant spatial autocorrelation was present.

3. Results and discussion

a. Flood hazard

We first evaluate flood severity by examining the exceedance thresholds of 213 USGS stream gauges for the 2019 flooding event (Fig. 3). Nearly one-half (103) of the gauges recorded discharges exceeding the moderate flood category, and 18% (39) exceeded major flooding thresholds. As shown in Fig. 1, many of these gauges were located on the Missouri River on the northern Nebraska and Iowa border, and on the Mississippi River on the western Iowa and eastern Illinois border. The severity of flooding found in these states aligns with Presidential Disaster Declarations (Webster et al. 2019), as major disaster declarations were issued for Nebraska and Iowa in mid-March because of flooding. Additionally, gauges across northern Missouri and northwestern Illinois near the Mississippi River also recorded discharges consistent with major flooding.

In addition to magnitude, flood duration also provides insight into flood severity across the affected study region; the duration of flooding for each exceedance threshold at each stream gauge is shown in Fig. 4. Approximately two-thirds of the stream gauges recorded maximum discharge levels above the action-stage threshold for at least 1 week, although some sites remained above this threshold for over 90 days between 1 March and 31 May (Fig. 4a). Many stations that recorded moderate or major flooding were also sites that experienced inundation for extended periods of time. Two stations located at the northeastern border of Nebraska and northwestern border of Iowa on the Missouri River recorded inundation at the minor flooding threshold for 60–90 days, while a cluster of stations on the Mississippi River between Iowa and Illinois remained above the threshold for 30–90 days (Fig. 4b). While only 38 stations recorded major flooding, some gauges remained above this threshold for up to 30 days (Fig. 4d).

Examining the flood hazard more broadly, we consider both the flood ratio and AEP of the 2019 flood. The spatially interpolated flood ratio at each USGS stream-gauge station provides context for flood severity in relation to discharge quantities (Fig. 5a), while the AEP describes the probability of occurrence of the discharge measured during the 2019 flood as a metric of severity (Fig. 5b); qualitatively, a low AEP represents a large-magnitude discharge that is rarely observed at a particular site, while a high AEP is representative of a frequently observed discharge.

Because flood ratios were calculated based on the 2-yr flood event, any value greater than 1 likely indicates that local discharges exceeded bank height, causing at least minimum minor-flooding conditions. Flood ratios varied significantly across the study area with a range from 0.4 to more than 10.
We observed the largest flood ratios (ranging between 3 and 8) across southern South Dakota and across much of Nebraska near the Missouri and Platte Rivers, along with western Iowa near the Missouri River. In addition, some gauges near the Mississippi River in Minnesota and Wisconsin also exhibited flood ratios up to 6, though much of the surrounding region had smaller values in the 0.4–2 range. The median flood ratio across the entire study area was 2.08, meaning that the peak discharge recorded in 2019 was twice the median discharge of the previous 10 years. Although some individual gauges display flood ratios less than 1, the cumulative impact across the region was severe. We also estimated the AEP using a generalized extreme value (GEV) distribution (Fig. S1 in the online supplemental material). While there are some differences between the AEPs estimated using these two distributions, what is clear is that this was an extreme event for many areas in the study region.

We find that the AEP for 543 USGS gauges varies significantly across the domain (Fig. 5b). Regions that experienced moderate or major flooding based on exceedance threshold were more likely to have a low AEP, particularly near the junction of the Platte and Missouri Rivers between Nebraska and Iowa. Regions distant from the Missouri and Mississippi Rivers, particularly in the central regions of most states, tend to exhibit a higher AEP, ranging between 0.1 (i.e., a 10-yr flood) to 0.95 (i.e., a 1.05-yr flood). Many gauges along the Missouri River near the South Dakota–Nebraska border and at the junction of the Platte and Missouri Rivers at the Iowa–Nebraska border exhibited AEP values between 0.04 (i.e., a 25-yr flood event) and below 0.01 (i.e., a 1000-yr flood event). In the most extreme cases, some gauges had AEP values between 0.005 (i.e., a 200-yr flood) and 0.001 (i.e., a 1000-yr flood). Areas with a high flood ratio and low AEP were found to be highly related; the correlation between the flood ratios at each USGS gauge (Fig. 5a) and the AEP estimates (Fig. 5b) was −0.74 (95% confidence interval, −0.86, −0.54) with a p value of less than 0.001. Areas with

![Fig. 4. Flood duration at 213 USGS gauges above action, minor, moderate, and major levels between 1 Mar and 31 May 2019.](image-url)
significant flooding and a low AEP may be regions with communities underprepared for significant flooding events and are less likely to have flood insurance policies in place. The rank of the peak 2019 flood discharge in comparison with all annual peak discharges for each gauge can be found in Fig. S2 in the online supplemental material, and it provides a broad context for how extreme this event was.

**Fig. 5.** (a) Spatially interpolated flood ratio values of the 2019 flood with overlaid USGS gauge locations. (b) Annual exceedance probability of peak discharge at USGS gauges during the 2019 flood.

**Fig. 6.** (top left) County-level aggregated NFIP claims. (top right) County-level aggregated NFIP claims per 1000 residents. (bottom) County-level aggregated average NFIP claim amounts in USD 1000s. Black dots represent USGS gauge locations that recorded moderate or major flooding discharges.
b. Socioeconomics: NFIP

To illustrate the extent of flood damage across the Midwest, county-level aggregated NFIP claims are shown in Fig. 6. Nebraska, Missouri, and Iowa had the highest numbers of claims; among the three states, there were 1368 claims across 104 counties (Table 1). When accounting for population, Nebraska, South Dakota, and Iowa had the highest number of claims per one million residents (Table 1). Counties in eastern Nebraska, western Iowa, and northwestern Missouri bordering the Missouri River and in eastern Missouri bordering the Mississippi River had the highest density of NFIP claims (Fig. 6, top left and right); these areas coincide with USGS gauge locations that recorded moderate and major flooding discharges. Counties with a high density of claims (Fig. 6, top left) tended to have substantial average claims (Fig. 6, bottom panel); across Nebraska and Iowa, many counties had an average of $40,000 to $80,000 per claim, with some exceeding $100,000 per claim. These values are generally higher than claim amounts from other severe flood events over the past 20 years (Tonn and Czajkowski 2022); for instance, average claims after storms like Hurricane Ivan ranged from $9,000 to more than $46,000. Individual counties within Minnesota, Illinois, and Wisconsin also reported average claim amounts exceeding $100,000, though these states have fewer claims and less total damage than Nebraska or Iowa.

NFIP claims from the 2019 flooding event were overwhelmingly from homeowners: approximately 82% of all claims were for single-family homes, as compared with less than 3% for both apartment units and nonresidential buildings (approximately 12% of claims did not have a specific building designation). Claims for apartments are representative of policies from apartment building owners rather than of renters. The majority of NFIP claims were from residences within SFHA zone A (Fig. 7). However, nearly 15% of the claims were from zone X locations (Fig. 7, left panel). Claims were made on more than one-half of the in-force policies in these zones, with a claim to active policy ratio of greater than 0.85 and greater than 0.62, respectively (Fig. 7, middle panel). Information on active policy location can be found in the online supplemental material (Fig. S3). While zone A had the highest number of claims, zone B had the largest median paid claim amount at $23,000, as compared with $17,000 for zone A. Zones C and X had median paid claims at $15,000 and $16,000, respectively (Fig. 7, right panel). However, claim amounts in SFHAs (zone A) are anticipated to be the highest due to residence proximity to a flooded water body. Mean claim amounts (Fig. 7, right panel) are similar across flood

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<th>Avg claim amount</th>
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Fig. 7. (left) Number of NFIP claims per flood zone. (center) Ratio of NFIP claims to active NFIP policies by flood zone. (right) NFIP claim amounts by flood zone. The limits of the boxes represent the 25th and 75th percentiles, with the line in the middle being the median; whiskers denote 5th and 95th percentiles of claim amount, and the average claim amount is denoted with a black point. Flood-zone letters correspond to the FEMA flooding risk designations as follows: A is high, B is moderate, C is low, and X is minimal.
zones, although zone B had the largest mean claim amount of more than $46,000; the remaining flood zones had mean claim amounts ranging between $32,000 and $43,000. Similar results were found when evaluating previous tropical-cyclone-driven flood events (Tonn and Czajkowski 2022). This indicates that, while zone A had more claims, significant damage occurred to residences within zones B, C, and X.

c. Socioeconomics: IHP

IHP grants were filed under Presidential Disaster Declarations in Iowa and Nebraska for this event; county-level aggregated grants are shown in Fig. 8. There were 2578 applications submitted from 10 counties in Iowa and 6878 applications from 31 counties in Nebraska, with most applications from counties either bordering the Missouri River between Nebraska and Iowa or bordering the junction of the Platte and Missouri Rivers in mideastern Nebraska (Fig. 8, top and middle). This is nearly nine times more applications than claims in Iowa, and 10.5 times more applications than claims in Nebraska, highlighting the lack of appropriate levels of flood insurance in place in these areas. Consistent with the locations of the majority of IHP applications, many applicants in counties in northeastern Nebraska and southwestern Iowa received grants, on average, between $5,000 and $10,000, with some near the junction of the Missouri and Platte Rivers reporting grants up to $20,000 per application (Fig. 8, bottom). Although the number of applications clearly demonstrates the need for financial assistance for disaster recovery, the allocated grants are significantly less than NFIP claim payouts.

In total, 9416 applicants were referred for IHP assistance from the 9456 total applications, whether for HA, ONA, or both. Of those referrals, only 64% (6080 applicants) were eligible. The eligibility of applicants for each type of IHP assistance is shown in Fig. 9. Nonpolicyholders were less likely to be eligible for financial assistance related to housing, relative to their counterparts; 72% of NFIP policyholders were eligible for IHP assistance as compared with 64% of nonpolicyholders. Strikingly, only half (52%) of referred nonpolicyholders were eligible for HA, as compared with 71% of policyholders. Reasons for ineligibility included insufficient damage to the residence, inability to prove occupancy, and unverified identity; these reasons are in line with findings from the U.S. Government Accountability Office (GAO 2020). However, policyholders had a significantly lower eligibility for ONA (31%) relative to nonpolicyholders (51%). One potential reason for this discrepancy is that policyholders tend to have higher incomes.

Assistance type for eligible applicants is also shown in Fig. 9 (bottom panel). The NFIP policy offers both building and contents coverage for repair and replacement yet does not cover rental costs for temporary housing. Conversely, non-policyholders rely on IHP grants for both home repair and temporary housing costs. The majority of eligible applicants received assistance for temporary housing rent (66%) or home repair (60%), as compared with only 20% for personal property and 4% for home replacement. Nonpolicyholders were more likely to receive personal property or home repair or replacement assistance, while a higher percentage of policyholders received rental assistance (Fig. 9, bottom panel).

To identify specific populations receiving aid from the IHP, we investigated the composition of demographics of IHP grant applicants (Fig. 10). There were 8103 applicants (86%) who did not have an active NFIP policy. Those without a policy were less likely to live in a house (73%) relative to their counterparts (91%). Furthermore, applicants without NFIP policies who lived in houses were less likely to own the home (80%) relative to applicants with a policy (97%). The largest difference between residence types of policyholder and non-policyholder applicants were those living in mobile homes or trailers: nearly 15% of applicants without policies reported this residence type as compared with less than 4% of applicants with policies.

We found a considerable difference in income level between applicants with and without an NFIP policy; greater than 70% of nonpolicyholders reported a gross income of less than $60,000 as compared with 50% of their counterparts. Approximately 40% reported a gross income of less than $30,000 as compared with 25% of policyholders. Across nearly all residence types, nonpolicyholders were more likely to have a lower gross income relative to their counterparts (the exception being residents living in “Other” residence types reporting income of less than $30,000) (Fig. 10, bottom left and right. Nearly 100% of apartment residents, regardless of
NFIP policy status, reported a gross income of less than $60,000; similarly, more than two-thirds of applicants living in apartments reported a gross income of less than $30,000. Applicants living in mobile homes or trailers also reported low gross income: 80% of nonpolicyholders make less than $60,000 as compared with just more than 50% of policyholders. Overall, applicants living in houses had higher gross incomes than any other residence type. Owning a house inherently requires more wealth than renting a property, so it is expected that applicants living in houses report higher income.

Investigating applicant age and household composition gives insight into the populations most impacted by flooding, including vulnerable groups such as elderly or young families, as summarized in Fig. 11. Overall, households without an NFIP policy were more likely to have at least one child (24%) occupant relative to those with a policy (22%). However, households without an NFIP were only marginally more likely to have at least one elderly occupant (28.4%) relative to households with a policy (28.2%). While the median applicant age range for applicants regardless of policyholder status was 50–64 years, a higher percentage (40%) of policyholders were within this category than nonpolicyholder applicants (33%). Furthermore, applicants in other age brackets were less likely to have an NFIP policy. While a 2019 survey by the National Association of Insurance Commissioners (NAIC) found that persons born between 1981 and 1996 were three times more likely to have purchased flood insurance than persons born between 1944 and 1964 (NAIC 2019), IHP applicants younger than 50 years were less likely to be NFIP policyholders than were applicants aged 50 years or older. Additionally, a similar percentage of young and older applicants were found to be homeowners. One potential reason older applicants were more likely to be NFIP policyholders could be due to financial strain or perceived knowledge about flooding events, that is, long-term residents of the area may be more aware of flooding risk than are younger residents.

d. Census-tract racial demographics and flood exposure

To evaluate the exposure of different racial groups during the 2019 flood, we compared the spatially interpolated flood ratio value within a given census tract in combination with the percentage of the census-tract population within a given racial group (Fig. 12). Four racial groups were mapped: White and Non-Hispanic, Black, Native American, and Hispanic (Figs. 12a,c,e,g). Across the study area, most census tracts have a predominantly White and Non-Hispanic population (Fig. 12a). Census tracts with predominantly Black populations are located near Saint Louis, Missouri (eastern border), and Chicago, Illinois (northeastern border) (Fig. 12c). Some census tracts in North and South Dakota, northern Minnesota, and northern Wisconsin report predominantly Native American populations, consistent with locations of land areas of federally recognized tribes (Bureau of Indian Affairs 2022) (Fig. 12e). Predominantly Hispanic population census tracts are clustered in the southwestern corner of Kansas (Fig. 12g). The relationship between the flood ratio and percent population of a given racial group by census tract is shown in the right column of Fig. 12. Regardless of racial group, the majority of census tracts had flood ratios around 2.0. Predominantly
White and Non-Hispanic, and Hispanic population census tracts had higher flood ratios (Figs. 12b,h, respectively) than predominantly Black or Native American population census tracts (Figs. 12d,f, respectively). These results reflect similar findings in a recent study of U.S. flood risk (Wing et al. 2022): while predominantly White communities currently experience the highest flooding risk, Black communities will experience the largest increase in future flooding risk.

\section*{e. NFIP claim models for selected HUCs}

We complement these analyses with spatial regression models to relate the number of NFIP insurance claims to different hydrologic and socioeconomic drivers. We find that the relationship between selected predictors and the number of NFIP claims is specific to each HUC and not consistent across them (Table 2). For the count portion of the model, in HUC 07090005 (Lower Rock) and 07110004 (The Sny), larger flood ratios result in a higher number of claims, while flood ratio is not significant in the remaining HUC models. One potential reason the flood ratio is not statistically significant for some models may be the proximity of USGS stream gauges to the HUC; for example, HUC 10230006 (Big Papillion–Mosquito Watershed; Fig. S4 in the online supplemental material) does not have a stream gauge without significant trend (and, therefore, was excluded in analysis) within the watershed boundary. Therefore, all flood ratio values are spatially interpolated based on gauges outside the watershed, leading to potentially less accurate representation of the flood hazard for that basin.

For demographics, NFIP claims increase with a larger White, non-Hispanic population in HUC 07090005 (Lower Rock), while the opposite is found in HUC 07110009 (Peruque–Piasa). One possibility is that we would expect higher claims to be positively related to higher flood ratios; however, this is not the case (i.e., the coefficient for the flood ratio is not statistically significant) and this relationship to a White, non-Hispanic population may be spurious. As anticipated, we find a consistent positive relationship between policy density and an increase in NFIP claims: census tracts with more policies in place per number of housing units have more claims. For the zero-inflated portion of the model, we find that neither flood ratio nor policy density is significant for any of the HUC models.

Beside the summary in Table 2, we have also explored the capability of the models in reproducing the observed claim
number, obtaining mixed results (Fig. 13). Two models have a high correlation between the observed and predicted number of NFIP claims: HUC 07110009 (Perque–Piasa) and 10220003 (Lower Elkhorn) have correlations exceeding 0.9 (0.99 and 0.98, respectively) with \( p \) values less than 0.001. We find that the HUC 07110004 (The Sny) model struggles in both the count and zero-inflated portions; the overall correlation coefficient of the model was 0.08 with a \( p \) value of 0.75. When considering only the count portion of the model, the correlation is 0.54 (\( p \) value of 0.13). Last, HUC 07090005 (Lower Rock) and 10230006 (Big Papillion–Mosquito) have correlations of 0.41 (\( p \) value < 0.001) and 0.15 (\( p \) value < 0.05), respectively. While we find inconsistent relationships between hydrologic and socioeconomic variables and flooding damages when examining these models as a whole, these results do suggest that contributing factors to flooding are highly localized. In addition, these relatively simple models attempt to capture a complex relationship among these variables and do not take into account factors such as local flood mitigation strategies that may play an important role in the number of NFIP claims in an area.

4. Conclusions

In this study, we first examined the hydrologic characteristics of the 2019 Midwest flood by analyzing annual peak-discharge time series from USGS gauges across nine states to determine flood magnitude, duration, and annual probability of occurrence. Our results indicated that a significant percentage of sites across the study area recorded peak discharges exceeding major flooding thresholds, particularly across eastern Nebraska and western Iowa near the Missouri River. Additionally, many of these sites remained above flood levels for up to 3 months. The AEP and flood ratios demonstrated the historic nature of the 2019 event: the annual exceedance probability of the 2019 flood for \( \sim 15\% \) of the USGS stream gauges was less than 1\% (i.e., a 100-yr flood event). Many gauges recorded peak discharge values in 2019 that were more than double the median peak discharge of the previous decade (used as a proxy for the bankfull condition), indicating the widespread severity of the event.

We additionally investigated the socioeconomic impacts of the flood by examining FEMA NFIP claim and IHP grant applications. Counties in eastern Nebraska, western Iowa, and northwestern and eastern Missouri had a high density of NFIP claims, which aligns with previous flood damage reports in the region (Hollingsworth 2019; Pitt 2019). We found that NFIP claims were primarily filed for houses, as compared with other residences, and paid claim amounts were significantly higher than IHP grants. Within the IHP, applicants with an NFIP policy were more likely to be homeowners, had higher gross incomes, and received more aid than applicants without a policy. Additionally, NFIP policyholders were more likely to be eligible to receive aid than their counterparts; this calls into question the ability of federal disaster recovery programs to provide aid to households without flood insurance in the face of growing future flood risk.

Last, we model the relationship between various hydrologic and socioeconomic factors to predict NFIP insurance claims at the census-tract level for select HUC watersheds. While we find some correlation between the predicted and observed number of claims, there are inconsistent relationships between these variables and the number of claims when examining the models broadly. This suggests that contributing factors to flooding may be highly localized and that the use of
FIG. 12. (left) Census tract–level racial demographics by percent population during the 2019 flood. (right) Number of census tracts that experienced a given flood ratio during the 2019 flood in comparison with the percent population within the census tract of a specific racial group; the red line denotes a flood ratio value of 1.
additional predictors and multiple storms may shed light on the underlying drivers.

Flood impacts can be quantified in additional sectors that were not addressed in this work, in particular losses in agriculture and public infrastructure. Data sourced from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) from Arizona State University (2022) estimated total crop damages across the nine states at nearly $112 million. Incorporating crop-loss information may be beneficial for assessing damages, particularly in counties with agricultural land use and low population density. Flood damages in the public sector can also be evaluated to understand impacts to public infrastructure and services; reported estimates from Nebraska and Iowa imply that damages can quickly exceed $1 billion (Hollingsworth 2019; Pitt 2019), and available grant amounts for federally funded public assistance disaster recovery projects related to the 2019 flood totaled more than $710 billion (FEMA 2022f).

While this study aims to provide insight into the socio-economic impacts of the 2019 flood on individuals and households through analysis of NFIP and IHP applicant demographics, this work does not provide comprehensive analysis of all available federal disaster recovery programs. For example, federally funded property acquisition programs,

### TABLE 2. Retained predictors for HUC NFIP claim models. HUC 8 codes are as described in Fig. 2. One, two, or three asterisks indicate statistical significance at $p < 0.05, p < 0.01$, or $p < 0.001$.

<table>
<thead>
<tr>
<th>Predictor</th>
<th>07090005</th>
<th>07110004</th>
<th>07110009</th>
<th>10220003</th>
<th>10230006</th>
</tr>
</thead>
<tbody>
<tr>
<td>Count portion of the model</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Flood ratio</td>
<td>2.59***</td>
<td>3.32***</td>
<td>9.08</td>
<td>-0.28</td>
<td>-0.44</td>
</tr>
<tr>
<td>White, non-Hispanic Population</td>
<td>1.35****</td>
<td>0.44</td>
<td>-1.78***</td>
<td>0.63</td>
<td>1.42</td>
</tr>
<tr>
<td>Hispanic population</td>
<td>-2.91*</td>
<td>3.72</td>
<td>-2.06</td>
<td>-0.44</td>
<td>-0.08</td>
</tr>
<tr>
<td>Policy density</td>
<td>0.67**</td>
<td>1.21***</td>
<td>0.14***</td>
<td>0.26***</td>
<td>1.22***</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.51</td>
<td>2.28</td>
<td>1.38</td>
<td>1.82***</td>
<td>-0.37</td>
</tr>
<tr>
<td>Zero-inflated portion of the model</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Flood ratio</td>
<td>1.90</td>
<td>9.66</td>
<td>2.03</td>
<td>-0.64</td>
<td>9.8</td>
</tr>
<tr>
<td>Policy density</td>
<td>-6.33</td>
<td>1.15</td>
<td>-0.91</td>
<td>-12.60</td>
<td>-870.0</td>
</tr>
<tr>
<td>Intercept</td>
<td>1.11</td>
<td>-3.63</td>
<td>1.81***</td>
<td>0.10</td>
<td>-221.0</td>
</tr>
</tbody>
</table>

**FIG. 13. Zero-inflated negative binomial regression models. HUC 8 codes are as described in Fig. 2.**
such as the Hazard Mitigation Grand Program (HMGP), have been utilized as tools for natural disaster recovery in the Midwest (FEMA 2022b; Muñoz and Tate 2016). Furthermore, this study does not analyze insurance claims from private insurers, as many companies do not offer flood insurance. Private flood insurance largely provides commercial coverage or secondary coverage for claim amounts above the NFIP maximum limit (Horn and Webel 2018) and often does not have publicly available data. This study is also limited by data availability for NFIP claims and IHP applications, and we were unable to directly compare applicant demographics between the two programs. However, we were able to analyze the demographic differences between NFIP policyholder and nonpolicyholder IHP applicants. Additionally, IHP data only existed for states that issued a Presidential Disaster Declaration in 2019 (Nebraska and Iowa); therefore, we were unable to characterize the extent of financial aid need in other affected states. The socioeconomic analysis in this paper is primarily descriptive; future work to demonstrate the connection between flood severity and socioeconomic demographics should utilize more robust statistical analyses to identify this connection. However, this research presents a unique analysis that provides context for the effects of flooding on federal aid distribution to various socioeconomic groups.

Acknowledgments. Author Kraft acknowledges support from the University of Iowa’s Recruitment Fellowship. Author Villarini acknowledges partial support by the U.S. Army Corps of Engineers (USACE) Institute for Water Resources. The comments by two anonymous reviewers and the editor are gratefully acknowledged.

Data availability statement. Data analyzed in this study were sourced from existing public data, which are openly available at the locations cited in the reference section.

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