Community Resilience-Focused Technical Investigation of the 2016 Lumberton, North Carolina, Flood: An Interdisciplinary Approach

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Abstract: In early October 2016, Hurricane Matthew crossed North Carolina as a Category 1 storm, with some areas receiving 0.38–0.46 m (15–18 in.) of rainfall on already saturated soil. The NIST-funded Center for Risk-Based Community Resilience Planning teamed with researchers from NIST's Engineering Laboratory (Disaster and Failure Studies Program, Community Resilience Group, and the Applied Economics Office) to conduct a field study focused on the impacts of the Lumber River flooding in Lumberton, North Carolina. Lumberton is a racially and ethnically diverse community with higher than average poverty and unemployment rates, a typical civil infrastructure for a city of 22,000 residents, and a city council form of government. The field data described in this paper are from the first wave in an ongoing longitudinal research project documenting the impacts and subsequent recovery processes following the 2016 riverine flooding in Lumberton. The initial data collection for this longitudinal community resilience-focused field study had two major objectives: (1) document initial conditions after the flood for the longitudinal study of Lumberton's recovery, with a focus on improving flood-damage and population-dislocation models; and (2) develop a multidisciplinary protocol providing a quantitative linkage between engineering-based flood damage assessments and social science-based household interviews that capture socioeconomic conditions (e.g., social vulnerabilities related to race, ethnicity, income, tenancy status, and education levels). This type of interdisciplinary longitudinal research is critical to better understand community processes in the face of disasters and ultimately provide data and inform best practices for enhancing resilience to natural hazards in US communities. This paper describes the development and implementation of this interdisciplinary effort and offers an example of combining an engineering assessment of flood damage to residential structures and social science data to model household dislocation. Dislocation probabilities were primarily driven by flooding damage but also varied significantly among Lumberton's racial/ethnic populations and by tenure. **DOI: 10.1061/(ASCE)NH.1527-6996.0000387.** *This work is made available under the terms of the Creative Commons Attribution 4.0 International license, https://creativecommons.org/licenses/by/4.0/.*

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The NIST-funded Center for Risk-Based Community Resilience Planning teamed with researchers from NIST's Engineering Laboratory (Disaster and Failure Studies Program, Community Resilience Group, and the Applied Economics Office) to conduct a field study focused on the impacts of the Lumber River flooding in Lumberton, North Carolina. This paper is adapted from the final NIST report.

Motivation and Background

Community resilience depends on the functioning of social, economic, and public institutions that are, individually and collectively, essential for immediate response and long-term recovery of communities following a disaster. These institutions are dependent on the performance of the built environment that are not designed to necessarily meet the needs and objectives (including postdisaster recovery) of collective community resilience. This requires a multidisciplinary approach (Koliou et al. 2018) that better reflects the complex interdependencies among the physical, social, and economic systems on which a resilient community depends (Sutley and Hamideh 2018).

The Center of Excellence (CoE) for Risk-Based Community Resilience Planning, funded by the NIST, aims to advance measurement science for community resilience assessment and risk-informed decision-making. The CoE is headquartered at Colorado State University in Fort Collins, Colorado and includes researchers from 12 universities and collaborates with several groups and divisions of the Engineering Laboratory at NIST. This paper presents the methodological approach to the fieldwork and example results of the first wave of an interdisciplinary longitudinal study on community resilience applied to the city of Lumberton, North Carolina; interested readers are referred to van de Lindt et al. (2018) for the full report documenting the project.

Research into community resilience demands interdisciplinary approaches in order to understand the factors shaping direct and indirect impacts, as well as restoration and recovery processes, more holistically. While natural hazards, such as floods, hurricanes, or tornadoes, might be considered natural, impartial phenomena, the communities they strike are the product of long histories, shaped by economic, social, demographic, and environmental factors (Bates 1982; Bates and Pelanda 1994; Peacock and Ragsdale 1997; Tierney et al. 2001; Tierney 2006; Wisner et al. 2003). A community's housing stock is often heterogeneous in age, quality, maintenance, and type and clustered into areas (i.e., neighborhoods) that vary along many dimensions, such as physical vulnerability, access to amenities, and socioeconomic attributes (Hendricks 2017; Logan 2006; Highfield et al. 2014; Massey et al. 2016). Access to safe and reliable housing and neighborhoods is shaped not simply by choice but by wealth, income, race, ethnicity, power, social capital, and stigma, among other factors (Bayer et al. 2014; Charles 2003; Choi et al. 2005; Dane 1993; Denton 2006; Foley 1980; Massey et al. 2016; Massey and Nancy 1993; Pendall 2000; Pendall and Carruthers 2003; Steil et al. 2018). The net effect of this interplay between hazards and communities—comprised of social systems and the built environment—is that the direct and indirect impacts of disasters and recovery processes, are not *natural*, impartial events (Bates et al. 1962; Cochrane 1975; Blaikie et al. 1994; Peacock et al. 1997; Mileti 1999; NRC 2006, 2011a, b; Bolin and Stanford 1998; Bullard 2009; Comerio 1998; Cutter et al. 2014; Girard and Peacock 1997; Lindell et al. 2006; Pais and Elliot 2008; Van Zandt et al. 2012; White et al. 2001). As a consequence, it is necessary to investigate not only the physical and technological factors shaping impact and recovery but also the distributional and differential ways that social and economic forces shape resilience outcomes (Masterson et al. 2014). This study links engineering and social science methods to capture the differential and distributional aspects of direct impacts, as well as indirect consequences, such as household dislocation. In addition, this study summarizes engineering tools for assessing flood damage to residential buildings in conjunction with new household survey instruments to collect fully integrated engineering-social science data to do the following: (1) lay the groundwork for a longitudinal study documenting community recovery, including connections of household dislocation, school closures, and infrastructure damage, taking into account decisions made over time by community leaders and stakeholders; and (2) to validate whole community-level recovery models, which require this inherent coupling of physical and social systems. This paper focuses on the interdisciplinary work required to understand and document community resilience issues for a longitudinal study.

Introduction to Lumberton, North Carolina

The City of Lumberton, named after the Lumber River, was among the most flood-devastated communities following Hurricane Matthew in 2016. A portion of the city sits in the floodplain of the Lumber River. The area north of the river sits at a higher elevation, while the southern portion of the city is only slightly above the river elevation. A levee system, completed in 1974, was designed to protect the low-lying areas south of the Lumber River. Just prior to Hurricane Matthew, the city planned to work with the Army Corps of Engineers to certify the levee at the Corps' request. It had been noted that the bridge opening (under I-95) for the railroad and another roadway was believed to be a potential vulnerability in the levee system where flooding from the Lumber River could potentially inundate areas south of the levee (FEMA 2014). This opening in the levee system is where water entered the city during the

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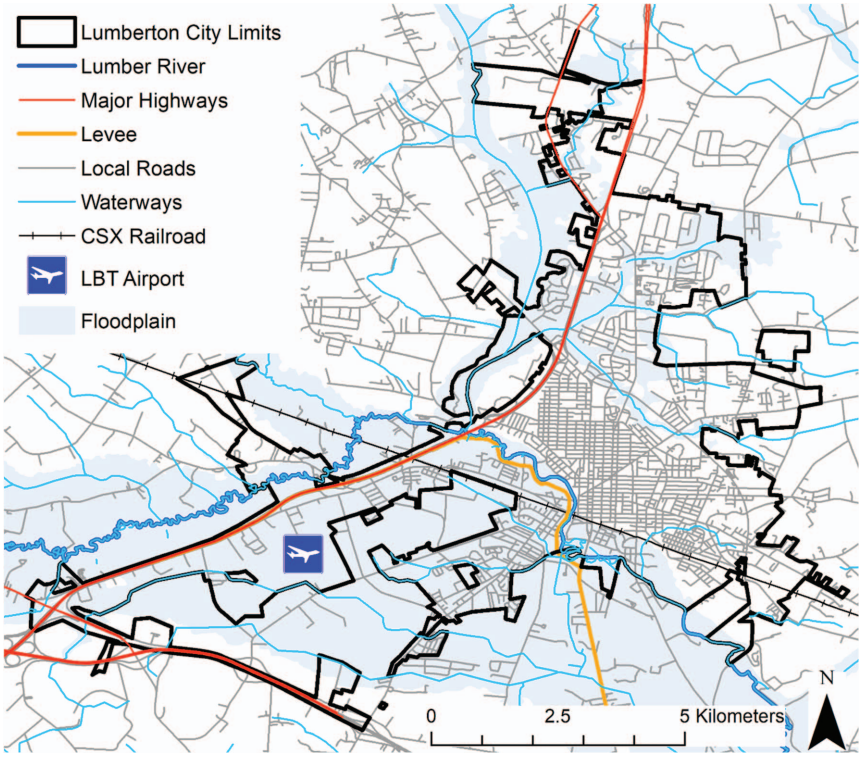

Fig. 1. (Color) Lumberton city limits in black, overlaid with major transportation infrastructure.

flooding caused by Hurricane Matthew. Fig. 1 presents a schematic of Lumberton including the Lumber River, roadways, and railroad.

The City of Lumberton is a racially diverse community with 37.3% of the population identifying as non-Hispanic White, 37.4% as non-Hispanic Black or African American, and 12.6% as non-Hispanic Native American, while 9.3% of the remaining 12.7% of the community is Hispanic (US Census Bureau 2018b). In terms of age distribution and poverty, 26.9% of the population of Lumberton is under the age of 18, while 14.2% is 65 years and over, which is consistent with national averages (US Census Bureau 2018b). Lumberton also has a substantial portion of its population, 35.6%, living at or below poverty levels, which is more than double the national average of 14.6%, with even higher poverty levels for families with children (46.6%) (US Census Bureau 2019). Low-income homeowners, who have fewer resources to pay for hotels or short-term rentals, may stay in damaged and sometimes unsafe, uncomfortable, and unhealthy structures (Girard and Peacock 1997).

In addition to income, housing occupancy and tenure status are important factors in determining disaster impacts and recovery. The US Census Bureau (2018a) reported that Lumberton had approximately 8,600 housing units with an occupancy rate of 83.8%. Lumberton had a much higher percentage of renter-occupied housing, 54.2%, compared to the state (35.0%) and national (36.2%) rates. Lumberton's housing stock was comprised of 62.6% single-family detached housing units, where 66.5% of those were owner-occupied and 33.5% were renter-occupied. Manufactured (or mobile) homes made up 8.7% of Lumberton's housing units, where 75.6% of them were renter-occupied. The remaining housing, approximately 26%, was generally found in some form of multifamily housing with 97% being rental units (US Census Bureau 2018a). The relatively high proportion of rental housing has the potential for generating important postdisaster consequences for dislocation, household and housing recovery, and overall community resilience. The literature on household dislocation due to hazard events has generally found that renters tend to dislocate from their residences more often than homeowners (Girard and Peacock 1997; Lin et al. 2008; Esnard and Sapat 2014, 2017), due to limited property rights and landlords asking them to leave, even if damages are minor. Previous research has demonstrated that housing recovery for rental units is a much longer and more protracted process (Comerio 1998; Hamideh et al. 2018; Peacock et al. 2014, 2018; Zhang and Peacock 2009). Again, depending on the differential levels of flooding associated with Hurricane Matthew, the high proportion of rental housing in Lumberton suggests a potential for relatively high household dislocation, at least temporarily following the event.

Many of Lumberton's children attend the Public Schools of Robeson County, a county school system made up of 44 schools with a student population greater than 24,000 (Public Schools of Robeson County 2017). Fig. 2 displays the attendance zone areas and boundaries of the three public schools, located south of the Lumber River and the levee, which were most heavily impacted during Hurricane Matthew, obtained through the National Center for Education Statistics (NCES 2016). This includes two elementary schools (W.H. Knuckles and West Lumberton) and one junior high school (Lumberton Junior High). The Lumberton Junior High School attendance zone includes the attendance zone areas of the West Lumberton School (light yellow on the map), the W.H. Knuckles School (light green on the map), and the blue area that extends to the south east and north.

Hurricane Matthew and the 2016 Lumberton, North Carolina, Flood

In the weeks prior to Hurricane Matthew making landfall in North Carolina, some areas in the state received more than 380 mm

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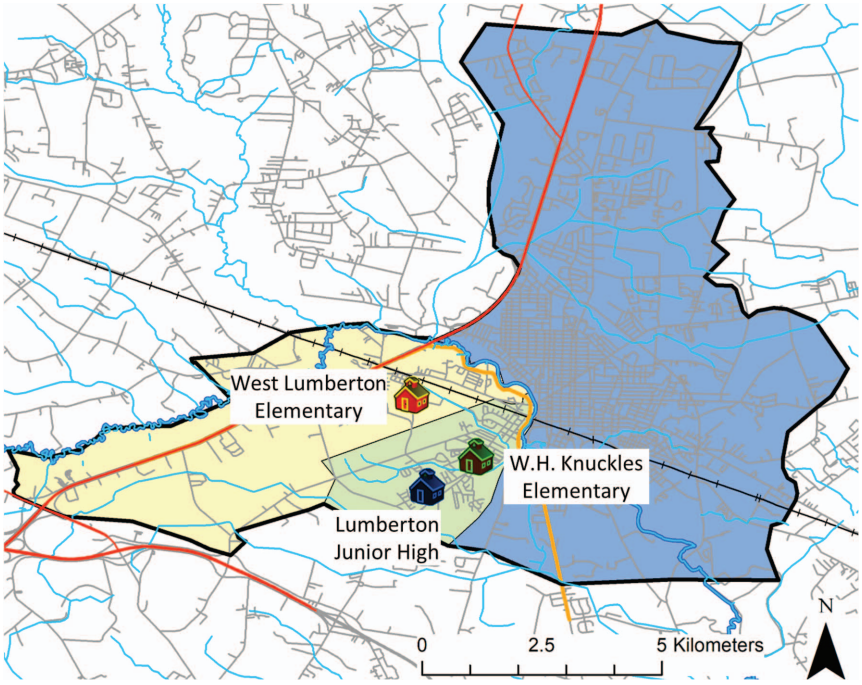

Fig. 2. (Color) Lumberton flooded school locations and boundaries.

(15 in.) of rainfall, causing flooding. Due to local heavy rains, the Lumber river reached the flood stage in Lumberton on October 3, 2016, attaining a local maximum on October 5th (USGS 2016). On October 8th, rain from Hurricane Matthew began to fall, and once again, the stream gage height rose until it peaked at a gage height of 6.7 m (22 ft) [36.12 m (118.5 ft) above the North American Vertical Datum 88] on October 11th. The river remained above the National Weather Service flood threshold of 3.94 m (13 ft) for nearly 3 weeks.

In their study (FEMA 2014), FEMA identified major problems with Lumberton's levee system, particularly at the I-95 bridge opening for the railroad and VFW Road. One of the study's conclusions is that the construction of the bridge opening may not block flow from the Lumber River into the areas that were supposed to be protected by the levee. The collection of photos detailing the flood through time at the railroad underpass of I-95 is shown in Fig. 3. Aerial imagery of the underpass captured on October 11th, the day when the stream gage indicated the crest of the flood, is shown in Fig. 3(a). The arrows and letters on the aerial image in Fig. 3(a) indicate the location and directions of photographs presented in Figs. 3(c–h). Fig. 3(b) show the underpass in its preflood state, while Fig. 3(c) shows mitigation efforts implemented before the flooding, including sandbags in the ditches surrounding the railroad tracks and VFW Road. The photo in Fig. 3(d) was taken at 3:44 p.m. on October 11th, with a water depth estimated to be 0.3 to 0.6 m (1–2 ft) above the roadway. This depth closely matches the digital elevation model (DEM) that estimates the ground elevation near 35.6 m (120 ft) and the USGS stream gage, which estimates the water elevation near 37.2 m (122 ft) at that time (USGS 2016). The roadway blowout below I-95 can be seen in Fig. 3(e), which was taken on October 15th, when the water elevation had dropped approximately 1.2 m (4 ft). The photo in Fig. 3(f) was taken on October 16th after some repairs had begun and shows erosion of the I-95 bridge abutment, exposing the foundation. Fig. 3(g), taken on October 17th, shows erosion under the rail line, which is seen hanging where the base material was washed away; this photo also shows blowouts and sediment that was eroded from the underpass and washed into the city. Fig. 3(h) shows the underpass on November 29th, after structural repairs were completed and the rail line and roadway were both functioning properly.

Even though the levee was in place to generally protect Lumberton, critical utilities remained vulnerable (e.g., the water treatment plant located inside the 100-year floodplain). Many residents of Lumberton lost electrical power, primarily due to downed trees and some substation flooding, which was not completely restored until 2 months (December 9, 2016) after Hurricane Matthew. Hurricane Matthew also disrupted the water service in Lumberton (R. Armstrong, personal communication, 2016) on October 10th, when the river intake pump suffered damage, a treatment plant generator failed, and the sole water treatment plant was inundated. Limited service was resumed by October 15, when four trailers carrying portable treatment units and accompanying membranes were brought in to treat water, bypassing the treatment plant. The treatment plant returned to operation by the end of October, but their generator was still not operational.

In Lumberton and other low-lying areas in Robeson County, the flood waters rose quickly, and many people who evacuated early were able to leave town; however, the flooding damaged or destroyed approximately 5,000 vehicles, which made it difficult for many others to get to safety (Gellatly 2016a). In Robeson County, shelters served nearly 1,800 evacuees in the early days following the storm, and over 5,000 people were placed in hotels and other temporary housing provided by FEMA (Gellatly 2016b). Lumberton Mayor Bruce Davis reported in January 2017 that there were still 695 families displaced from their homes, and 500 families were still living in hotels awaiting an option for more permanent shelter (Brown 2017; Gellatly 2016b).

The flooding that followed Hurricane Matthew had a major impact on the Public Schools of Robeson County. All 42 schools, serving 24,000 students in the district, were closed for 3 weeks 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. West Lumberton Elementary School was

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Fig. 3. (Color) Imagery of the CSX and VFW Road–I-95 underpass. (Modified from van de Lindt et al. 2018.)

completely flooded, and all of their 130 elementary students, teachers, and staff temporarily occupied a wing of Lumberton Junior High School (Public Schools of Robeson County 2017; Willets 2016). In June 2018, the district decided to close West Lumberton permanently and have remaining students attend W.H. Knuckles Elementary beginning in the fall 2018 (Fodera 2018).

Field Study Methodology: Linking Engineering Housing Damage Assessments with Social Science Household Surveys

The general goal of the first wave of the Lumberton longitudinal field study was for investigators to document as much as possible

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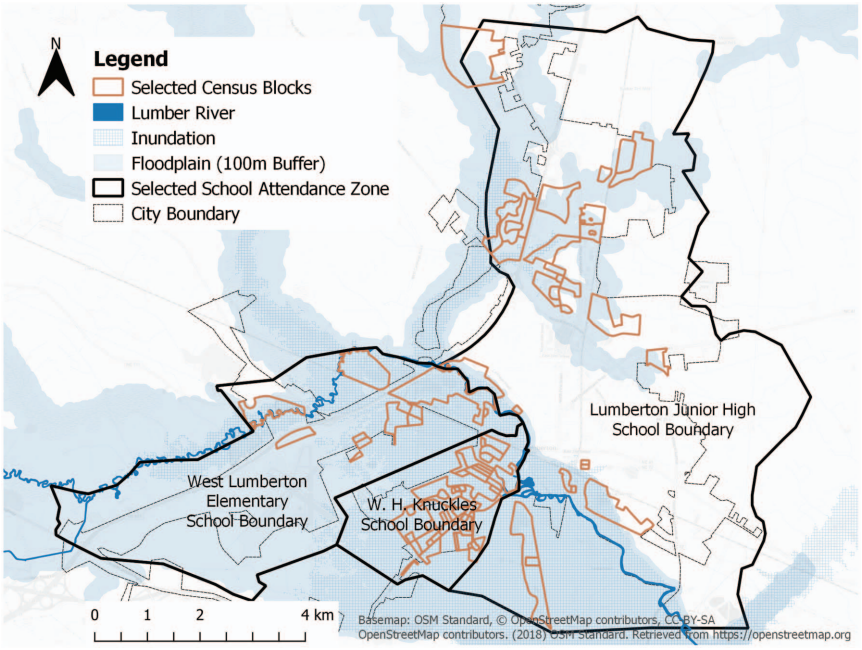

Fig. 4. (Color) Target sampling area with sampled blocks.

about the initial conditions related to the impacts and early recovery efforts from the flooding experienced by Lumberton, focusing on households, residential building stock, critical infrastructure, and the heavily impacted schools. The linkage of these survey instruments and interdisciplinary teams served to form the new study protocol discussed in this study. Investigators sought to gather representative data that could be utilized to (1) improve flood hazard fragilities for residential housing; (2) improve household dislocation models and algorithms; (3) better understand issues confronting households dependent upon public schools, infrastructure, and other factors impacted by disasters; and finally, (4) establish baseline data for household and housing recovery modeling. To achieve these, the study included qualitative interviews with key stakeholders as well as representative data on housing and households.

A housing/household survey was conducted by the team during the first wave of this effort in order to obtain a representative sample of housing units within the study area (defined by the school attendance zone for Lumberton Junior High School) and, where possible, the households occupying those units. As discussed previously, this school attendance zone (the dark black boundary line) is identified in Fig. 4 and includes most of Lumberton City along with areas adjacent to the city, with the exception of some minor appendages that extend beyond the attendance zones to the west and south of the city. The school attendance zone also includes areas inundated by flooding as well as areas not directly impacted by the flooding. It was important to ensure that the sample would have variability and be representative of Lumberton with respect to damage (flood heights and structural damage), sociodemographic characteristics of the population (race/ethnicity, income, and tenure), and housing types (single family detached and attached and various forms of multifamily structures).

A two-stage nonproportional stratified cluster sampling strategy was designed and implemented. The penultimate sampling units were census blocks, and the primary sampling units were housing units and the households residing in those units. Using these data, census blocks were selected utilizing a probability proportion–to-size (PPS) random sampling procedure, with blocks in high probability flooding areas selected 3-to-1 over low probability flooding areas. High probability flooding areas were defined as those census blocks falling within the 100-year and 500-year flood plains. The flood zones in and around the Lumberton area and the boundaries for the census blocks selected during the first stage of the sampling procedure are shown in Fig. 4. With each of the selected census blocks, a combination of county parcel geographical information systems (GIS) data and maps, Google Street View, and census data were utilized to identify and number residential housing units within each block. Housing units were then randomly selected at a fixed rate (eight units per block, along with two randomly selected alternate units). After the sample of eight primary and two alternate housing units were drawn for each sample block, a spreadsheet of sample housing units was created. The combination of PPS selection at stage one, along with a fixed number of randomly selected primary housing units at the final stage, after weighting, assures a representative sample of the area (Kish 2004).

In total, 568 housing units were visited over the 75 census blocks selected in the first stage, averaging 7.6 housing units per census block. Damage assessments were undertaken in areas that experienced flooding and completed for 404 structures. Household surveys were not possible in the 259 housing units severely damaged and clearly abandoned, and of the 309 remaining housing units, the following was determined: (1) 115 appeared to be potentially occupied but survey teams were never able to contact a household member; (2) for 13 housing units, contact was established, but they declined to participate; (3) for three housing units, contact was established, but the household did not occupy the home at the time of the flood or no adult was available to interview; and (4) household surveys were completed for 178 housing units. Details on the survey can be found in the study by van de Lindt et al. (2018).

Field Survey Instruments and Team Management

Damage Assessment Instrument

The damage assessment survey was designed with three main goals: (1) inspect the general physical condition of the buildings;

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Table 1. Overall damage description for residential structures

Damage state level	Description
0	No damage: water may enter crawlspace or touch foundation (crawlspace or slab on grade) but water has no contact to electrical or plumbing, in crawlspace, no or limited contact with floor joists, and so forth. No sewer backup into living area.
1	Minor water enters house; damage to carpets, pads, baseboards, flooring. Approximately 25.4 mm (1 in.), but no drywall damage. Touches joists. Could have some mold on subfloor above crawlspace. Could have minor sewer backup and/or minor mold issues.
2	Drywall damage up to approximately 0.6 m (2 ft) and electrical damage, heater and furnace and other major equipment on floor damaged. Lower bathroom and kitchen cabinets damaged. Doors or windows need replacement. Could have major sewer backup and/or major mold issues.
3	Substantial drywall damage, electrical panel destroyed, bathroom/kitchen cabinets and appliances damaged; lighting fixtures on walls destroyed; ceiling lighting may be ok. Studs reusable; some may be damaged. Could have major sewer backup and/or major mold issues.
4	Significant structural damage present; all drywall, appliances, cabinets, and so forth destroyed. Could be floated off foundation. Building must be demolished or potentially replaced.

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(2) record the high-water marks; and (3) assess the external and the internal damage sustained by the structure and its contents. Damage state descriptions for structural components were adapted from Tomiczek et al. (2017), who modified the wind and flood damage scale for structural subassemblies presented by Friedland (2009). In general, flooding without significant velocity results in damage to contents and nonstructural components in buildings (Deniz et al. 2017a, b), and this trend was also observed in Lumberton. Therefore, the CoE/NIST team established a flood damage assessment methodology focused on postflood conditions of nonstructural components in residential buildings. The survey instrument employed for the damage assessments can be found in Appendix 4 of the study by van de Lindt et al. (2018), with the basic damage description shown in Table 1.

Household Survey Instrument

The CoE/NIST household survey instrument was developed and modified based on an instrument that had been initially developed, fully tested, and used to assess the impact of Hurricane Andrew on households in southern sections of Miami-Dade County (Peacock et al. 1997). The household survey instrument was designed to, at a minimum, collect information on a housing unit's occupancy status, either based on determinations made by the interviewing team or on the basis of information obtained from surrounding neighbors, property managers (or some other source), or adult members of the occupying household. The survey instrument focused on the following: (1) a disruption of major lifeline utilities (e.g., electricity, natural gas, and water) and communications (phone and internet); (2) the enumeration of household members along with basic demographic information (gender and age); (3) the dislocation/displacement with respect to each household member; (4) the employment and student status of each member; (5) the amount of time each member missed work or school; (6) if others joined the household due to the flooding; (7) the tenure status (i.e., rental versus owner); (8) applications to disaster assistance programs [insurance, FEMA, Small Business Administration (SBA)]; and (9) additional household socioeconomic and sociodemographics (e.g., highest education status, race/ethnicity, and annual income). The survey instrument utilized in the Lumberton field study can be found in Appendix 5 of van de Lindt et al. (2018).

Interdisciplinary Team Composition

A goal of the Lumberton study field deployment was to create a fully integrated interdisciplinary field team. To achieve that goal, each data collection team had at least one engineer and one social scientist. Prior to deploying, all engineers and social scientists participated in a series of field survey training sessions that included information on research ethics, data collection protocols, safety procedures, damage assessment protocols, and many other topics. All members of the team were required to have completed individual Institutional Review Board (IRB) training and all of the universities involved in the study had signed an IRB Authorization Agreement (IAA) with Colorado State University, which served as the lead institution. Upon deployment, the multidisciplinary teams completed damage assessments, measurements, and photo documentation and conducted structured interviews with the occupants (when available) in the sampled buildings.

Empirical Flood Damage Fragility Development

As noted previously, full damage assessments were not undertaken for all housing units, especially in areas well outside of the designated 100-year and 500-year flood zones and/or those that did not experience any flooding during this particular event. Consequently, damage assessments were focused in census blocks likely to have experienced flooding to allow for more time, effort, and resources to be dedicated toward completing household surveys in all sampled census blocks. Consequently, full damage assessment data was available and utilized for fragility development based on 402 damaged residential properties. A fragility is a conditional cumulative distribution function that is used in engineering to assess risk to physical infrastructure, often in terms of damage or loss, as a function of one or more hazard intensity parameters. For example, this includes the probability of reaching or exceeding a damage state for a house as a function of flood inundation depth and/or wind speed for a hurricane. This could be used to identify a particular building design performance requirement that has an acceptable level of risk.

In engineering applications, a lognormal distribution is often used for fragility functions because it allows values to remain positive without the need for statistical manipulation (Ellingwood 2001; Li and Ellingwood 2006; Porter et al. 2007; Deniz et al. 2017a, b). Kolmogorov-Smirnov (or K-S) goodness-of-fit tests (for a significance level of 5% or $a = 0.05$) were used to assess the appropriateness of using lognormal distributions for characterizing exceedance probabilities of damage for flooded homes after performing goodness-of-fit tests for the empirical fragility curves. Because flood depth is relative to the chosen datum, the fragilities are shown for two datums typically used to characterize floods in buildings: the first-floor elevation (FFE) and the ground. Definition sketches for hazard intensity measures using either datum are shown in Figs. 5(a and b), respectively. For the ground datum, the models for both building types (slab and crawlspace foundations) passed the K-S test. For the FFE datum, all damage models for

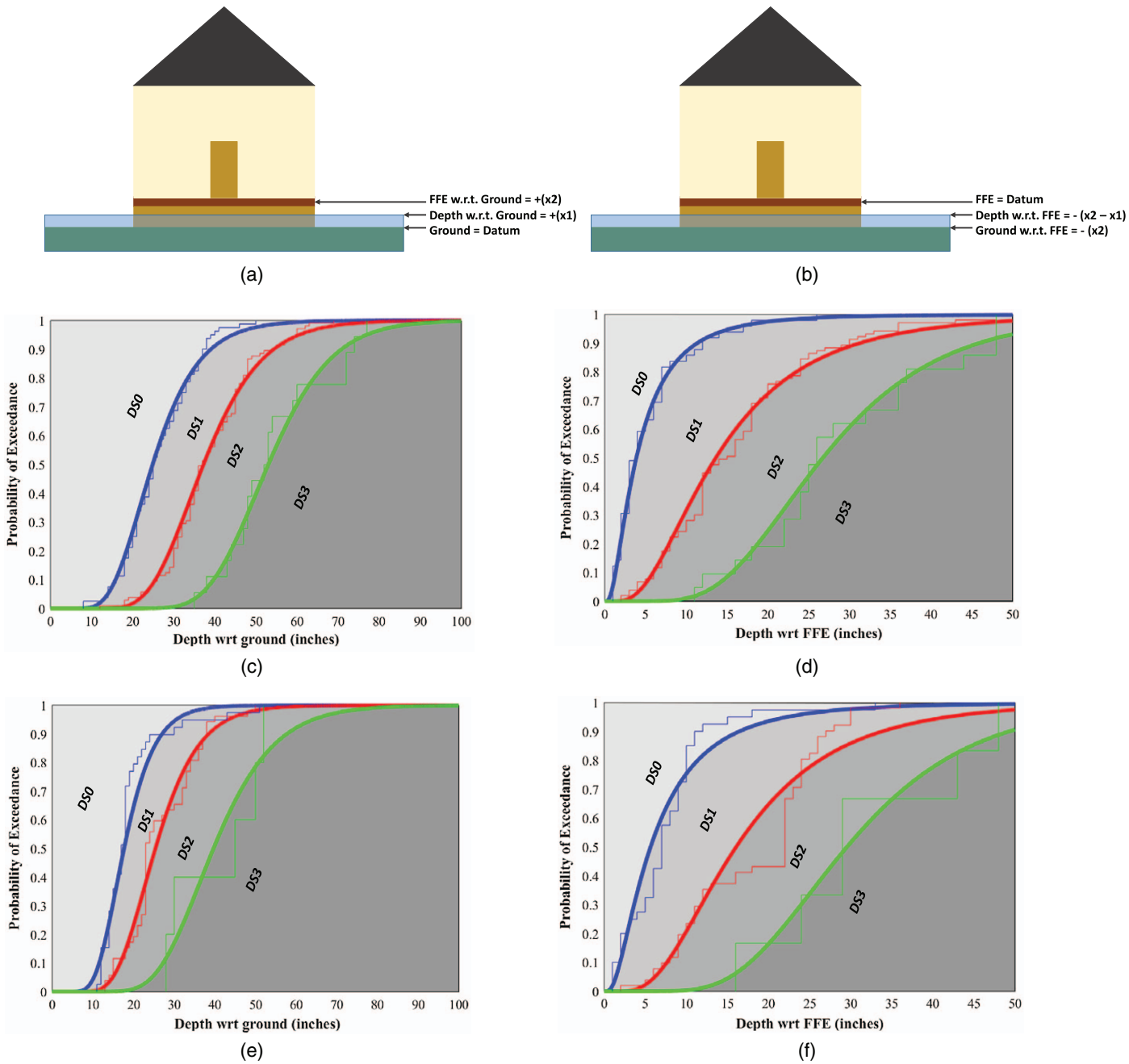

Fig. 5. (Color) Flood depth measurements taken in the field with respect to the (a) ground; and (b) first floor elevation (FFE), and associated fragility curves as a function of: (c) flood depth with respect to (w.r.t.) the ground for homes with crawlspaces; (d) flood depth w.r.t. the FFE for homes with crawlspaces; (e) flood depth w.r.t. the ground for homes with slabs-on-grade; and (f) flood depth w.r.t. the FFE for homes with slabs-on-grade [1 in. = 25.4 mm].

buildings with crawlspaces passed the K-S test. However, for buildings with slabs on grade, the Damage states 1 and 3 models passed the K-S test, but the Damage state 2 model did not pass the K-S test for the specified significance level. Accounting for the ground datum, for both buildings with slabs on grade and crawlspaces, models for all damage states passed the K-S test. Given the high degree of variability involved in damage evaluation, such as building properties, flood characteristics, and data collection variability (human error), and the fact that majority of the models passed the K-S test, the lognormal distribution was selected as appropriate for all data in the study. Therefore, the probability that the uncertain damage state, D, is greater than or equal to specific damage state, d, conditioned on the uncertain flood depth with respect to a datum, X, taking on flood height, x, is given

$$P[D \geq d|X = x] = F_d(x) = \Phi\left(\frac{\ln(x) - \lambda_d}{\xi_d}\right) \tag{1}$$

which is the fragility function of damage state, d, evaluated at x, and where x = water depth above the selected datum in inches [either FFE or the ground as shown in Figs. 5(a and b)]; λ_d = median capacity of homes to resist damage state, d, measured in units of flood depth, D; and ξ_d = standard deviation of the natural logarithm of the capacity of homes to resist damage state, d. In Eq. (1), Φ denotes the lognormal distribution.

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Table 2. Summary of lognormal fragility parameters

Datum	Damage state	Crawlspace Mean (λ)	Crawlspace Standard deviation (ξ)	Slab-on-Grade Mean (λ)	Slab-on-Grade Standard deviation (ξ)
FFE	DS1	1.36	0.84	1.73	0.83
	DS2	2.61	0.65	2.78	0.58
	DS3	3.29	0.42	3.39	0.40
Ground	DS1	3.21	0.35	2.87	0.33
	DS2	3.62	0.29	3.23	0.32
	DS3	3.97	0.22	3.68	0.29

The values of λ_d and ξ_d for each damage state (DS) considered in this study are given in Table 2 for buildings with slab-on-grade and crawlspace foundations. Using the cleaned set of data (excluding erroneous measurements or missing data fields), damage fragility functions were developed for the homes in the sample. The developed fragilities are shown in Figs. 5(c and d), for residential buildings with crawlspaces, and in Figs. 5(e and f), for residential buildings with slab-on-grade foundations for both datum considered in this study.

These probabilities of exceedance are shown in the shaded regions in between the fragility curves in Figs. 5(c–f). For example, buildings with slab-on-grade foundations that experience a flood depth of 508 mm (20 in.) with respect to the FFE have a 16%, 49%, 28%, and 7% probability of being in DS3, DS2, DS1, and DS0, respectively. It should be noted that no DS4 observations were reported for the inspected buildings with slabs, while only five cases of DS4 were reported for buildings with crawlspaces. Given the small sample and potential bias on data collection, DS3 and DS4 were merged into a single damage state, DS3+, and shown in the fragility functions as the exceedance probability of reaching DS3.

The damage fragilities, whose lognormal parameters are provided in Table 2, may be used to compare to building damage in other communities that experience riverine flooding events, with similar local conditions and building types, e.g., where flood velocity is not significant. Damage models, like these, can also be integrated with flood hazard models for life-cycle performance assessments of similar types of structures as a predictive tool in communities with similar construction practice.

It should be noted that the predominate damage-state ratings in Lumberton from flooding impacts due to Hurricane Matthew are the DS1 and DS2 levels, indicating minor to major damage particularly to the contents of these structures, but neither have substantial internal nor external (structural) impacts to the residence. It should also be noted that simply because a structure was rated at DS0, it does not necessarily mean that there was no damage. Particularly in structures with crawlspaces, a DS0 could mean that water did not touch floor joists, but damage could have occurred to central air-conditioning units directly placed on the ground and storage areas behind carports that may have contained hot-water heaters, and so forth.

Household Dislocation

As noted previously, in addition to gathering data to improve the technical basis of damage fragilities for residential buildings, one of the other objectives of the Lumberton field study was to collect data to improve household dislocation models. Household dislocation has become an increasingly pressing issue of concern in the United States, especially since Hurricane Katrina in 2005 (Weber and Peek 2012). As noted previously, the household survey instrument was designed to collect both direct and indirect information about household dislocation. In cases in which no household was present, household displacement information was obtained from neighbors, property managers, or by field team assessments as to whether the housing unit appeared to be occupied. Based on these direct (household interview) and indirect (neighbor/manager or field team assessments) data, determinations were made as to whether some household members were displaced or the entire household was dislocated. In general, as is often found in the disaster literature (Esnard and Sapat 2014; Fothergill and Peek 2015; Maghelal et al. 2017), households in Lumberton tended to dislocate as a unit when possible; rarely did only some members displace, leaving others at the home. Hence, the focus in the present study is on household dislocation. Based on direct information gained from the household itself and the most reliable indirect information obtained from a neighbor/manager, it was estimated that 69.8% (±4.3%) of surveyed households dislocated for at least some period of time due to the hurricane and subsequent flooding. If data based on survey team assessments is combined with the household and neighbor/manager data, the estimated household dislocation rate climbs slightly to 75.6% (±3.6%). The length of dislocation, for dislocated households, ranged between 1 and 61 days in which the maximum value was set by the fact that the interview team completed its survey work 61 days after the flood. Therefore, it is possible that with the second round of survey work, this maximum dislocation duration will be longer. Nevertheless, the average days of dislocation was 45.5 days (±2.3 days); however, considering only those households for which interview data were available, the average was 39.0 days (±2.9 days). On the whole, these data clearly suggest that dislocation impacted a substantial proportion of households in Lumberton, and for many households, this has been a protracted process.

Fig. 6 presents a map of Lumberton that includes the sampled housing units, the estimated dislocation status of households in the housing unit, the 100-year and 500-year flood zone, and predicted areas of inundation due to the Lumber river flooding. The red dots reflect housing units where households were dislocated, and green dots indicate housing units whose members did not dislocate. In general, as one would expect, dislocated households are more likely found in flood plain areas, particularly in areas estimated to have experienced inundation. Furthermore, it is also clear that there are high concentrations of dislocated households south of the Lumber River in areas that were supposed to be protected by the levee. The pie-charts display the percentage of sampled households dislocated both north and south of the river. It is also interesting to note that non-White households with both African Americans and Native Americans are disproportionately located in flood zones areas, particularly areas south of the river. Indeed, while only 18.7% of the Lumberton's White population that is located in the Junior High School attendance zone demarcated by the black boundary is located in the flood plain, 40.7 % of the non-White population located in the attendance zone is located in the flood plain.

As discussed previously, the literature on dislocation has noted that there are many factors that can influence dislocation. Damage to the housing unit is an expected driver of dislocation, with the general expectation being that higher levels of damage will force households to leave their homes for safety due to discomfort reasons. Tenure is another factor often cited. In general, renters have been found to dislocate at higher levels. Because renters do not own their home, they do not have the same levels of property rights and can be asked or forced to leave by the owners of the property who are potentially liable should the renters be hurt or somehow harmed by the damaged property or may simply want to affect repairs. Homeowners, on the other hand, own their properties and

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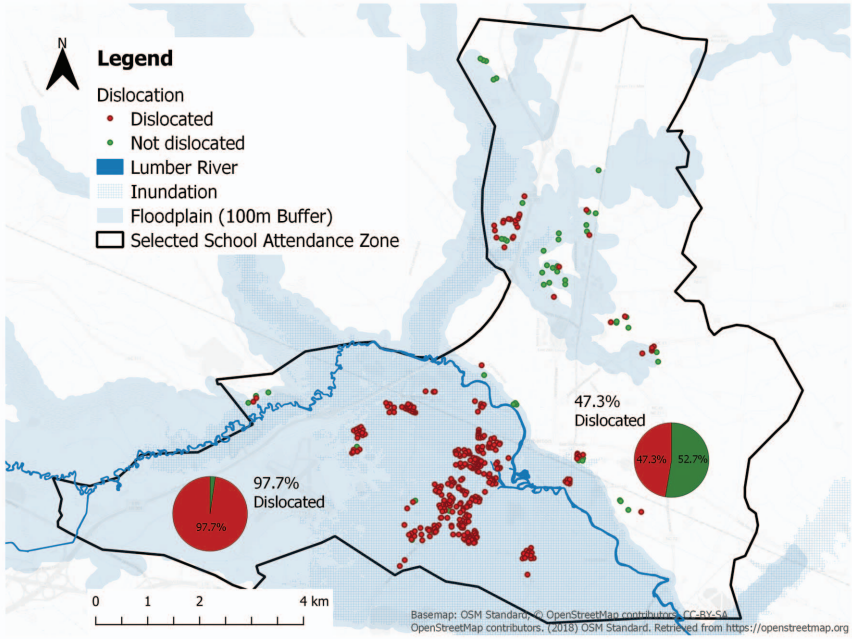

Fig. 6. (Color) Estimated dislocated status of households for sampled housing units.

tend to want to stay, even with badly damage property, although this is more likely the case with low income households that have fewer resources (Hamideh et al. 2018; Peacock et al. 2018). The literature has also shown that other factors, such as race/ethnicity, income, social networks, and discrimination, can also have consequences for dislocation (Esnard and Sapat 2014, 2017; Girard and Peacock 1997; Logan 2006).

Table 3 presents the results from three models predicting household dislocation. Model 1 employs only damage state data, with two binary variables indicating housing units at DS1 or DS2+. There were relatively few housing units at DS3 and DS4, hence they were collapsed into a single category capturing DS2 or above damage. Households located in housing units at DS0 serve as the excluded or comparison group. Model 2 adds household racial/ethnic variables in which binary variables capture non-Hispanic Black and Native American households, where non-Hispanic White households are the comparison group. Finally, Model 3 adds the percentage of rental housing units in the block where the housing unit is located as an indicator of the likely tenure of housing occupants. All models are statistically significant, with pseudo R^2s suggesting that the base model accounts for 25% of the variance, climbing to just over 31% in the final model. Logit coefficients are presented in the shaded rows, and the coefficients representing the change in logged odds are presented in the unshaded rows. The standard errors were estimated using a robust estimation to account for mixing individual and block measures in the equations.

The results from Model 1, not unexpectedly, suggest that households located in structures with higher damage states are more likely to dislocate. Households in homes classified as DS1 have odds of dislocating nearly 12 times higher than households in DS0 structures, and those in DS2+ were nearly 61 times more likely to dislocate. These changing odds can clearly be seen in Fig. 7, which displays the predicted dislocation probabilities of households living in housing units with different damage states. At DS0, the probability of dislocation is approximately 0.38 with a margin of error

Table 3. Logistic regression results predicting household dislocation

Independent variables	Model 1	Model 2	Model 3
Constant	-0.49^{**}	-1.08^{**}	-1.46^{**}
	0.61	0.34	0.23
Damage state 1	2.47^{**}	2.18^{**}	2.20^{**}
	11.88	8.86	9.04
Damage state 2+	4.10^{**}	3.83^{**}	3.88^{**}
	60.62	46.09	48.58
Non-Hispanic black	—	1.10^{**}	0.98^{**}
	—	3.00	2.67
Native American	—	1.66^{**}	1.79^{**}
	—	5.25	6.00
Proportion renters	—	—	1.06^{*}
	—	—	2.88
Log likelihood	−99.0973	−93.0922	−91.3985
χ^2	32.97^{**}	44.72^{**}	43.25^{**}
Pseudo R^2	0.2532	0.2984	0.3112
AIC	204.2	196.2	194.8

Note: ** = two tail significance at ≤0.05; * = one tail significance at ≤0.05; and $N = 195$.

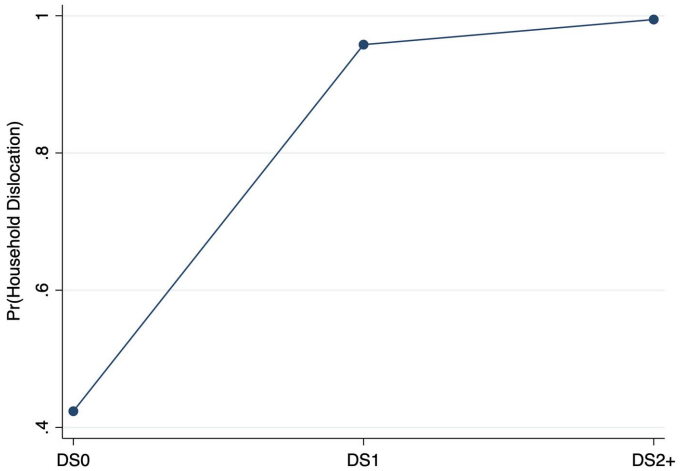

Fig. 7. Probability of household dislocation by different damage states.

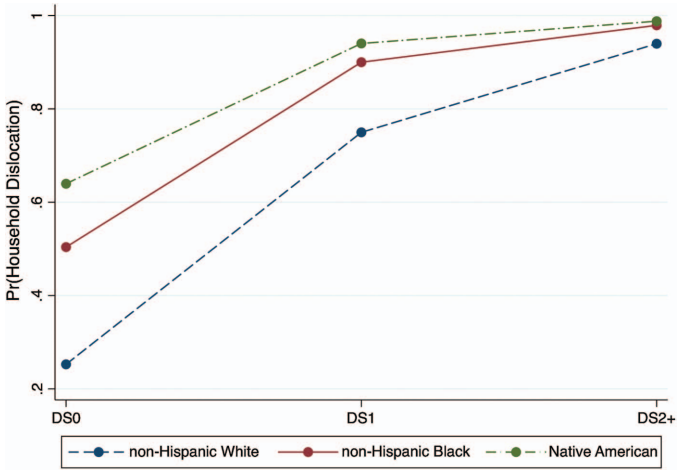

Fig. 8. (Color) Probability of household dislocation by damage state and race/ethnicity.

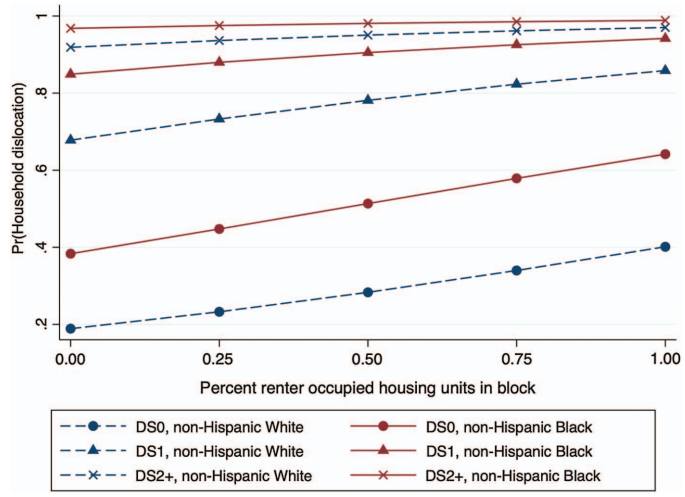

Fig. 9. (Color) Probability of household dislocation by damage state, race/ethnicity, and tenure.

(MoE) of ±0.09, at DS1 the probability rises to 0.88 (MoE of ±0.11), and at DS2+, it is 0.97 (MoE of ±0.05). As can be seen in Model 2, when household race/ethnic indicators are added to the equation, there is an attenuation in the odds associated with the two damage states, when compared to Model 1, but both minority households, non-Hispanic Black and Native American, have statistically significant elevated odds of dislocation when compared to non-Hispanic White households. The odds for non-Hispanic Black households are approximately three times the odds of non-Hispanic White households, and for Native American households, the odds are approximately five times the odds of non-Hispanic White households. These differentials are illustrated in Fig. 8, which presents the probabilities of dislocating at each damage state for each type of household. The navy-blue dashed line is for non-Hispanic White households, the maroon solid line for non-Hispanic Black households, and the green dash-dot line for Native American households. Again, we see higher dislocation probabilities as the damage state increases, but consistently non-Hispanic White household probabilities are the lowest, with Native American households having the highest probabilities and non-Hispanic Black households falling in between. It should be noted that the probabilities of all three types of households converge with higher levels of damage, and there are not statistically significant differences between the two minority households.

In the final model of Table 3, the percent renter in the block where the housing unit is located is included as an indicator for likely tenure status of households within the block. As noted previously, the literature has generally found that renters dislocate at higher rates than do homeowners, hence the expectation would be that this measure should have a positive effect on dislocation, which indeed we see in the model. For ease in readably, Fig. 9 displays the predicted probabilities for non-Hispanic White and Black households, at each damage state, for various proportions of rental units on the block. The color scheme is similar to Fig. 8, with non-Hispanic Whites displayed in a dashed navy-blue line and non-Hispanic Blacks in a solid maroon line, but now the lines with circles are for DS0, triangles for DS1, and Xs for DS2+. The same pattern is observed with non-Hispanic Whites having the lowest dislocation probabilities and non-Hispanic Black households having higher probabilities regardless of the damage state or proportion renters within the block. If the probabilities for Native American households were displayed, they would have the highest probability among ethnic/racial groups at each damage state and renter proportions. However, now we see that probabilities increase with the proportion of renters on the block, indicating that as the percent of renters increases, and hence the likelihood that the household is a renter household, the higher the dislocation probability.

Discussion and Future Directions

At the core of this interdisciplinary field study is the ability to fully integrate the physical building damage data with the socioeconomic demographics on households—specifically, to better understand how the combination of measurable parameters (e.g., building damage state, tenure, and race/ethnicity) affect their probability of dislocation following a disastrous event, such as the flooding associated with Hurricane Mathew in Lumberton. In order to understand how these physical and nonphysical parameters affect households, this study first considered them independently.

The building damage fragilities can be further used to predict damage states, i.e., provide a probability of a building being in or exceeding each damage state as a function of flood depth with respect to a specified datum (either FFE or ground), for wood, light-frame residential single and multifamily buildings in North America. Although it may be possible to further subdivide the damage data, given the size of the data set, this is not recommended because only the uncertainties in the data collection methodology, and not uncertainties in construction quality or modeling moving forward, are included in the lognormal standard deviations. It is also important to note that the developed fragilities should only be used for static or slow-moving flood waters because these were the conditions that occurred in Lumberton. These fragility functions are an important contribution to the literature to help predict residential damage during flooding events.

Preliminary findings also suggest that not only damage but also race/ethnicity and tenure status improve the ability to predict dislocation. The findings suggest that households in structures rated as DS1 were nine times more likely to dislocate than were households in structures rated as DS0, and those in structures rated DS2 or higher were nearly 50 times more likely to dislocate. However, even after controlling for the damage state, non-Hispanic Black households were 2.7 times more likely to dislocate when compared to non-Hispanic White households. Similarly, Native American households were six times more likely to dislocate than non-Hispanic

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White households. It should be noted that the overall probabilities of dislocation rose and converge across all groups with higher levels of damage, but there were significant and pronounced differentials at lower levels of damage. The analyses also suggest that housing in areas with higher percentages of rental housing had higher probabilities of dislocation as well after controlling for damage and race/ethnicity factors.

Our results suggest that goals of combining both engineering-based damage assessment data, along with measurable socioeconomic and demographic data, will allow improvement in the modeling of important dimensions of community resilience, such as household dislocation in the wake of natural disasters. As this longitudinal study progresses, refined damage and dislocation models will be created for residential buildings to better capture the performance and impacts of flood events, respectively. There are, of course, many issues that arise with applying these epistemic probabilities based on a single case study for applications in other situations. However, it should be recalled that current practice, for those employing the HAZUS-MH dislocation algorithms for example, are based on the limited observational data undertaken after the Northridge earthquake and expert opinion (DHS-FEMA 2009). Therefore, by developing postdisaster survey techniques that will allow for more representative data collection in which state-of-the-art engineering and social science survey techniques are coupled, a host of post event data collection field studies will generate data and, subsequently, findings that can be combined to develop more robust and generalizable models upon which to base future algorithm development.

The preliminary success at integration in this study suggests future possibilities of capturing the complexities of recovery trajectories of households based upon a combination of measurable parameters (e.g., housing repairs, financial assistance, race/ethnicity, insurance, and income). In order to capture recovery data, community resilience is best understood and studied over time in a series of field studies. As such, this is the first of a series of field studies for Lumberton by the CoE and NIST. The concept of a longitudinal field study is that the same cases will be observed over time to track changes, both positive and negative, in the postdisaster experience of a community and its constituent parts—households, schools, businesses, buildings, and supporting infrastructure. Because the social impacts of a disaster unfold slowly, longitudinal studies provide a mechanism of tracking the same variables through time using standardized data collection instruments. In addition, the ability to document disaster impacts to a local community, including population loss/gain, business disruption, housing recovery, and financial loss, requires the assessment of change over time. Thus, the interdisciplinary CoE/NIST research team expects to study Lumberton over a duration of 5 (or more) years, and business disruption, public housing, and potentially other important community components of recovery will be added to the data collection investigation. The team hopes that the findings of this and similar research can help guide and shape future policies to help create more disaster resilient communities.

Data Availability Statement

Some or all data, models, or code generated or used during the study are proprietary or confidential in nature and may only be provided with restrictions (e.g., anonymized data). This includes the following:

1. All damage data at a level of detail in which individual houses can be identified.
2. All household survey data at a level of detail in which individuals and their responses to any survey/interview questions can be identified.

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Disclaimers

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4. All maps in the report, except where noted, were created using ESRI ArcGIS version v10.4.

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