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Estimating long-term K-12 student homelessness after a catastrophic flood disaster

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ABSTRACT

Despite efforts to end homelessness in the United States, student homelessness is gradually growing over the past decade. Homelessness creates physical and psychological disadvantages for students and often disrupts school access. Research suggests that students who experience prolonged dislocation and school disruption after a disaster are primarily from low-income households and under-resourced areas. This study develops a framework to predict post-disaster trajectories for kindergarten through high school (K-12) students faced with a major disaster; the framework includes an estimation on the households with children who recover and those who experience long-term homelessness. Using the National Center for Education Statistics school attendance boundaries, residential housing inventory, and U.S. Census data, the framework first identifies students within school boundaries and links schools to students to housing. The framework then estimates dislocation induced by the disaster scenario and tracks the stage of post-disaster housing for each dislocated student. The recovery of dislocated students is predicted using a multi-state Markov chain model, which captures the sequences that households transition through the four stages of post-disaster housing (i.e., emergency shelter, temporary shelter, temporary housing, and permanent housing) based on the social vulnerability of the household. Finally, the framework predicts the number of students experiencing long-term homelessness and maps the students back to their pre-disaster school. The proposed framework is exemplified for the case of Hurricane Matthew-induced flooding in Lumberton, North Carolina. Findings highlight the disparate outcomes households with children face after major disasters and can be used to aid decision-making to reduce future disaster impacts on students.

1. Introduction

Homelessness creates physical and psychological disadvantages for students and often disrupts their access to school. Schools provide more than education for students; schools impact children's development, relationships, and health. The inability to successfully attend and participate in school can impact a student's future trajectory and diminish their life outcomes and future income-earning potential [1,2]. Students experiencing homelessness are less likely to graduate from high school compared to other low-income children, and the general population. As it is reported by Education Leads Home, a national campaign focused on improving outcomes for students experiencing homelessness, only 64% of students experiencing homelessness graduated from high school in the 2016–17 school year, whereas the national average is 78% for low-income students, and 84% for all students [3]. During the COVID-19 pandemic and the transition to online or hybrid learning, many students experiencing homelessness found it difficult to remotely access school and complete their classwork and homework assignments given their housing situation [4]. This illuminates the challenges students experiencing homelessness face to remain engaged in schools when their environment is disturbed due to a disaster. In this paper a household-level analysis is performed to estimate the number and approximate location of K-12 students becoming homeless following a flooding scenario. The objective of this research is to provide a computational framework capable of capturing the disparate trajectories and long-term consequences experienced by households faced with disasters, and highlighting the specific impact these disparities have on children. The goal of this research is for the computational framework to be incorporated into benefit-cost and other decision-making tools to help motivate policy and other interventions to protect children in future disasters.

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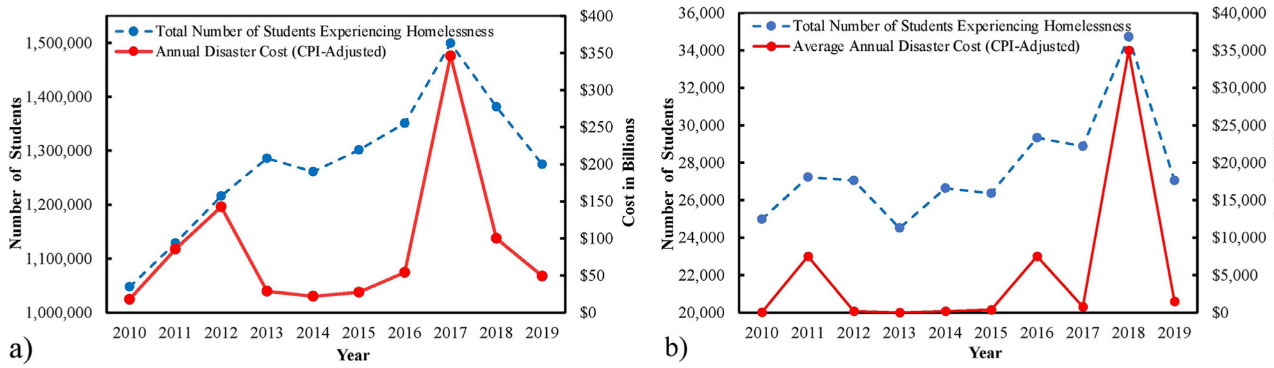

Fig. 1. The cost of billion-dollar disasters and the number of students experiencing homelessness between 2010 and 2019: (a) in the United States; (b) North Carolina.

1.1. Policy context

The federal government and the U.S. Interagency Council on Homelessness work to end homelessness among families, youth, chronically homeless individuals, and veterans [5]. In 1983 the Emergency Food and Shelter Program was created and was the first federal program that focused on people experiencing homelessness. In 1987, the Stewart B. McKinney Homeless Assistance Act, later renamed the McKinney-Vento Homeless Assistance Act, helped create a number of new programs that would comprehensively address the needs of the people experiencing homelessness [5]. While there is no single federal definition of the term "homelessness", a majority of federal programs define the term based on what was originally enacted in the McKinney-Vento Act. According to the act, someone is considered to be homeless "if they are living in a shelter, are sleeping in a place not meant to be used as a sleeping accommodation (such as on the street or in an abandoned building), or will imminently lose their housing" [5]. The Education for Homeless Children and Youth program further adds to this definition to define children and youth homelessness by also including those who share housing with other persons due to loss of housing or economic hardship, live in hotels or motels, trailer parks, or campgrounds due to lack of alternative arrangements, those awaiting foster care placement, living in substandard housing, and children of migrant workers [5]. According to the National School Boards Association, during the 2018–2019 school year, 77% of students experiencing homelessness lived in shared housing, 12% lived in shelters, transitional housing, or were awaiting foster care, 7% lived in hotels or motels, and 4% were unsheltered [3]. Local educational agencies are required to provide annual data on the number of enrolled students experiencing homelessness to the Department of Education regardless of if they are receiving funding from a McKinney-Vento Homeless Education grant [5]. According to the National Center for Homeless Education, local educational agencies receive $57.43 per pupil in McKinney-Vento funding from states to help address the needs of students experiencing homelessness [5].

1.2. Student homelessness and disasters

Despite efforts to end homelessness in the United States, there has been a gradual growth in the number of students experiencing long-term homelessness during the past decade. The number of students experiencing homelessness identified by public schools has increased by more than 100% from 680,000 in 2008 to 1277,772 students in the 2019–20 school year with a peak of 1504,544 students in the 2017–18 school year [4]. Coincidentally, disaster cost statistics in the U.S. show 2017 is the costliest year in U.S. history with over $346 billion in losses caused by billion-dollar disasters [4]. The number of students experiencing homelessness in public schools is estimated by Point-In-Time (PIT) counts that are conducted by local communities on one certain day in January each year. Taking the 2017–18 school year as an example, the PIT count took place during one predetermined day in January 2018. Of note, PIT counts do not represent the total number of students who experience homelessness over the school year. The counts are only a snapshot of the number of students experiencing homelessness on that given day. On the contrary, disaster costs are calculated at the end of a calendar year and are supposed to represent the total accumulated cost over that year. As shown in Fig. 1(a), the number of students experiencing homelessness for the 2017–18 school year corresponds to the peak disaster cost in 2017. Fig. 1 compares the count of students experiencing homelessness with annual disaster costs between 2010 and 2019 in the United States and North Carolina. Fig. 1 highlights the positive relationship between disaster costs and student homelessness. In years with high disaster costs the number of students experiencing homelessness increases; conversely, years with lower disaster costs the number of students experiencing homelessness decreases or stays constant. Although there is a wide range of disastrous events, such as war, civil or racial disturbance, and economic recession that trigger homelessness around the world [6], natural hazards, among them, have been the primary challenge facing the U.S. in the past decade and perhaps have had the greatest contribution in exacerbating homelessness [7].

Millions of children are impacted by natural hazards each year [2]. Children are among those most at risk and can experience physical and psychological negative impacts, as well as disruptions in their educational progress [8]. However, disasters do not affect all communities and students equally. Natural hazards can result in both short-term and long-term homelessness. Housing recovery is not just physical reconstruction, it includes the reoccupying of houses, restoration of essential living services and safety, and recovery of the local community's social and economic condition. Households with different levels of social vulnerability (SV) experience disparate housing recovery trajectories [9]. SV is defined as the characteristics of a person or group in terms of their capacity to anticipate, cope with, resist and recover from the impacts of a natural hazard [10]. SV indicators for households typically include poverty, age, disability, housing tenancy, disadvantaged status, minority racial status, and low educational attainment [1,11–13]. Students from more socially vulnerable households are more likely to experience long-term homelessness, especially after disasters. In 2005, Hurricanes Katrina and Rita initially displaced approximately 372,000 students. However, the students that experienced prolonged displacement and disruption to their schooling were primarily from low-income families and neighborhoods [2].

Natural hazards can also compromise schools' functionality. Schools can lose their functionality due to damaged buildings, physical access disruption, loss of external utilities, as well as unavailability of staff, students, and suppliers [14]. Therefore, school recovery involves more than just repairing the school building(s). In fact, school staff, suppliers, and students differentiate a school's functional recovery from its physical space recovery. The availability of school staff, local suppliers, and students highly depend on their housing recovery. Thus, in more

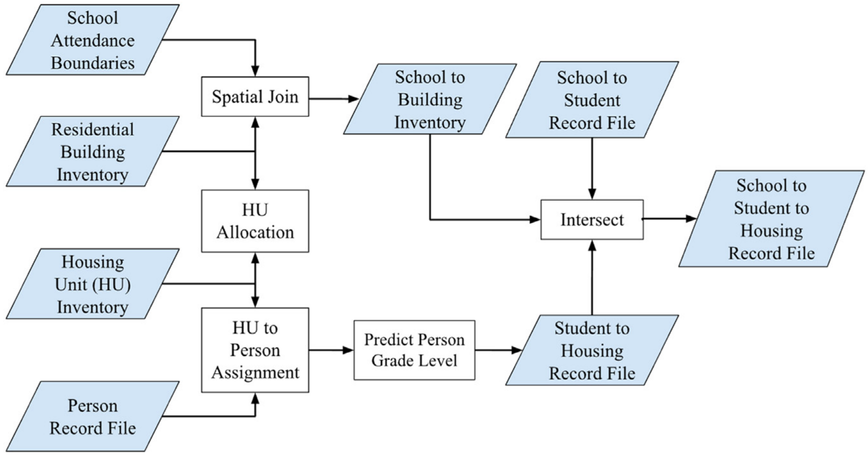

Fig. 2. Linkage between students, housing inventory, and schools.

socially vulnerable communities where student homelessness is more likely, schools also experience longer functional recovery trajectories. An example of differential school recovery trajectories was observed after Hurricane Matthew-induced flooding in North Carolina in 2016, which resulted in Princeville Elementary School closing for 13 days compared to West Lumberton Elementary School which closed permanently because of the significant drop in student attendance [15]. The West Lumberton Elementary School closure was also a function of the relationship between housing recovery and school recovery [16]. Ultimately, student recovery trajectories, household recovery, and community recovery are all complementary facets of school recovery [17–19].

1.3. IN-CORE

The Interdependent Networked Community Resilience Modeling Environment, IN-CORE, has the capacity of computing comprehensive resilience measures at the community-level [20]. The ability to model community disaster resilience comprehensively requires experts from multiple disciplines work in concert to systematically model how physical, economic, and social infrastructure systems within a real community interact and affect recovery. IN-CORE has been used for probabilistic risk assessment of coupled natural-physical-social systems [21], for modeling population dislocation [22,23], and housing recovery predictions [9], among other resilience analyses. Primary data collected from a multi-disciplinary, longitudinal field study is used to validate algorithms within IN-CORE. The field study takes place in Lumberton, North Carolina and was initiated after 2016 Hurricane Matthew. During the six years of the field study to-date, impact, recovery, mitigation, and decision-making data has been collected for households, housing, businesses, schools, and public works sectors [15,24–26]. Collectively the field study data provides a rich understanding of how communities are impacted by and recover from disasters over time. The analyses presented in this paper utilize IN-CORE, and its novel housing unit inventory, stochastic population model, dislocation model, social vulnerability score, and household-housing recovery model to predict household-level outcomes on student homelessness. The present work expands on these existing models through integrating them in a novel framework to estimate the number and pre-disaster location of students experiencing long-term homelessness.

2. Methodology for predicting homeless student population

This section describes the base models and how they were expanded and integrated in order to predict student-level disaster outcomes. The first set of models are used to link students to housing and to schools. The second model estimates household-level social vulnerability using socio-demographic data. The third model predicts household-level stages of housing recovery, including students experiencing long-term homelessness.

2.1. Linking schools, housing, and students

The connection between schools, housing and students plays a key role in the prediction of post-disaster student homelessness. The model described in this section (see Fig. 2) requires five input files. First, the National Center for Education Statistics (NCES) *School Attendance Boundaries* (SAB) provides the geographic polygon boundaries for each school in a community [27]. Second, an inventory of the point location of all buildings in the study area with a classification for residential structures provides a *Residential Building Inventory* [28]. Third, a *Housing Unit Inventory* [22] which provides a census block level synthetic list of each housing unit and detailed household and housing unit characteristics. Fourth, a *Person Record File* [29] which provides a census block level synthetic list of each person and a prediction of each person's age, sex, race and ethnicity. The NCES Common Core of Data provides the foundation fifth required dataset (the *School to Student Record File*) which has a list of all schools and the number of students by grade level, sex, race and ethnicity.

The combination of the first four input files produces two interim files. The first interim dataset provides the link between schools and housing units; this *School to Building Inventory* file requires a spatial join between the SAB polygons and the point location of each building. The second interim file contains the link between students and housing. The *Student to Housing Record File* requires the combination of three sub-methods: Housing Unit Allocation, Housing Unit to Person Assignment and a method to predict a person's grade level.

For the Housing Unit Allocation (HUA) method, previous research [22,30,31] has established and used the HUA to link detailed household characteristics to an inventory of housing structures. With household characteristics linked to housing, researchers have predicted the impact of hurricane damage on access to critical facilities for non-evacuated population [21], the difference in disconnection of utilities after a seismic tsunami event for homeowners versus renters [32], and analysis of policies on recovery time for populations by income after a tornado [23]. This paper presents an extension of previous work by adding person level data to each household. The person level characteristics are based on U.S. Census Bureau data collected at the census block level, the smallest geographic level available that generally represents a neighborhood block. Census block level data provides details on the age, sex, race, and ethnicity of people living within each block across the U.S. The methodology used in this study generates a disaggregated person record file following a similar methodology developed by Rosenheim

Table 1
Household social vulnerability values based on SVS zone.

SVS Zone	Range 1*	Likelihood of Range 1	Range 2	Likelihood of Range 2	Range 3	Likelihood of Range 3
zone 1	0.0 - 0.2	95%	0.2 - 1.0	5%	–	–
zone 2	0.2 - 0.4	85%	0.0 - 0.2	5%	0.4 - 1.0	10%
zone 3	0.4 - 0.6	80%	0.0 - 0.4	10%	0.6 - 1.0	10%
zone 4	0.6 - 0.8	85%	0.0 - 0.6	10%	0.8 - 1.0	5%
zone 5	0.8 - 1.0	95%	0.0 - 0.8	5%	–	–

* value < 0.2 → low; 0.2 ≤ value< 0.4 → medium to low; 0.4 ≤ value <0.6 → medium; 0.6 ≤ value <0.8 → medium to high; 0.8≤ value → high.

et al. [22]. For each person in the file there is a predicted sex, age, race and ethnicity.

The connection between people to households requires a novel methodology (for more details see [29]) to assign persons to households based on the number of people in each household, the race and ethnicity of the head of household, the family type (single parent or two parent families), the sex of the parent(s), and the age of the householder. Together this suite of characteristics, all based on U.S. Census data, provide a demographic spine to first link adults to housing units. After the initial linkage between adults and housing units, the remaining population is linked to each housing unit based on race, ethnicity, and age groups. While the small level of geography and initial knowledge of the head of household characteristics limits most of the uncertainty in the data linkage the process includes significant uncertainty that may be propagated through a Monte Carlo Simulation.

With each housing unit linked to a residential structure [22] and each person linked to a household [29] the next step in the methodology predicts the grade level of each person. Grade levels may be assumed to correlate with a person's age (e.g., a person that is between 4 and 5 years old is more likely to be in pre-kindergarten than a person that is between 6 and 7 years old). Additionally, state education systems generally have age requirements for when a person must start kindergarten [33]. Initially the algorithm predicts three possible grade levels for each person based on age at the time of the decennial census (April 1). This process generates the *Student to Housing Record File*, which includes a list of each student within the community linked with a specific housing unit located within the community.

The data files generated before the intersection each share common characteristics. The *School to Building Inventory* and the *Student to Housing Record File* both share a unique building identifier which facilitates a one-to-many relationship (one building may have many students); this intersection adds a set of unique school identifiers for each student. The *Student to Housing Record File* and the *School to Student Record File* share demographic characteristics (grade level, sex, race, and ethnicity); With each student assigned a set of possible schools, the final intersection attempts to match students with schools based on the reported school attendance. The resulting *School to Student to Housing Record File* provides the input to the predictive Household Housing Recovery Model that tracks the stage of housing for each student after a disaster based on predicted building damage.

2.2. Household social vulnerability

Social vulnerability is not directly observable or measurable but has been well-documented in the literature to play an important role in disaster experience [34]. In this study, the Social Vulnerability Score (SVS), developed by Enderami and Sutley [35], is employed to assess household social vulnerability. The SVS is a scalable composite indicator that synthesizes a set of demographic variables measured at the desired location and produces a number that represents the relative SV of different communities at the census block group resolution. As race and ethnicity, housing tenure, poverty level, education, age, and disability status are identified as major social characteristics contributing to social vulnerability in the exposure to natural hazards [11,36–38], the SVS aggregates the ratios of these demographic variables for designated SV drivers against their national averages using U.S. Census data. The ratios are measured in terms of the percentage of the non-vulnerable population, where zero represents the highest possible social vulnerability, and as the value of the ratio increases, the vulnerability level reduces. Assuming the same importance for each ratio, their average is calculated as the SVS value for the intended block group. The SVS maps to five levels, called zones, ranging from very low vulnerability (zone 1) to very high vulnerability (zone 5) using a standard deviation classification approach. Every household within a study area is randomly assigned a SV value based on the SVS zone assigned to their corresponding block group and ranges, as defined in Table 1 [35]. As shown in Table 1, to address the consequences of spatial clustering of sociodemographic characteristics in real-world communities, multiple social vulnerability ranges are allocated to the households residing in a particular zone. For example, in zone 4, the likelihood of households with values ranging between (0.6 to 0.8), (0 to 0.6), and (0.8 to 1.0) are 85%, 10%, and 5%, respectively. The proposed ranges were chosen based on the authors' judgment and can be adjusted for the given study area and the user's judgment as required. The assigned SV value is then used in the predictive household housing recovery model.

2.3. Predictive household housing recovery model

Sutley and Hamideh [9] developed a predictive multi-state Markov chain of the household housing recovery process, which captures the sequences that households' transition through the four stages of post-disaster housing, namely, emergency shelter, temporary shelter, temporary housing, and permanent housing. Initial household dislocation is estimated based on logistic regression models developed by Lin [39] and Rosenheim et al. [22] with residential building damage and demographic information as the primary predictive variables. This initial household dislocation provides the initial stage in the sequence, with dislocated households starting in any of four stages, and non-dislocated households starting in permanent housing. Transitions are modeled as a function of the household's SV, and the model captures progressive and regressive steps through the process. A transition probability matrix is defined as a function of household SV, and a roulette wheel simulation determines which stage the household is in for the subsequent time step. The model runs as a function of time, where a time step equates to one month. The roulette wheel simulation captures the variability in the relationship between social vulnerability and realized household housing recovery sequence, such that a household with identical sociodemographic characteristics will not have identical housing recovery experiences. A fifth stage of failure is modeled for when households fail to reach permanent housing. Instead of modeling the transition to 'failure' as a function of SV, rules were established, including (a) if a household takes longer than seven years (e.g., 84 time steps) to reach permanent housing, (b) if the household experiences more than 4 regressive steps in 12 time steps (one year), (c) 7 regressive steps in 24 time steps (two years), or (d) 10 regressive steps during the analysis, then the Markov chain automatically sends the household to Stage 5 (identified as languishing in unstable housing or experiencing homelessness). Outputs of the model include the sequence and time spent in each stage at

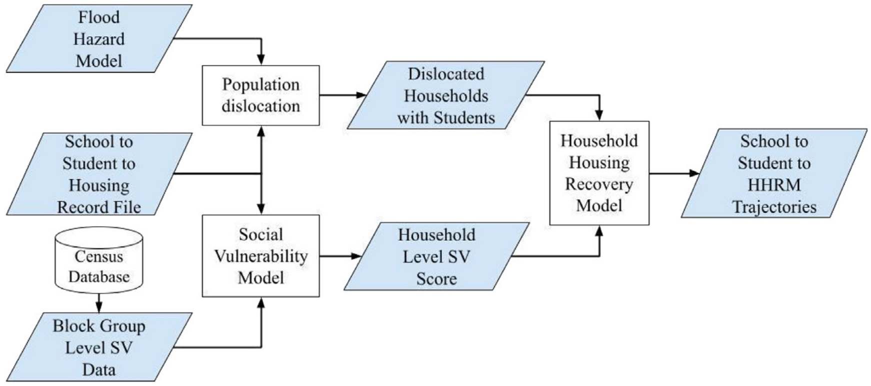

Fig. 3. Model chaining for predicting student homelessness in IN-CORE.

the household level starting from initial dislocation through seven years post-disaster.

3. Illustration via testbed analysis

Using the flow shown in Fig. 3, this section chains the models described in Section 2 and utilizes the Lumberton testbed to estimate the number of K-12 students experiencing long-term homelessness following Hurricane Matthew. Field study data is used, where possible, to validate the analytical findings. The Lumberton community is first described, including reporting statistics used in the models, then the intermediate and final outputs are presented and discussed in sequence with Fig. 3. Verification and validation are discussed intermittently and at the end of Section 3.

3.1. The Lumberton community

Lumberton is an inland city holding the county seat in predominantly rural Robeson County, North Carolina. Lumberton was one of the communities most-impacted by Hurricanes Matthew (2016) due to historic flooding of the Lumber River. The impacts of Hurricane Matthew, and two years later, Hurricane Florence (2018), were exacerbated by many of the hardest hit areas also being some of the most disadvantaged in terms of health, wealth, and infrastructure. According to 2010 Decennial Census data, the Lumberton population were just over 21,500 people with approximately 39.1% of population members identifying as non-Hispanic white, Caucasian, 36.7% as non-Hispanic black, African American, 12.7% as non-Hispanic American Indian, and 6.7% as Hispanic [40]. Based on the same U.S. Census data, 24.8% of Lumberton's population was under the age of 18, and 14.6% was over 65 [41].

Nearly one-third (29.9%) of the community lives at or below poverty levels. Lumberton's poverty rate is more than double the national average of 13.8% [42]. The poverty rate of Robeson County is even more extreme for children. In 2011, 43% of those under the age of 18 were in poverty and this rose to 45.2% for children under the age of 5 [43]. The unemployment rate is slightly lower than the national average, 6.2% compared to 7.9% [44]. However, based on the same U.S. Census data, the median household income was $29,838, far below the national average [45]. In terms of education, 25% of Lumberton's population age 25 and over lacks a high school diploma (or its equivalent), while the national average is 15% [46]. Also, the disability rate in Lumberton is 16.3% which is 6.3% higher than the national average [47]. According to 2010 Decennial Census data, more than 90% of the existing 8877 housing units in Lumberton are occupied [48], and the renter-occupancy rate is equal to 51.7%, which is much higher than the State of North Carolina (33%) and national (35%) rates [49].

In 2016, children in Lumberton attended the Public Schools of Robeson County, a county-wide school system consisting of 44 schools with a student population over 24,000. There are also seven private or alternative schools in Robeson County, three of which are located in Lumberton. There are 17 public schools that serve the students of Lumberton, including 11 elementary, 3 middle, and 3 high schools. During the 2011 to 2012 school year, Robeson County had the second lowest per pupil spending in the state [50]. Many students come from low-income families; as a consequence, 84% of students had access to free or reduced lunch, compared to 56% statewide [43].

In early October 2016, Hurricane Matthew hit North Carolina, resulting in approximately $1.5 billion of losses due to physical damage to homes, businesses, and government buildings. Most of Lumberton, particularly the southern part of the Lumber River, is within the coastal flood plains. Hurricane Matthew resulted in a 500-year rainfall and subsequent flooding for Lumberton, dislocating many households. Just two years later, Lumberton experienced another catastrophic flood following Hurricane Florence. As mentioned in Section 1.3, Lumberton became the site for a longitudinal community resilience focused field study. Immediately after Hurricane Matthew, the field study team documented significant impacts on the public schools in Robeson County [51]. All public schools were closed for three weeks following the hurricane due to a combination of road closures, loss of electricity, damaged water systems, flooded buildings, contaminated kitchens from rotting food, the need for air quality testing, and displaced students and staff members. As the field study continued through 2023, the field study team continued to conduct interviews with school representatives to track long-term impacts, recovery, and student homelessness.

3.2. Associating households with students to Lumberton schools

For the purposes of the present analysis, the study boundary is defined by the Lumberton Senior High School attendance boundary to match the flood hazard model boundary. Lumberton high schools have very large attendance boundaries which extend beyond the building inventory and hazard model, and thus only two high schools (i.e., Junior and Senior High Schools) were included here. The middle school in Lumberton also has a similar boundary. Overall, five elementary schools, one middle school, and two high schools fall within the Lumberton Senior High School attendance boundary included in this analysis. Using the process described in Fig. 2, K-12 students' pre-disaster home are matched with schools. Table 2 provides the number of students by school estimated using *Person Record File (PREC)*, which closely matches with the NCES Student Count reported in 2009–2010 data. The PERC recorded a total of 4758 students within the Lumberton Senior School attendance boundary, including 2058 in Lumberton Senior High School, 598 in Lumberton Junior High School, 590 in L Gilbert Carroll Middle School, 208 in Janie C Hargrave, 474 in Rowland Norment, 442 in Tanglewood, 274 in W.H. Knuckles, and 114 in West Lumberton elementary schools. Although there are differences in the two datasets ranging between 0% to 29% across the eight schools, the total error is just over

Table 2
Comparison of number of students by school in person record file model and reported by National Center for Education Statistics (NCES).

School Name	PREC Student Count	NCES Student Count 2009–2010	Percent Difference
West Lumberton Elementary	114	162	−29.63%
Janie C Hargrave Elementary	208	208	0.00%
W H Knuckles	274	291	−5.84%
Tanglewood Elementary	442	499	−11.42%
Rowland Norment Elementary	474	597	−20.60%
L Gilbert Carroll Middle	590	602	−1.99%
Lumberton Junior High	598	598	0.00%
Lumberton Senior High	2058	2083	−1.20%
Total	**4758**	**5040**	**−5.56%**

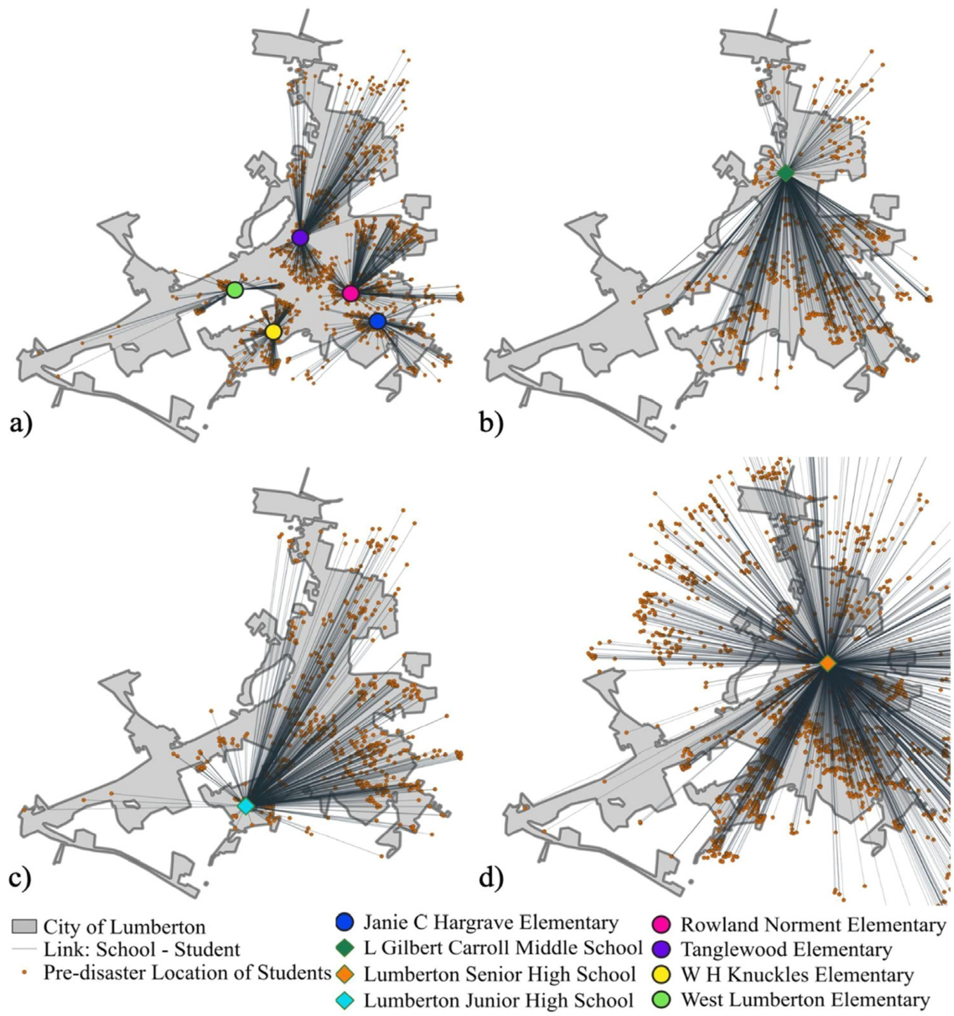

Fig. 4. Estimated mapping of K-12 students' pre-disaster home to schools: (a) elementary schools; (b) middle school; (c) junior high school; (d) senior high school.

5%. Thus inputs at the school-level may contain varying uncertainty as shown in Table 2, but overall for the study area, the PREC closely matches NCES data.

Fig. 4 shows the students' pre-disaster home mapped to their presumed affiliated schools, where Fig. 4(a) shows elementary school linkages, Fig. 4(b) shows linkages to L Gilbert Carroll Middle School, Fig. 4(c) links students to Lumberton Junior High School, and Fig. 4(d) links students to Lumberton Senior High School. This map is generated based on *the 'School to Student to Housing Record File'* described in Fig. 2. The *'School to Student to Housing Record File'* assigned 4758 students to 3441 households in Lumberton. As shown in Fig. 4, many of the students' homes are outside the Lumberton city boundary, with the elementary schools casting the smallest nets.

3.3. *Assigning social vulnerability to Lumberton households*

As described in Section 2.2, the SVS was used to assign social vulnerability zones for each census block group in Lumberton, as shown in Fig. 5. Social vulnerability zones were determined using 2009–2013 ACS 5-year estimates in this study.[1] Lumberton is a community with a low-to-medium income and a diverse population [52]. Thus Lumberton's

[1] The ACS 5-year is an ongoing survey that has been conducted by the U.S. Census Bureau since 2010 and releases five-year average estimates for all geographic areas across the country every year [52]. These estimates are based on data collected over a 5-year period, i.e., from 2009 through 2013 herein.

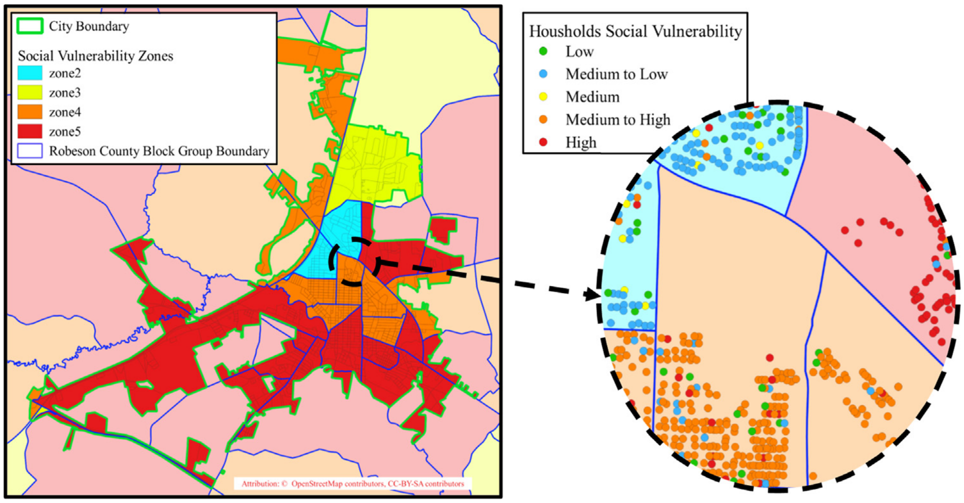

Fig. 5. Mapped SVS block group zones and household-level SV.

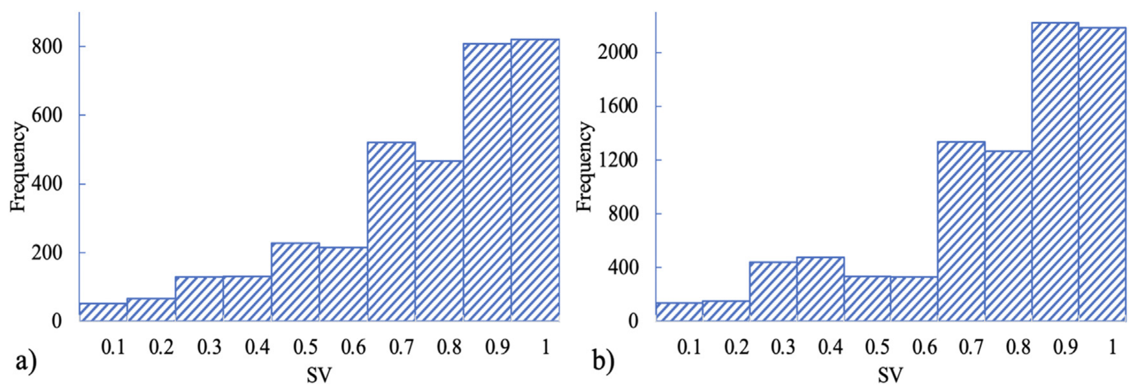

Fig. 6. Histogram of assigned SV scores for: (a) households with students (N = 3441); (b) all households within the Lumberton (N=8889).

32 block groups are classified into four SVS zones ranging from zone 2 (medium to low vulnerability) to zone 5 (high vulnerability), as shown in Fig. 5. Taking the block group zone assignments, household-level SV is then assigned randomly based on the SV ranges and corresponding probabilities defined in Table 1. The household-level SV assignment process does not explicitly consider social characteristics; hence, uncertainty associated with SV assignment is accounted for through Monte Carlo Simulation (discussed in Section 2.2).

Fig. 5 demonstrates a sample of household-level SV from one iteration. As can be seen in Fig. 5, despite no block group being assigned zone 1 (the lowest SVS zone), some households have been assigned a low SV level. This outcome stems from defining more than one social vulnerability range for each zone in Table 1 and accounts for the fact that there are certain households in Lumberton who fall into the lowest SV level but do not constitute the majority within their respective block group(s).

For the same single iteration, Fig. 6 compares histograms of SV for households with students and all households within Lumberton. The median SV for households with a student in kindergarten through high school is 0.78 (N = 3441), which is very close to the median SV for all households living in Lumberton (0.80, N = 8889). Table 3 shows the mean and median SV of households with students by school. Students who go to West Lumberton, Janie C. Hargrave, and W H Knuckles are estimated to have higher SV levels than the other five schools in Lumberton, and this finding was confirmed through our interviews with school representatives in Lumberton. These three elementary schools are located in the southern part of Lumberton (in flood plain area), where their school boundaries fall within high vulnerability zones of Lumberton (as can be seen by overlaying Figs. 4a on 5).

Table 3
Mean and median SV score by school.

School Name	Mean SV	Median SV
West Lumberton Elementary	0.87	0.88
Janie C Hargrave Elementary	0.86	0.89
W H Knuckles Elementary	0.88	0.90
Tanglewood Elementary	0.55	0.58
Rowland Norment Elementary	0.78	0.83
L Gilbert Carroll Middle	0.74	0.82
Lumberton Junior High	0.74	0.81
Lumberton Senior High	0.70	0.74

3.4. Household dislocation and long-term housing recovery

In this study, we used 2016 Hurricane Matthew-induced flooding as the disaster scenario that led to school closures, household dislocation and return [53]. Fig. 7(a) shows the simulated flood inundation map for Lumberton, and Fig. 7(b) shows the estimated initial population dislocation. Household dislocation analysis estimated 136 dislocated households as a result of Matthew-induced flooding. These 136 households have 200 school-age students (ages 5 to 18 years). As evident from Fig. 7(b), dislocated households are clustered in the southern portion of the city aligning with the inundation map in Fig. 7(a).

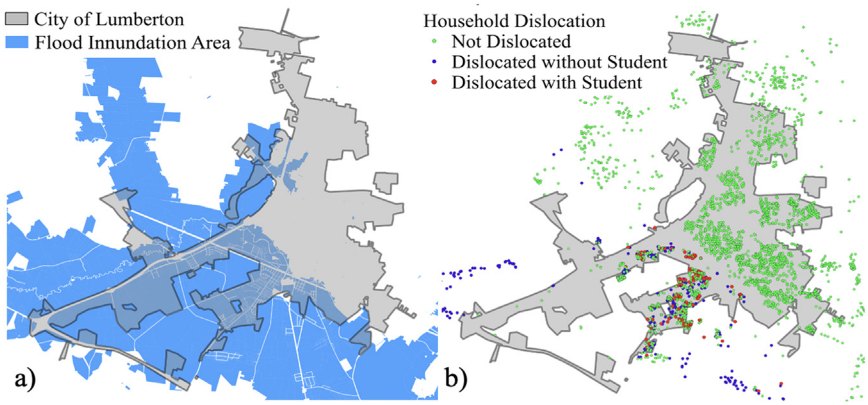

Fig. 7. Simulated Hurricane Matthew-induced Flooding a) Inundation map in Lumberton, NC (sources: Esri, DigitalGlobe, GeoEye, i-cubed, USDA-FSA, USGS, AEX, Getmapping, AeroGRID, IGN, IGP, Swisstopo, and the GIS user community), and (b) Dislocated households due to flooding.

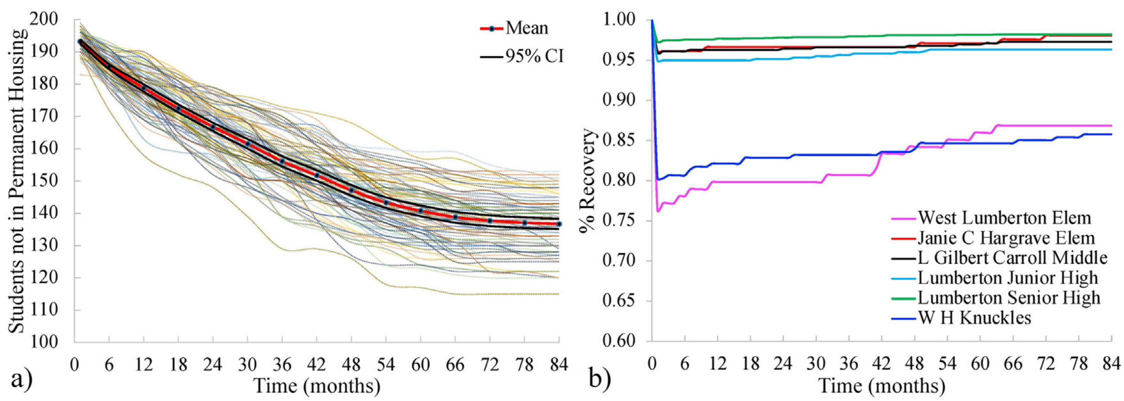

Fig. 8. Household-level housing recovery model results from 100 simulations over seven-years of post-flooding: (a) number of students not in permanent housing, and (b) average ratio of students in permanent housing by school.

3.5. Student return and homelessness by school

Dislocated households with students (shown in Fig. 7(b)) are used as an input to the household housing recovery (HHHR) model; the HHHR model then predicts the long-term housing recovery trajectory for dislocated households which enables the determination of post-disaster homelessness. The HHHR model requires a user-defined input specifying the probability of each household's initial housing recovery stage (see [9] for more information and sensitivity analyses). The initial stage probability vector used in this analysis is [0.95, 0.017, 0.016, 0.016] for stages 1, 2, 3, and 4, indicating that the vast majority (95%) of dislocated households will start in stage 1, emergency shelter, and that a few dislocated households (1.6%) will immediately find permanent housing (Stage 4). This initial probability vector was chosen based on the assumption that a large part of the high SV community will likely go to an emergency shelter immediately after flooding.

To account for the uncertainty in household social vulnerability and housing recovery trajectory, 100 simulations are performed with the SVS and HHHR. In each of the 100 simulations, the same inputs are used from the HUI, stochastic population model, and student-to-home-to-school mapping. Fig. 8 shows permanent housing loss and recovery trends from the 100 simulations. Fig. 8(a) shows the number of students without permanent housing throughout the recovery process with the mean estimate shown in red. Fig. 8(b) represents the recovery ratio by schools, which captures the percentage of students in permanent housing (Stage 4) over seven years post-flooding. Of note, the McKinney Vento definition of homelessness includes intermediate stages of housing recovery. Therefore point-in-time homeless student estimates are based on the summation of school aged-children identified in all of the HHHR model stages other than permanent housing.

Of eight schools considered in the analysis, none of the households with students associated with Tanglewood Elementary and Rowland Norment Elementary Schools were dislocated due to the flooding. These two schools' boundaries fall outside the flood inundation area. The mean SVS of households with students associated with these two schools is lower than the other three elementary schools (see Table 3). Immediately after the flooding, 55, 30, 24, 54, 8, and 27 students from Lumberton Senior High, Lumberton Junior High, L Gilbert Carrol Middle, W H Knuckles Elementary, Janie C Hargrave Elementary, and West Lumberton Elementary schools, respectively, were dislocated from their pre-disaster home. On an average from 100 simulations, 37, 21, 16, 40, 6, and 16 students became permanently homeless from Lumberton Senior High, Lumberton Junior High, L Gilbert Carrol Middle, W H Knuckles Elementary, Janie C Hargrave Elementary, and West Lumberton Elementary schools, respectively.

As evident from Fig. 8, the housing recovery pattern stabilizes around five years after the flooding for a few schools (e.g., West Lumberton Elementary) as the recovery model may send unrecovered households to Stage 5 (i.e., failure to recover housing). Fig. 8(a) also provides 95% confidence intervals drawn based on the 100 simulations. Although a vast majority of households with students were never dislocated, a large percentage of dislocated students became homeless, including 59% from West Lumberton Elementary (16 out of 27), 75% from Janie C Hargrave (6 out of 8), 74% from W H Knuckles (40 out of 54), 67% from L Gilbert Carrol Middle (16 out of 24), 70% from Lumberton Junior High (21 out of 30), and 67% from Lumberton Senior High (37 out of 55).

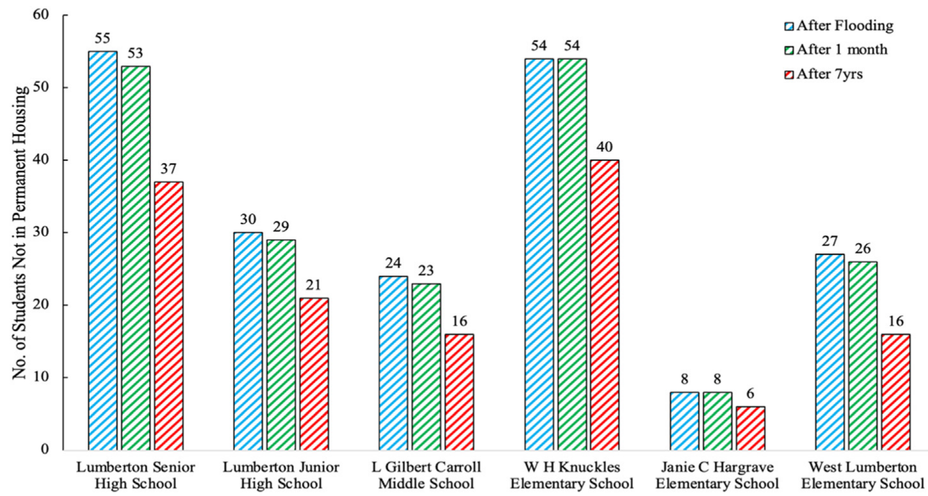

Fig. 9. Number of students not in permanent housing at three post-disaster timepoints by schools.

Fig. 9 shows the number of students who lost their permanent housing at schools at different post-disaster timepoints.

4. Validation with interview and survey data

Flooding from Hurricane Matthew resulted in school closures that lasted about three weeks in Lumberton [51]. W.H. Knuckles and West Lumberton Elementary School experienced the most severe damage and West Lumberton Elementary was permanently closed in June of 2018 [54,25]. After Hurricane Matthew, the district lost 447 students in 2016 and 393 in 2017 for a total of 940 lost students post-Matthew [55]. The loss of students' enrollment was mainly attributed to the loss of affordable and public housing [25]. About two years later, Hurricane Florence flooded Lumberton again in September 2018. Flooding damaged the Robeson County schools and they were closed for about four weeks ([56]). By March 2019, there was an additional loss of 748 students from the previous year. Therefore, after both events, the total enrollment in the Robeson County district decreased by about 1700 students [55,51].

To understand the context of school recovery in Lumberton after Hurricane Matthew and Florence, semi-structured interviews were conducted with school district representatives and administrators. The longitudinal interviews were initiated in December 2016, after Hurricane Matthew, and occurred again in January 2018, in April 2019, and i November 2021 [24,25,51]. Communication with school district representatives continued through emails and virtual meetings, with the last one being held in April 2023. From our team's communications with school district representatives, the district found it difficult to keep track of and communicate with students after the two flooding events. School administrators were not able to track the displacement of individual students and they did not have data showing where students moved [25]. After Hurricane Matthew many McKinney Vento students were living in hotels, and after Hurricane Florence, there were about 100 new McKinney Vento students living with family, friends, or someone else that needed to be served (as per Personal Interview, 2019) [24]. The difficulty in tracking the number of McKinney Vento qualifying students in particular created challenges in receiving and allocating donations, resources, and transportation services (as per Personal Interview, 2016; Personal Interview, 2018) [25,51].

The results of the analysis align with the interview and survey data. In the assignment of social vulnerability to households, West Lumberton and W.H. Knuckles were shown to have higher levels of social vulnerability compared to a majority of the other schools and in fact, these schools also experienced the most damage which had a high impact on the student population. The model results show 59% and 74% of students from West Lumberton and W.H. Knuckles, respectively, have failed to recover permanent housing after Hurricane Matthew. While the models underestimated the number of dislocated students, the trajectory of recovery for dislocated students was similar to the actual event. Both the models and data report a decrease in dislocated students after 1 year of the event. The model shows a decrease of 200 to 178 students (11% recovered) and the data describes a change from 447 to 393 students (12% recovered). Discussions with school district representatives also included discussions of the many times some students would change housing locations in the years following Hurricane Matthew.

There are important limitations to the analyses presented here. One limitation of the current model is the inability to analyze the impacts of multiple disaster events similar to the sequential events of Hurricanes Matthew and Florence and followed by the COVID-19 pandemic. The current model also does not account for individuals who leave/enter the K-12 range during the recovery simulation period. Finally, the model assumes students strictly attend schools based on an estimated age and the associated school boundary where their home is located. In reality, it is not uncommon for students to attend a school in which they live outside the school boundary through the granting of exceptions. Despite these limitations, the models' prediction of long-term student homelessness generally aligned with the post-disaster data.

5. Discussion and closing remarks

Fothergill and Peek [18], in their ethnographic study on children's recovery trajectories following Hurricane Katrina, identified stable housing as the single most critical factor contributing to a child establishing normalcy after a disaster. When children lose their housing, it can have long-term implications on their future. The loss of students' enrollment caused by disaster induced dislocation also has direct financial consequences and policy implications. The loss of students' enrollment from Hurricanes Matthew and Florence resulted in a total loss to Robeson County Public Schools of nearly $13 million in per-pupil funding from the state ([55]; [56]). This loss of funding impacts the district's ability to implement recovery and mitigation projects and magnifies the preexisting social disparities that existed in the socially vulnerable district with many low-income students [25]. Displacement caused by Hurricanes Matthew and Florence within Lumberton has led to economic and social instability highlighting the need to address disaster impacts and recovery ([56]).

While the intensity and frequency of climatic natural hazards, such as hurricanes, floods, severe storms, freezes, droughts, and wildfires, are increasing as evident consequences of climate change, it is expected that more students will experience homelessness in the future without major policy (or other) changes. Currently, the U.S. Department of Housing and Urban Development (HUD) only requires communities to conduct an annual Point-In-Time count of student homelessness. Although this data collection can increase public awareness, attract resources, and help policymakers better plan towards the goal of ending homelessness among students, it underrepresents the needs of (actual and potential) students experiencing long-term homelessness caused by disasters. Equity-based resilience should consider the most vulnerable community members. This calls for the need for high resolution data for household-level analyses.

The modeling framework presented here highlights disaster disparities and provides researchers and decision makers with a novel tool to estimate potential long-term homelessness of a community's student population. These predictions can be used to identify vulnerabilities and needs under future stressors for supporting students and households with children in their community, as well as for supporting the community's school district. Federal, state, and local governments, as well as insurance companies, businesses and other organizations commonly use benefit-cost analyses to determine if a given option is viable. Benefit-cost analyses used in the resilience and disaster contexts greatly underestimate social and long-term consequences of disasters. The present study shines light to the tragic outcome of disasters that is far too common: children becoming homeless. The quantitative framework presented here is a first step in being able to incorporate this post-disaster outcome into benefit-cost analyses and other risk-based decision-making tools.

This paper demonstrates the potential of intersecting detailed household and person level data with school data to link students to residential housing. This novel approach provides resilience model results for individual schools that may allow communities to make equity-based inferences and decisions. Being able to map post-disaster homelessness to a pre-disaster home location can enable targeted investments in low-income neighborhoods, stable and secure affordable housing, and additional school funding to support children before they face homelessness before, during, or after disasters.

Relevance to resilience

This study develops a novel framework to capture the recovery and long-term K-12 student homelessness after a major flood disaster. This paper illustrates the potential of intersecting detailed household and person-level data with school data to link students to residential housing. Using a predictive multi-state Markov chain model, the framework predicts the number of long-term homeless students by schools. The outcomes of the model can be used to identify needs under future stressors for supporting students and households with children in their community and assisting the community's school district. Overall, the novel approach provides resilience model results for individual schools that may allow communities to make equity-based inferences and decisions.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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