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Measuring post-disaster accessibility to essential goods and services: proximity, availability, adequacy, and acceptability dimensions

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Abstract

Rapid restoration of access to essential goods and services has long been regarded as paramount for community recovery. Yet, there remains ambiguity in how access should be defined, measured, or operationalized. Defining accessibility as the ability to use available goods and services with a reasonable level of effort and cost requires evaluating it across six dimensions (*proximity*, *availability*, *adequacy*, *acceptability*, *affordability*, and *awareness*) while considering the perspective of both users and providers in the evaluation. But common distance-based metrics that focus solely on physical access and travel time often fall short of fully capturing these requirements, overlooking the user's perception. This paper introduces a new spatio-temporal accessibility metric that combines four out of these six dimensions, including proximity, acceptability, adequacy, and availability. The metric considers uncertainty in measuring each dimension and addresses both user and provider perspectives in measuring the acceptability and adequacy dimensions. The variation in the metric across the disaster timeline serves as a proxy for community recovery. The metric aligns with common engineering-oriented functionality-based resilience frameworks as the functionality level of the providers has been incorporated in its development. Operating at the household level, the metric determines the ratio of post-disruption access time to the intended good or service against its pre-disruption access time and yields a unitless ratio between zero and one, with zero expressing a total loss in accessibility and one signifying the same level of accessibility as pre-disruption. The proposed metric, while being scientifically principled, is a practical tool whose output is easily understood even by non-expert individuals. The metric is illustrated for schools and pharmacies using the Lumberton Testbed and data collected following the 2016 flood in Lumberton, North Carolina after Hurricane Matthew. Findings provide new insight into recovery plan prioritization and can be used to trigger protective actions. The paper concludes by discussing issues and barriers related to developing and validating accessibility metrics while highlighting areas for future research.

Keywords Accessibility, Education, Pharmacy, Community resilience, Virtual testbeds

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Introduction

Conceptualizing and measuring community members' access to goods and services that address their needs is a classic, but still developing field of research that has been approached from multiple perspectives (e.g., urban planning, social justice, equity, and equality), in different contexts (e.g., education, public health, community resilience), and various scales (e.g., federal, state, and local) [1–15]. These studies, collectively, have provided the foundation for advancing the state of knowledge on quantifying access. Even still, in the context of community resilience, more research is needed to advance the measurement of access beyond simply physical access. There is no doubt that access to goods and services such as sustenance, education, healthcare, and recreation, in addition to shelter and typical critical infrastructure, is crucial for communities to function [12]. Lack of access to such essential goods and services disrupts the quality of life and may lead to permanent relocation [16]. To improve resilience, communities need to ensure that *organizations* providing essential *products* become functional within a reasonable period following disruptions and are capable of supplying sufficient and acceptable amounts of their offerings to the community [17]. Here, the term *product* captures both goods and services, either tangible or intangible, offered by organizations to satisfy a want or need [18] and the term *organization* is used to refer to any entity in the community providing products, including but not limited to, social institutions (e.g., schools and healthcare facilities), non-profit organizations, and for-profit businesses. This terminology sets the focus on the users and products of organizations, rather than their social and commercial aspects [17].

The concept of access has not been precisely defined and is somewhat ambiguous in community resilience literature. Access is typically characterized by the presence of physical access to a functional organization [9], excluding the user's perception from the definition of functionality [17]. Functionality-focused community resilience frameworks have predominantly adopted this provider-centered definition of access and utilized distance-based indicators, such as travel time, to quantify it [19–22]. Physical access and functional organization are necessary components of access, representing the potential of use [23]. However, the presence of these two components does not guarantee actual use or realized access, as the user's perception is overlooked. Social norms and stigmas, cultural and religious beliefs, and economic constraints are a few examples of users' perceptions that can prevent realized access, even though the resource is functionally available and physically accessible. Realized access, referred to herein as "accessibility", occurs when community members are able to use products offered by functional organizations.

From a comprehensive literature review across various disciplines, Logan and Guikema [9] concluded that accessibility needs to be evaluated across six different dimensions. The six dimensions are *proximity*, *availability*, *adequacy*, *acceptability*, and *affordability*, originally introduced by Penchansky and Thomas [7], as well as *awareness*, which was later appended to the first five by Saurman [6]. Together, these six dimensions, termed herein as "PA5", are capable of capturing the user's perception alongside the provider's perspective regarding the accessibility of a product. However, in *demonstrating* their proposed equity-based community resilience assessment framework, Logan and Guikema [9] exclusively utilized proximity to measure accessibility, omitting the measurement of other dimensions due to constraints in existing research. Taking only physical access and distance into account, proximity implies the spatial distribution of access across the population and may serve as a proxy for ease of use in a non-remote environment [23, 24]. However, proximity is not applicable for measuring accessibility in virtual or remote environments.

In practice, assessing accessibility across the PA5 dimensions requires the definition of an indicator for each dimension alongside the establishment of a normative threshold for each indicator. These indicators and their thresholds should be determined through community engagement and considering the community's social, cultural, and financial characteristics [25]. For example, the proximity dimension can be indexed using the travel distance, which takes physical access and distance into account, or the travel time, which in addition to physical access and distance, considers the transportation mode, reflecting the specific characteristics of the community. Thus, in communities with high vehicle ownership rates, the proximity can be measured based on driving time. Conversely, in communities where vehicle ownership rates are low, the proximity might be measured based on walking time or public transportation routes. Once the appropriate indicator is chosen, the normative threshold needs to be determined through community engagement, ensuring it aligns with the community's characteristics and reflects the actual needs and expectations of the community members. Of note, the way PA5 dimensions would be indexed may also be product-specific. For example, while the acceptability dimension from the provider's perspective pertains to the product's quality and suitability, the measurement indicators differ when assessing accessibility to distinct products, such as education and sustenance. In the case of education, the acceptability dimension might be quantified through an indicator such as the student–teacher ratio, whereas for sustenance, acceptability could be indexed by the availability of diverse food groups.

We define accessibility to essential goods and services as the *ability to use available products by community members with reasonable effort and cost to meet an essential need*. This definition bridges the gap between the community's social, cultural, and economic characteristics with conventional functionality-focused community resilience frameworks. While these frameworks are grounded based on the provider's perspective and primarily address the physical access and functionality of the organization, our definition spans a broader spectrum and incorporates the user's perception. The proposed definition also aligns with the six dimensions of accessibility introduced by Logan and Guikema [9]. Evaluating access across proximity, adequacy, acceptability, and awareness dimensions ensures that only a reasonable level of effort is needed to use the available product. Affordability certifies that the product is available for use at a reasonable cost.

This paper provides a means to measure accessibility in community resilience contexts, drawing upon the proposed definition of accessibility and leveraging the PA5 dimensions, with a specific focus on proximity, availability, acceptability, and adequacy. Acknowledging the importance of evaluating accessibility across awareness and affordability dimensions, the integration of these dimensions into the measurement tool is under investigation by the authors and is out of the scope of this paper. As such, the remainder of this paper is structured as follows: "Organizational functionality, accessibility, and community resilience" section first elaborates on quantifying the functionality of organizations. It reconciles organizational functionality with four out of the six accessibility dimensions (proximity, availability, acceptability, and adequacy) and explains how accessibility will be integrated into a functionality-focused community resilience model. Following this, "Quantitative metrics of accessibility to essential goods and services" section introduces two quantitative metrics for measuring temporally varying, multi-dimensional accessibility. In "Illustrative example using the Lumberton testbed" section, these metrics are illustrated for pharmacies and schools using the data collected through a longitudinal field study following the 2016 catastrophic flooding in the city of Lumberton, North Carolina after Hurricane Matthew. The computational results demonstrated that, even 15 months after the flood, 8.1% of households and 20.6% of students still did not have the same level of accessibility to tangible pharmacy products and intangible education services, respectively. These findings align with the results from the housing surveys conducted during the longitudinal study. The paper concludes in "Discussion and conclusions" section with a discussion of our findings during the development of accessibility metrics, insights from the quantitative study, potential remedies for addressing the challenges we faced, and explores areas for future research on incorporating accessibility in community resilience frameworks. These metrics can serve as a predictive tool, enabling community decision-makers to assess the effectiveness of their resilience strategies and prioritize recovery efforts solely through the lens of access among different community members. For the reader's convenience, a comprehensive table of all variables used throughout this paper is provided in Appendix.

Organizational functionality, accessibility, and community resilience

Organizational functionality

Organizational functionality refers to "the quality of the performance of an organization and its ability to be used for its intended purposes", and it is restored through five discrete states after a disruption [17]. These states include Out of Service, Intrinsically Operable, Fully Operable, Minimum Acceptable Level Functionality (MALF), and Fully Functional. The states are listed in increasing order, with the percentages corresponding to Fully Functional and Out of Service states set at 100% and 0%, respectively. Most, if not all, organizations provide multiple products to their customers. To characterize post-disruption organizational functionality states, Enderami et al. [17] distinguished primary products from secondary products. Primary products are the main objective and intended purpose of an organization; any other offered product(s) are denoted as secondary products. The availability of the primary product is an indispensable but insufficient factor to deem an organization functional. For example, motor fuel is the primary product of a gas station whereas snacks and a carwash may serve as secondary products. A gas station without gas is never deemed functional. However, a gas station with an out-of-service carwash can still be considered functional as long as it continues to serve its primary purpose of providing fuel at an acceptable and adequate level. Thus, just availability of the primary product indicates that the organization is fully operable, but it is not sufficient for the organization to be deemed functional. Instead, the primary product must be available at an acceptable and adequate level, ensuring a lower threshold of functionality, which is MALF. In this case, some or all of the secondary products are still not available at an acceptable and adequate level. If a functional organization's secondary products become available at an acceptable and adequate level, then it is considered Fully Functional according to Enderami et al. [17].

Using a Fault Tree model, Enderami et al. [17] identified essential components contributing to the availability, acceptability, and adequacy of primary products within an organization. Physical space components (structural or non-structural), physical access, utilities, staff, and supply chain are introduced as general components crucial for organizational functionality in non-remote environments. The COVID-19 pandemic has shown that many organizations can operate remotely. In a remote environment, the essential components evolve, and organizational functionality may no longer depend on the original physical access and space, yet accessibility is still important.

Then, by quantifying the probability of an organization becoming functional within a specific timeframe following a disruption, Enderami et al. [17] proposed estimating the expected capacity of an organization at a given time after a disruption as:

$$C^a(t) = Q(t) \times C^b \times \left[\frac{L_3 - L_2}{100 - L_2}\right] \quad (1)$$

where $C^a(t)$ is the expected capacity of the organization at time t after a disruption, and C^b is the pre-disruption capacity of that organization. The remaining parameters in Eq. (1) are defined as follows: $Q(t)$ denotes the probability that the organizational functionality level is equal to or greater than the MALF before t; L_2 and L_3 represent percentages corresponding to Fully Operable and MALF states, respectively. The values of L_2 and L_3 are specific to each organization and should be determined considering the role that organization plays within the community. More details about post-disaster functionality states, $Q(t)$, L_2, and L_3 can be found in Enderami et al. [17].

Reconciling accessibility and organizational functionality for community resilience

Three of the PA5 dimensions, including *availability*, *adequacy*, and *acceptability*, directly relate to an organization's functionality; a fourth, *proximity*, is indirectly related as follows: a functional organization ensures the primary products offered by that organization are available at an acceptable and adequate level. Thus, the provider's perspective on the adequacy and acceptability dimensions is already taken into account when measuring accessibility to a functional organization; still, it is essential to include the users' perception of these two dimensions. We, herein, propose to adapt Eq. (1) to capture users' perception of the adequacy of the product and tailor it to organizational functionality. Equation (1) is a functionality-based expression that estimates the expected capacity of an organization post-disruption. A decrease in an organization's post-disruption capacity may require users to exert additional effort to use the offered product and meet an essential need. This additional effort may affect the user's perception of the adequacy of the product and is not taken into account by common functionality-focused accessibility frameworks. Finally, availability and physical access go hand-in-hand, where physical access is needed to measure *proximity*.

Given that organizational functionality varies across the disaster timeline, changes in community members' accessibility to essential products can be evaluated before and at any time after a disruption. As discussed earlier, to move towards resilience, community members must have access to essential products within the timeframe specified in the community's recovery and mitigation plan. This opens up the opportunity to use accessibility metrics as a means for assessing the resilience of that community.

Quantitative metrics of accessibility to essential goods and services

This section presents two novel metrics for evaluating accessibility to tangible and intangible goods and services as a function of time. The metrics operate at the household level and are intended to be measured within and across a given community. The metrics quantify the ratio of access time to the product at a specific time post-disruption against its pre-disruption time. This means we presume the pre-disruption accessibility level of every household to the desired product as the standard to evaluate accessibility, and then measure post-disruption accessibility against this standard. While lying outside the scope of this current work, we recognize that this assumption skips the opportunity of leveraging the disaster recovery window to rebuild a more resilient community and address pre-existing accessibility disparities; acknowledging this limitation opens the door for future research on developing more inclusive metrics. To simplify the development process, we also normalized the pre-disruption accessibility for any variations before the disruption and ignored any temporary or long-term gain or loss in post-disruption accessibility, referred to as service equilibrium shift by Davis [26]. The metrics yield a unitless ratio between zero and one, with zero representing a complete accessibility loss and one indicating the same level of accessibility as pre-disruption. These metrics are aligned with the proposed definition of accessibility and summarize multiple dimensions of access, as far as data limitation allows. Of note, a zero value of the accessibility metric does not necessarily indicate that the product is unattainable. Instead, it signifies that the product is no longer available with reasonable effort and cost. Metric values of less than unity represent decreased levels of accessibility, suggesting a higher level of effort and cost compared to the pre-disruption state for attaining the product. This indicates that the product is not as accessible as it was before (closer to one), nor is it exceptionally unreasonable and expensive to attain (closer to zero). The metric enables its users to determine a value of less than one as an acceptable threshold for accessibility, as standards, expectations, and user satisfaction can vary depending on the community's characteristics and situation.

Accessibility to tangible products

The first metric provides a measurement of accessibility to tangible products. Examples of tangible products include fuel from gas stations and groceries from grocery stores. The access time to tangible products provided by an organization is comprised of the *travel time* to where the organization is located, and the time required to receive the desired product. Time to receive is referred to herein as *response time*. For each community member, accessibility to tangible products at time t after the disruption can be estimated as:

$$\Delta A_T(t)=\frac{AT^{max}-AT_T^a(t)}{AT^{max}-AT_T^b}\geq 0 \tag{2}$$

where AT^{max} is the maximum threshold for reasonable access time to receive the intended product, $AT_T^a(t)$ represents the access time to the tangible product at time t after the disaster, and $AT_T^b(t)$ is the access time to that tangible product during the normal period before the disruption. Of note, $\Delta A_T(t)$ is a non-negative value; thus, if $AT_T^a(t)$ exceeds AT^{max}, the $\Delta A_T(t)$ will be forced to zero, indicating a complete accessibility loss. This means that whenever the calculated post-disruption access time surpasses the defined maximum threshold (AT^{max}), the product is no longer available with reasonable effort. The proposed metric captures how accessibility to the intended tangible product changes across the disaster timeline within a community.

The value of AT^{max} may vary based on the characteristics of a community. For example, the usual travel time to a grocery store in a rural community may be longer than its maximum reasonable threshold in an urban area. Assuming that the maximum reasonable threshold for travel times is equal to the mean of travel time to all organizations providing the intended product in the study area before the disruption, AT^{max} can be estimated using

$$AT^{max}=T_{tr}^{ave}+RT^b \tag{3}$$

where T_{tr}^{ave} represents the mean of drive time to all organizations providing the intended product in the study area before the disruption and RT^b is the usual response time in the target community before the disruption.

To estimate the access time to the intended product during normal times and in the aftermath of the disaster, the travel time to the nearest MALF organization providing that product is used, thus, AT_T^b and $AT_T^a(t)$ can be calculated as:

$$AT_T^b=T_{tr}^b+RT^b \tag{4}$$

$$AT_T^a(t)=T_{tr}^a(t)+RT^a(t) \tag{5}$$

where T_{tr}^b and T_{tr}^a represent the travel time to the nearest MALF organization providing the desired product before the disruption and at time t after the disaster, respectively, RT^b indicates the usual pre-disruption response time in the target community, and $RT^a(t)$ is the response time at the nearest MALF organization at time t after the disaster.

Assuming there is no waiting line to receive the product before the disruption, we set the pre-disruption response time equal to the service time (ST_0), which represents the typical duration taken by the organization to provide its product to the customer under normal circumstances. There is no doubt, in real-world communities, the nearest organization is not necessarily the organization a given household will use. However, taking the nearest organization is felt to be an admissible assumption herein, as this presumption is applied to measure accessibility at both pre- and post-disruption times. A conceptual illustration of the parameters that are used to develop the metric for evaluating accessibility to tangible products within a community is shown in Fig. 1. The stick-figure icon shown in Fig. 1 signifies arriving customers, whereas the cross mark and check mark icons symbolize customers waiting in line and departing customers, respectively.

Both travel time and response time may vary across the disaster timeline and be different from corresponding pre-disruption values. As shown in Fig. 1, as the disaster occurs, the travel time to the nearest MALF organization providing the intended product is likely to increase due to disaster-induced disruption in the community road network, among other disaster-prompted supply and demand issues. Inside the MALF organization, the response time, $RT^a(t)$, might also be prolonged due to a loss of functionality (e.g., staff shortage) and/or an increase in product demand (e.g., customers). As shown in Fig. 1, after a disruption, it becomes very likely that newly arriving customers will have to wait in line. In light of Queuing Theory [27], the response time is associated with service time (ST_0). Thus, using the fundamentals of Queuing Theory, we estimated the $RT^a(t)$ as:

$$RT^a(t)=ST_0\left[\exp\left(2.5\times\frac{C^b-C^a(t)}{C^b}\right)\times\left(2.55\times\frac{D^a(t)}{D^b}-1.55\right)\right] \tag{6}$$

where ST_0 represents the service time, $C^a(t)$ and $D^a(t)$ are, respectively, the expected capacity of the intended organization and product demand at time t after the disruption, C^b is the pre-disruption capacity, and D^b

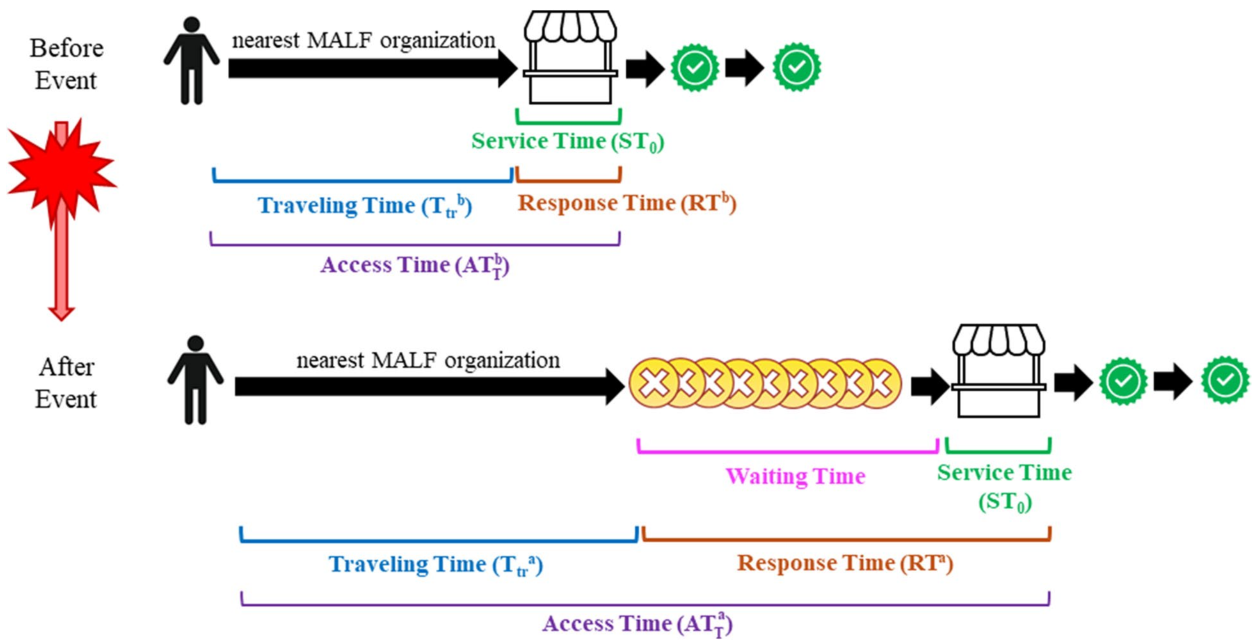

Fig. 1 Conceptual illustration of quantifying accessibility to tangible products

represents the pre-disruption product demand for that organization. Of note, the $RT^a(t)$ is assumed to be always longer or equal to RT^b. Thus, the ratio of $D^a(t)$ to D^b in Eq. (6) must be set to one if the product demand decreases at the post-disruption time. The exponential form of the $RT^a(t)$ function signifies that the response time grows without any upper bounds as the demand-to-capacity ratio approaches one, indicating an unstable queue condition.

The amount of $C^a(t)$ depends on the intended organization's functionality level and can be estimated using Eq. (1). Then, by combining Eqs. (1) and (6) and inserting ST_0 into the developed formulas, Eqs. (3), (4), and (6) can be rewritten as:

$$AT^{max} = T_{tr}^{ave} + ST_0 \tag{7}$$

$$AT_T^b = T_{tr}^b + ST_0 \tag{8}$$

$$AT_T^a(t) = T_{tr}^a(t) + ST_0\left[\exp\left(2.5 \times \left(1 - \left\{Q(t) \times \frac{L_3 - L_2}{100 - L_2}\right\}\right)\right) \times \left(2.55 \times \frac{D^a(t)}{D^b} - 1.55\right)\right] \tag{9}$$

where all parameters are as defined earlier.

The metric developed in this section ($\Delta A_T(t)$) combines four of the PA5 dimensions. The *proximity* and *availability* dimensions are considered through the travel time to a MALF organization (T_{tr}^b and $T_{tr}^a(t)$). The inclusion of MALF organizations also accounts for the *adequacy* and *acceptability* dimensions from the product provider's perspective. The users' viewpoint on the *adequacy* dimension is regarded by incorporating the adverse effects of decreased organizational functionality ($Q(t)$) and increased product demand () into post-disruption response time ($RT^a(t)$) and defining a maximum reasonable threshold for access time (AT^{max}). Finally, users' view on the *acceptability* is addressed by comparing the metric value with the predetermined threshold.

Accessibility to intangible products

The second metric calculates accessibility to intangible products, which include organizations such as hospitals which provide inpatient services, and schools which provide education services. The time to access intangible products provided by an organization can be calculated by subtracting the travel time to where the organization is located from the time devoted exclusively to the recipient of the intangible product by that organization. The latter is termed *individual attention time* (*IAT*). For example, doctor-to-patient and bed-to-patient ratios are often major factors affecting *IAT* for inpatient care in healthcare facilities, whereas teacher-to-student and desk-to-student ratios are the primary factors governing *IAT* for education services in schools.

For each community member, accessibility to intangible products at the time t after the disaster can be estimated as:

$$\Delta A_I(t) = \frac{AT_I^a(t) - AT^{min}}{AT_I^b - AT^{min}} \geq 0 \tag{10}$$

where is the access time to the intangible product at time t after the disaster, is the access time to that intangible product during the normal period before the disruption, and AT^{min} represents the minimum threshold for reasonable access time to receive the intended product. Similar to the metric for tangible products, is a non-negative value. Thus, if falls short of AT^{min}, the will be forced to zero, indicating a complete accessibility loss. This means that if the calculated post-disruption access time fails to meet the defined minimum threshold (AT^{min}), the product is no longer available with reasonable effort and cost.

The values of and are calculated as

$$AT_I^b = IAT^b - T_{tr}^b \tag{11}$$

$$AT_I^a(t) = IAT^a(t) - T_{tr}^a(t) \tag{12}$$

where T_{tr}^b and $T_{tr}^a(t)$ represent the travel time to the nearest MALF organization providing the desired product before the disruption and at time t after the disaster, respectively, IAT^b is pre-disruption individual attention time estimated for the organization providing the intended intangible product before the disruption, and $IAT^a(t)$ is post-disruption individual attention time estimated for the organization providing the intended intangible product at the time t after the disruption.

The travel time to the nearest MALF organization providing the intended intangible product is likely to increase after a disruption. Furthermore, the post-disruption individual attention time of that MALF organization, $IAT^a(t)$, might be shortened due to similar reasons that prolong response time for tangible products. Thus, the individual attention time needs to be updated across the disaster timeline to address the effects of a probable increase in product demand and a likely reduction in the organization's functionality.

To estimate the minimum threshold for reasonable access time to the intended intangible product, AT^{min}, the mean of travel time to all organizations providing that product in the study area before the disruption is subtracted from the minimum reasonable individual attention time as follows:

$$AT^{min} = IAT^{min} - T_{tr}^{ave} \tag{13}$$

where is the mean of pre-disruption drive time to all organizations providing the intended intangible product in the study area before the disruption, and IAT^{min} represents the minimum reasonable individual attention.

The metric developed in this section (AT_I^b) enables assessing the accessibility to any intangible product within the community across the disaster timeline. Like the metric developed for calculating accessibility to tangible products ($\Delta A_T(t)$), the combines four of the PA5 dimensions. The *proximity* and *availability* dimensions are considered through the travel time to a MALF organization (T_{tr}^b and T_{tr}^a). The inclusion of MALF organizations also accounts for the *adequacy* and *acceptability* dimensions from the product provider's perspective. The users' viewpoint on the *adequacy* dimension is incorporated into post-disruption individual attention time through the adverse effects of decreased organizational functionality ($Q(t)$) and increased product demand (), alongside considering a minimum reasonable threshold for access time. In addition, it is possible to evaluate the users' perception of the *acceptability* dimension by comparing the metric value with a predetermined threshold.

As uncertainty is unavoidable in dealing with real-world variables, it is essential to take it into account when computing the accessibility metrics through a functional relationship. Uncertainties in the input variables such as service time, pre- and post-disruption demands, capacities, and travel time, propagate through the computing process and lead to uncertainty in the resulting metrics. Various mathematical approaches exist for incorporating uncertainty into functional relationships, and the choice of method should be in line with the desired level of confidence in capturing uncertainty. Of note, due to the complexity and difficulty in quantifying uncertainties associated with some variables, comprehensive uncertainty assessment may be computationally expensive and pose mathematical challenges. Estimating travel time, for example, involves considering several sources of epistemic and aleatory uncertainties, however, incorporating these uncertainties can significantly increase the computation efforts. Therefore, when utilizing these new metrics, one should determine the uncertainties to incorporate and accordingly select the appropriate method for uncertainty quantification based on needs and acceptable preferences. In this paper, we employ the Monte Carlo simulation method [28, 29] to quantify and propagate uncertainty in the accessibility model, and use expected values to interpret results in the illustrative example in "Illustrative example using the Lumberton testbed" section. The expected value is the average of multiple possible outcomes given a Monte Carlo simulation with a prescribed stopping rule. It is a common tool for interpreting the results when dealing with uncertainty, as it simplifies the results into a single value that represents the characteristics of the outcome. Of note, due to incorporating uncertainty into the process, an expected value of less than one may still represent the same level of accessibility as pre-disruption. Therefore, users should find a threshold for the expected value of accessibility corresponding to one on the deterministic metric. This threshold depends on the level of uncertainty included in the process.

Illustrative example using the Lumberton testbed

To demonstrate the practical implementation of the metrics introduced in "Quantitative metrics of accessibility to essential goods and services" section, the metrics were utilized to assess accessibility to products offered by pharmacies and schools within the Lumberton Testbed after a catastrophic flooding event. Pharmacies and schools were selected here given that they exemplify two critically important types of products offered in a community. As a business, pharmacies provide tangible goods, including prescription and non-prescription medicines, and often groceries and basic household items. Schools, on the other hand, are social institutions satisfying intangible human and social needs through educational services and social development for children, and employment for staff. In reality, both pharmacies and schools provide tangible and intangible products; these relationships are simplified here for illustrative purposes.

Lumberton is a small inland city in Robeson County, North Carolina, significantly impacted by flooding from the Lumber River following Hurricanes Matthew (2016) and Florence (2018). In October 2016, many areas of Lumberton were inundated for several days, which resulted in disruption in businesses, power, communication, water, and transportation networks as well as significant building damage and lasting social impacts [30]. The Lumberton Testbed is a virtual community resilience testbed that has been developed using public, secondary data and based on observations from a longitudinal field study on the impacts and recovery process of the community [30–33]. A community resilience testbed is a virtual "environment with enough supporting architecture and metadata to be representative of one or more systems such that the testbed can be used to (a) design experiments, (b) examine model or system integration, and (c) test theories" [34]. The field study also captured data on school and business functionality at different points in time, including operational status and customer loss, which provides information needed for calculating the accessibility metrics proposed here.

Lumberton longitudinal field study

In November 2016, a joint team of researchers from the Center of Excellence for Risk-Based Community Resilience Planning (CoE) and the National Institute of Standards and Technology (NIST), launched a longitudinal study on the impacts and recovery of Lumberton following Hurricane Matthew-induced flooding. As of 2023, five waves of data collection, each with its own goals and objectives, have been completed in on approximately annual basis. The first field study, denoted as Wave 1, was performed in November 2016 and documented the initial physical and socio-economic impacts of the flooding on the community, including for housing, households, schools, and a few public sectors. The information on the response of the public sectors, schools, and businesses to the flood event was collected through qualitative interviews with Robeson County school district's representatives, infrastructure managers, and Local, State, and Federal officials [33].

The second field study, denoted as Wave 2 and performed in January 2018, included systematic surveys of the same housing units and schools as in Wave 1, a new sample of businesses, as well as interviews with select public officials, with the overall intention to document recovery progress [31]. To sample the businesses for the survey, a total of 350 businesses out of the 2,017 records of for-profit organizations with a valid Lumberton address existing in the ReferenceUSA [35] database were drawn. This sample size of 350 includes all businesses located inside a 100-m buffer around the Hurricane Matthew inundated area (i.e., 218 records) and 132 additional randomly selected businesses that fell out of the inundated area but still were within the FEMA 100-year floodplain for Lumberton [31].

The third field study, denoted as Wave 3 began immediately after Hurricane Florence in September 2018, followed by a complementary assessment in April 2019 to document the recovery from Hurricanes Matthew and Florence. Wave 3 data collection consisted of an initial damage investigation, two systematic surveys on the impact and recovery process of the most heavily affected housing and businesses as well as interviews and meetings with the same schools and public officials as in Wave 2 [32]. The data collection has continued, including a virtual data collection during the COVID-19 pandemic in Spring 2021 [36], and an in-person recovery follow-up in June 2022.

This paper uses findings on flood impacts and recovery of businesses during Waves 2 and 3, as well as reported findings from interviews with school representatives during Waves 1 and 2. The Wave 2 survey asked businesses (1) if their organization is dependent on its physical location, (2) whether they experienced any access problems such as a street or sidewalk closure after Hurricane Matthew, (3) how much their property was physically damaged due to Hurricane Matthew, (4) whether their business experienced any utility loss, and, if yes, how long it took to fully recover, (5) if they completely ceased operating at their location immediately after the flood, (6) how long it took for them to resume operation, and (7) their operational capacity percentage at the time of the survey compared to the pre-flood time [31, 37]. During the Wave 3 survey, businesses responded to similar questions about the kind and severity of the physical damage caused by Hurricane Matthew, as well as a question about their operational capacity (%) immediately before Hurricane Florence compared to the pre-flood time [32]. The responses to these questions were used to estimate the post-disaster capacity of pharmacies in Lumberton. In addition, we applied the summary of findings from qualitative interviews, as presented in the Wave 1 and Wave 2 reports, to estimate the post-disaster functionality of schools within Lumberton. For example, the Wave 1 report asserted that the schools' transportation systems, after reopening of schools (three weeks post-disaster), were on a two-hour delay since they had to accommodate new and longer routes [33].

Lumberton testbed

In parallel with the field studies, an expanded research team from the CoE and NIST has been developing the Lumberton Testbed using secondary data and incorporating the testbed into an Interdependent Networked Community Resilience Modeling Environment, IN-CORE [38]. IN-CORE is a state-of-the-art open-source computational platform developed for performing community-level resilience analysis. More information about the Lumberton Testbed, as well as details of the algorithms, models, and datasets that have been already appended to it, can be found elsewhere [39–45]. This paper applies the testbed's building inventory, detailed household and housing unit characteristics, and student datasets developed by Rosenheim [45] to estimate accessibility metrics to pharmacies and schools.

Furthermore, to calculate the travel time between different locations within the testbed, a mathematical simulation of the testbed road network is needed. This component of the Lumberton Testbed has not yet been incorporated into IN-CORE. Thus, here, we developed the Lumberton roads network model including geospatial data about the routes' footprint, speed limit, and traffic direction. These data were procured from OpenSteetMap OSM, [46] using the OSMnx Python package [47] and the North Carolina Department of Transportation (NCDOT) open data. OSMnx applies Graph Theory [48] to the geospatial data downloaded from OSM to yield a mathematical simulation of real-world street networks for the desired region, as shown in Fig. 2(a). Graphs are collections of nodes connected by edges. Nodes represent the locations where route footprints intersect, while edges depict the routes that connect these intersections. Although the study area in this research is restricted to the geographical scope of the city of Lumberton, the testbed's road network

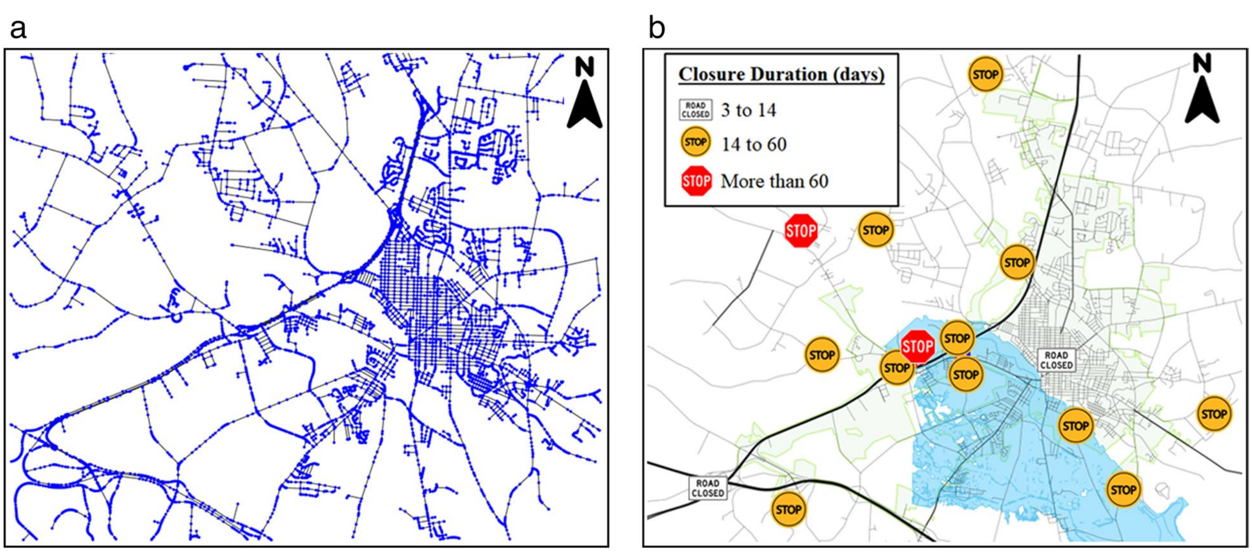

Fig. 2 Lumberton roads network (**a**) mathematical graph model; (**b**) long-term closures following the 2016 Hurricane Matthew

goes beyond the city's geographical boundaries and spans other regions of Robeson County in the vicinity of the study area. This larger extent of the road network is necessary as commuters' shortest driving routes do not always lie within the city limits. The free-flow speed was also estimated for streets located in urban areas using Google Maps data and added to the road network dataset. Free-flow speed is the term used to describe the average speed that a motorist would travel if there were no congestion or other adverse conditions. While this assumption may lead to an underestimation of travel times in comparison to real-world conditions, it is consistently applied for calculating both pre- and post-disruption access times. Thus, its impact on the calculation of the accessibility metrics is negligible, as these metrics rely on the ratio of these access times. Researchers may obtain more accurate speed data from other databases that provide traffic information (e.g., INIRIX,[1] Waze,[2] Uber,[3] etc.). As documented in the Wave 1 report, the flood washed out some access roads in the study area and damaged transport infrastructure, resulting in long-term road closures [33]. Using NCDOT's Traffic Incident Management System records, we determined the location and duration of such road closures within the testbed area. Figure 2(b) shows the spatio-temporal distribution of the long-term road closure incidents in Lumberton's roads after Hurricane Matthew.

In addition to physical damage to the transportation infrastructure, flood events may disrupt traffic flow in urban areas [49]. Such disruptions do not necessarily result in fully blocked and impassable streets and may only slow the running traffic speed for a while. Observations from flooding events in the past have shown that inundated roads do not necessarily preclude people from driving along them, and to assess the disruptive impacts of flooding on roads, the relationship between flood depth, vehicle size, and speed should be taken into account [50]. To assess the flood impact on the Lumberton road network, the flood hazard maps, including flood depth and duration, were overlaid on the road network, and the routes' traffic speeds were modified across the disaster timeline based on a set of rules, as follows: (a) no changes in traffic speed if the inundation depth is not more than 10 cm, (b) the traffic speed will be limited to 10 km/h if the inundation depth is between 10 and 20 cm, and (c) roads with over 20 cm of inundation depth will be assumed to be closed to traffic. The upper and lower bounds incorporated in the applied rules are based on the safe-driving thresholds found for a typical average-size passenger vehicle (e.g., Ford Focus, Honda Accord, in the research conducted by Pregnolato et al. [50] on the relationship between flood depth and vehicle speed.

[1] https://inrix.com/

[2] https://www.waze.com

[3] https://www.uber.com/

Quantifying post-disaster accessibility to tangible pharmacy products

Before the 2016 flood, Lumberton had 29 active pharmacies with the spatial distribution shown in Fig. 3. According to the sampling procedure employed in the aforementioned longitudinal field study, three pharmacies, including one that was located inside the inundated area and two other pharmacies from outside the flooded region, were surveyed during Waves 2 and 3.

Although none of the surveyed pharmacies reported significant physical damage, all three completely ceased operation for a few days immediately after the 2016 flood, according to the survey results. It took three days for pharmacies located outside of the inundated area to resume their operations, whereas the one situated within the flooded region remained closed for six days [31]. All three pharmacies reported power and water losses immediately after the flood which took between 4 to 10 days to fully restore; the pharmacy located within the flooded area also faced physical access interruptions, lasting six days. Of note, the collected data does not explicitly state the operational capacity of the reopened pharmacies at the time of reopening but does provide this information for the time of Wave 2, fifteen months after the flood [31]. At the time of Wave 2, all three pharmacies were open but operating at different functionality levels; the pharmacy sampled from within the inundated area declared operating at 75% capacity compared to pre-flooding time, while the other two reported that they were operating at full capacity. The data on operational capacity was collected in response to question #16 of the Wave 2 Business Survey [37], where respondents characterized capacity considering aspects of the business that are most important to the business such as the quality and/or quantity of service or product offerings. This information was used to infer the expected operational capacity, at four days and fifteen months post-disaster, for all pharmacies within Lumberton, as shown in Table 1. These two particular points in time were selected due to the availability of first-hand data by the authors.

Given that the post- to pre-disaster operational capacity ratios are provided in this example, these ratios were substituted for the functionality-related component $(Q(t) \times \frac{L_3-L_2}{100-L_2})$ in Eq. 6, and the post-disaster response time, $RT^a(t)$, was calculated as follows:

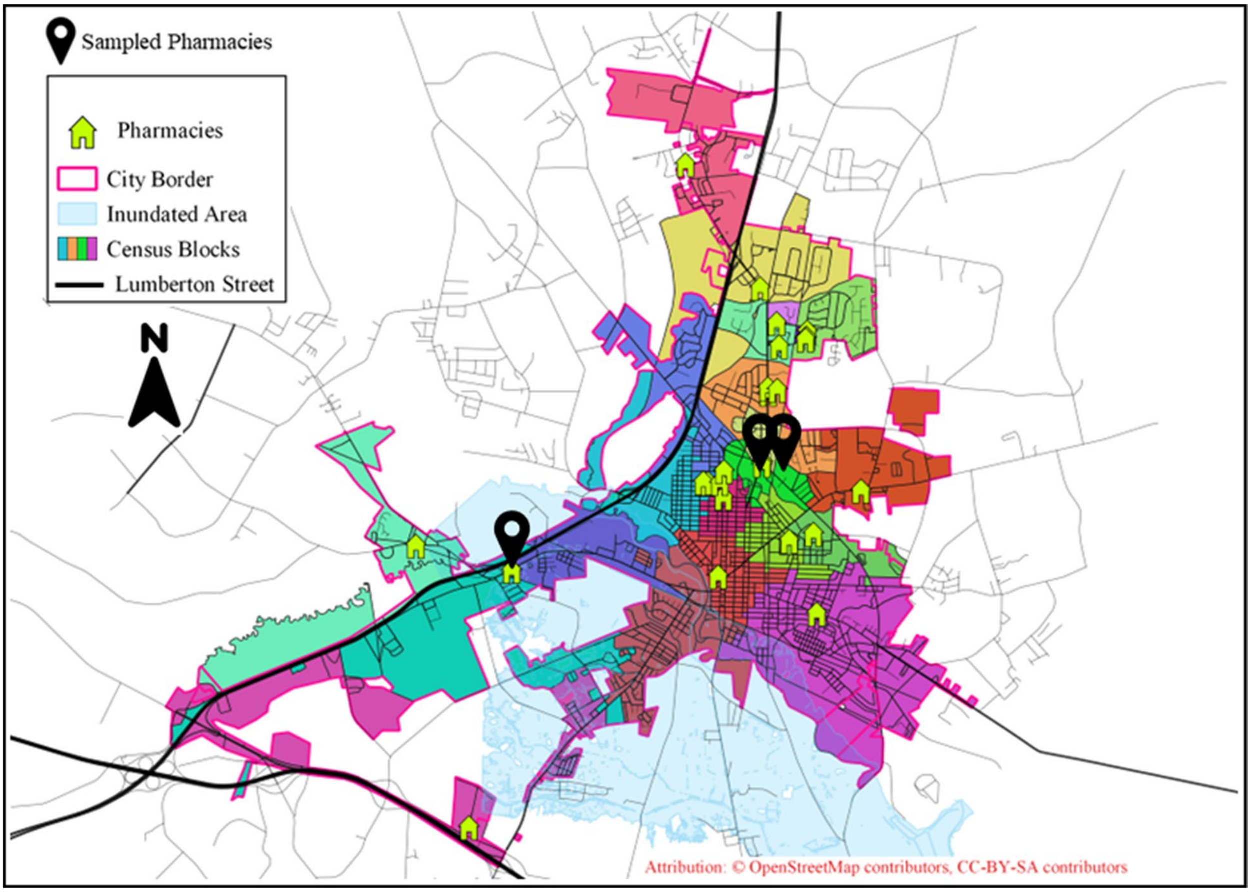

Fig. 3 Spatial distribution of pharmacies in Lumberton and their nearby census blocks

$$RT^a(t) = ST_0\left[\exp\left(2.5 \times \left(1 - \left\{C^a(t)/C^b\right\}\right)\right) \times \left(2.55 \times D^a(t)/D^b - 1.55\right)\right] \quad (14)$$

where all parameters are defined earlier and the post- to pre-disaster capacity ratio ($C^a(t)/C^b$) can be retrieved directly from Table 1. To estimate the post- to pre-disaster demand ratio ($D^a(t)/D^b$) ratio, the nearest MALF pharmacy for each household was determined based on the driving time at three different points in the disaster timeline including: before, four days after, and fifteen months after the disaster. Then, the $D^a(t)/D^b$ ratio was calculated by dividing the post-disaster population assigned to each pharmacy by its pre-disaster population.

Table 1 Ratio of post- to pre-disaster operational capacity of pharmacies in Lumberton

Pharmacy location (count)	4 days after the flood	15 months after the flood
inside the inundated area (1)	0%	75%
outside of the inundated area (28)	90%	100%

To account for the uncertainty, input variables, including ST_0, T_{tr}^b, $T_{tr}^a(t)$, T_{tr}^{ave}, $D^a(t)/D^b$, and $C^a(t)/C^b$ were assumed to be random variables with appropriate probability distributions. Table 2 summarizes the statistical characteristics of these variables. Given that ST_0, T_{tr}^b, $T_{tr}^a(t)$, T_{tr}^{ave} are in time domain variates and exclusively take positive real values, they were assumed to be lognormally distributed [51]. For $D^a(t)/D^b$, the Pareto distribution was considered, which is a Probability Distribution Function (PDF) defined strictly only for random variables greater than or equal to one [51]. The beta PDF was used to model $C^a(t)/C^b$ since the post- to pre-disaster capacity ratio only takes values between zero and one, and beta is an appropriate function for variates with finite lower and upper bounds [51]. A hypothetical coefficient of variation of 0.05 was assumed for all random variables. The mean value of the random variables was determined as follows: (i) For T_{tr}^b, $T_{tr}^a(t)$, T_{tr}^{ave}, it was obtained from the travel time analysis model; (ii) For ST_0, it was specified as

Table 2 Statistical characteristics of input variables for the accessibility metric to tangible pharmacy products

Input variable	Unit	Lower bound	Upper bound	Mean-value source	Coefficient of variation	Distribution type
ST_0	sec	0	$+\infty$	300	0.05	Lognormal
T_{tr}^{b}	sec	0	$+\infty$	Computational model	0.05	Lognormal
$T_{tr}^{a}(t)$	sec	0	$+\infty$	Computational model	0.05	Lognormal
T_{tr}^{ave}	sec	0	$+\infty$	Computational model	0.05	Lognormal
$D^{a}(t)/D^{b}$	—	1	$+\infty$	Computational model	0.05	Pareto
$C^{a}(t)/C^{b}$	—	0	1	Table 1	0.05	Beta

300 s (five minutes), based on the engineering judgment of authors in this particular example; (iii) For $D^a(t)/D^b$, it was calculated as earlier explained; and (iv) For $C^a(t)/C^b$, it was directly obtained from the Table 1.

Running a Monte Carlo simulation, 100k possible values of the metric were calculated for every housing unit at two different points in time, including four days after floodwaters from Hurricane Matthew peaked in Lumberton, and 15 months later. The 100k iterations in this example produced a consistently stable mean and ensured a coefficient of variation of less than 10%. Figure 4 showcases this process for one example housing unit located outside of the flooded area. The random variables shown in the input component of Fig. 4 are realized as in Table 2. In this example, the travel time to the assigned pharmacy increases from 96.1 s before the flood to 133 s four days after the flood, and returns to pre-disaster travel time 15 months later. On day four post-flood, the assigned pharmacy operates at 90% of its pre-disaster capacity, while the post-disaster demand for tangible pharmacy products increases by 2%. After 15 months, both operational capacity and product demand return to their pre-disaster level. The output component of Fig. 4 shows the 100k possible outcomes of the Monte Carlo simulation, the expected value, and the Cumulative Distribution Function (CDF) of the accessibility metric for that particular housing unit at both 4 days post-flood and 15 months later. As can be seen, 15 months after the disaster, the expected value of accessibility to tangible pharmacy products, in this specific example, is less than one (i.e., 0.91) even though this housing unit has the same level of accessibility as pre-disaster. Thus, we need to find a threshold for the expected value of accessibility corresponding to the same level of accessibility as pre-disaster.

To determine this threshold, the Monte Carlo simulation was repeated while post-to-pre-disaster product

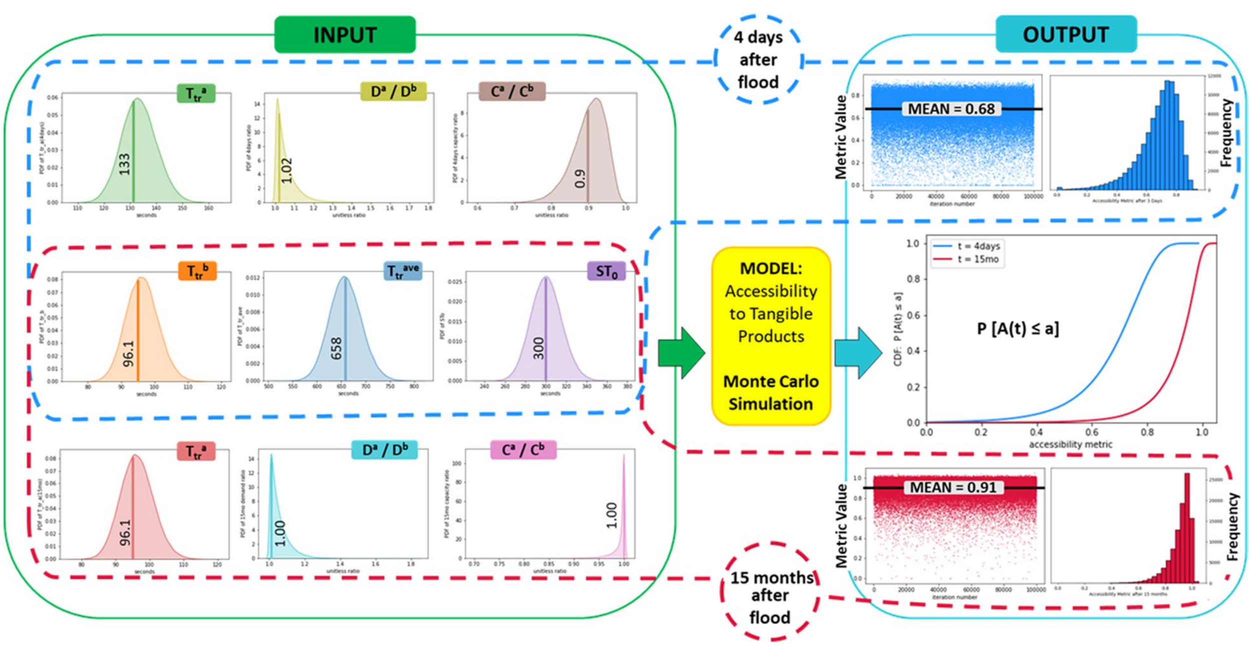

Fig. 4 Schematic Overview Monte Carlo simulation to quantify an example household's post-disaster accessibility to tangible pharmacy products

demand, operational capacity, and travel time ratios were hypothetically set to one for all 8963 housing units. This assumption resembles the condition that all households have exactly the same accessibility to tangible pharmacy products as pre-disaster. Then, we took the lower bound of 95% confidence interval of 896.3 M possible outcomes with a burr distribution (i.e., 0.83) as the point above which expected value of accessibility corresponding to one on the deterministic metric. Figure 5 shows the expected value of each household's accessibility to tangible pharmacy products across Lumberton.

As shown in Fig. 5(a), even though 28 out of 29 pharmacies in Lumberton were operational on day four post-flood, accessibility to tangible pharmacy products was impacted for at least four days after the flood for almost all housing units regardless of their location in the study area. However, the impact was more significant on the housing units located inside and near the inundated zone, where household accessibility to tangible pharmacy products is expected to decline by at least 50% or even be completely lost. This is primarily due to the restricted physical access to these housing units as the flood simulation shows that many streets in the flooded area remain inundated for more than 4 days [39, 42]. Of note, a complete loss of accessibility to tangible pharmacy products in this example indicates that the product is no longer available with reasonable effort and does not necessarily mean that the product is unattainable.

It is also important to approach the concept of accessibility from both product provider and user perspectives. In the case of Lumberton and Hurricane Matthew, the Wave 1 report [33] discusses the widespread, long-lasting, and disproportionate dislocation experienced by Lumberton households. As such, physical access to tangible pharmacy products at these specific locations was not needed within four days post-flood for most households in the inundated area given that the households had dislocated. However, it is likely that customers of those pharmacies were unable to get their prescription transferred if the pharmacy was closed. Thus, it is expected that some proportions of customers were without necessary tangible pharmacy products (e.g., medications) during this period of time.

Even 15 months later, the accessibility to tangible pharmacy products for some households is expected to remain impacted with a metric value of less than 0.83 [see Fig. 5(b)]. This analysis demonstrates that even 15 months after the flooding event, 728 households (8.1%) still did not have the same level of accessibility to pharmacies as they did before the flooding in their pre-flood housing unit. Question #23 of the Wave 2 housing survey asked households, "Do you and your household have the same access to school, work, grocery stores, and other essential needs in this home as you did before the flooding?" Responses reported in the Wave 2 report show that 267 households responded to this question

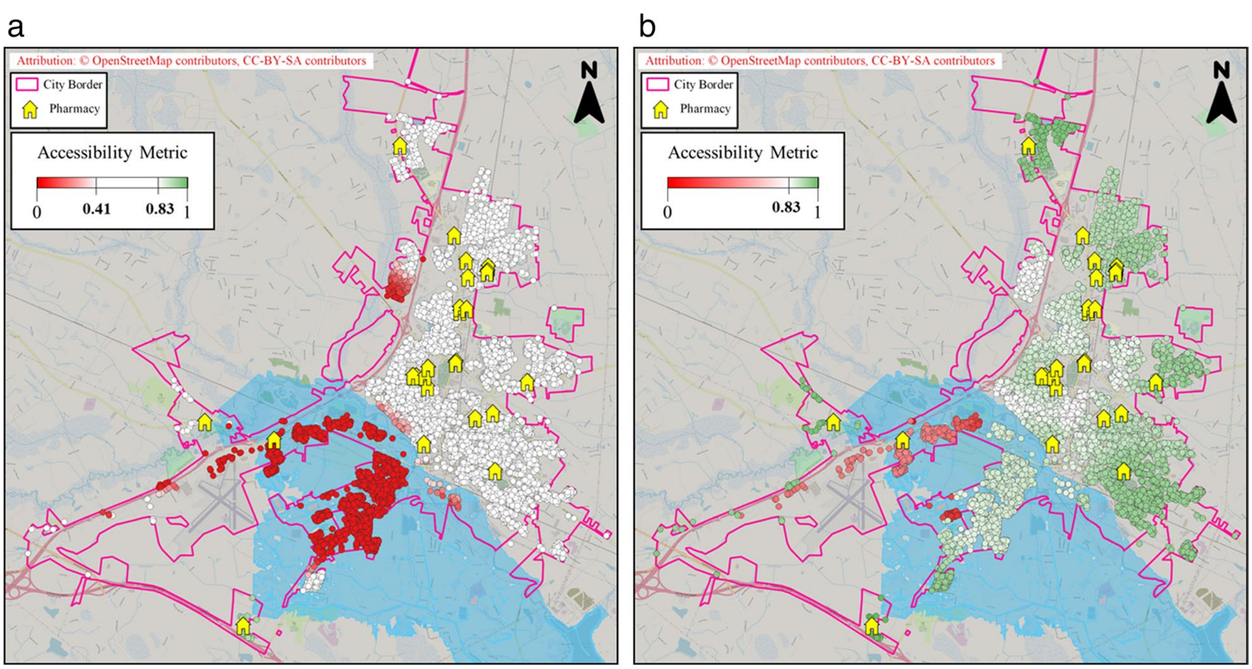

Fig. 5 Housing unit expected accessibility to tangible pharmacy products in Lumberton at time of (**a**) four days and, (**b**) fifteen months after the 2016 flooding following Hurricane Matthew

and 24 households (9%) responded 'no', indicating that their access was still disrupted 15 months post-flood. While pharmacies were not directly listed in the survey question, the response supports the validation of the computational results.

Quantifying post-disaster accessibility to intangible education services

As explained in "Accessibility to intangible products" section, individual attention time, *IAT*, is an organization-specific parameter and should be determined based on the characteristics of the product and organization. In this paper, by considering publicly available data for schools, we propose using the student–teacher ratio (*STR*) for determining *IAT* in schools. According to the Glossary of Education Reform, "a student–teacher ratio expresses the relationship between the number of students enrolled in a school, district, or education system and the number of full-time equivalent teachers employed by the school, district, or system" [52]. This ratio implies the amount of individual attention any single student is likely to receive during a typical school day, assuming that all class sizes are the same. Thus, the IAT^b, is calculated here by dividing the school time in a typical school day (including lunch, recess, and study periods) by the pre-disaster student–teacher ratio:

$$IAT^b = \frac{ScT}{STR^b} \tag{15}$$

where IAT^b is pre-disaster individual attention time for each student, STR^b represents the pre-disaster student–teacher ratio, and ScT is a typical day's school time. Similarly, the $IAT^a(t)$ and IAT^{min} can be estimated as:

$$IAT^a(t) = \frac{ScT}{STR^a(t)} \times \Omega^a(t) \tag{16}$$

$$IAT^{min} = \frac{ScT}{STR^{max}} \tag{17}$$

where $IAT^a(t)$ and $STR^a(t)$ represent post-disaster individual attention time and student–teacher ratio, respectively; $\Omega^a(t)$ is the school's post-disaster functionality; IAT^{min} represents minimum reasonable individual attention time; STR^{max} is the maximum student–teacher ratio across the corresponding school district.

In 2016, the Robeson County Public School district had 17 public schools that served the students of Lumberton, including eleven elementary, three middle, and three high schools [33]. However, according to the National Center for Education Statistics [53], the attendance boundary for only eight of these schools (five elementary, two middle, and one high school) lies within the city limits of Lumberton, as shown in Fig. 6. This paper considers these eight schools to demonstrate the application of accessibility metrics to education. As seen in Fig. 6, the elementary schools in Lumberton have discrete attendance

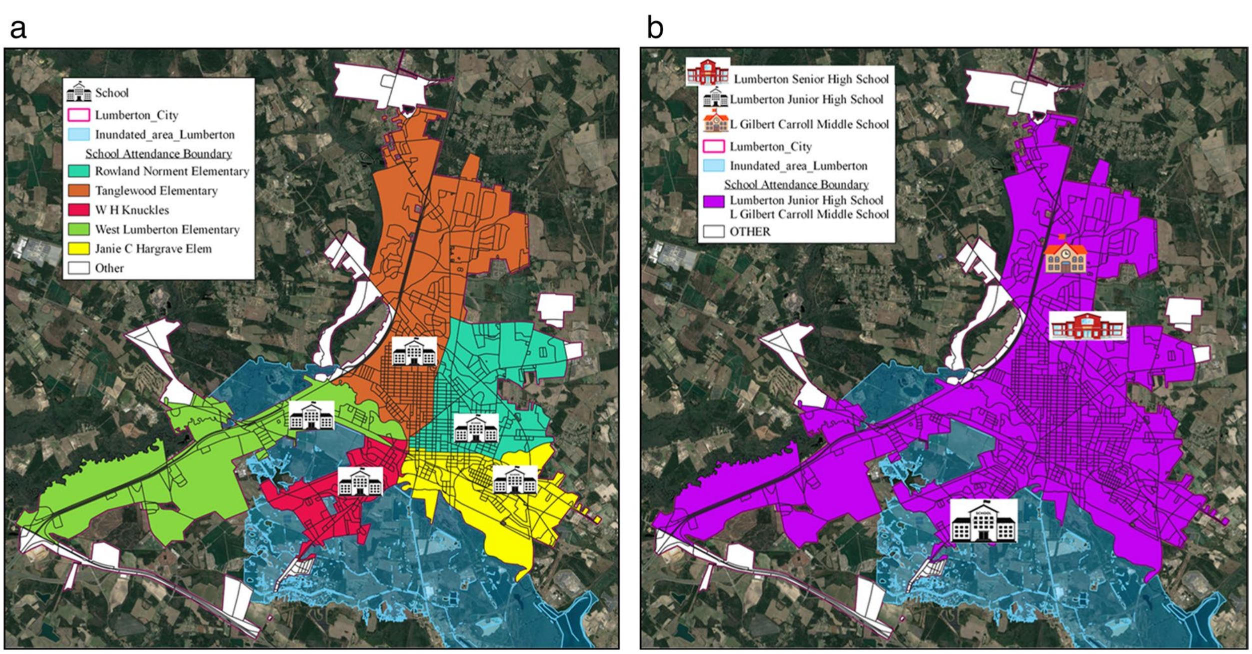

Fig. 6 Location and attendance boundary of (**a**) elementary schools, (**b**) middle and high schools in Lumberton

boundaries, whereas the attendance boundaries overlap for the middle schools. Of the approximately 4,402 students enrolled in these schools before Hurricane Matthew in 2016, 37% were in primary school, 29% were in middle school, and 34% were in high school [53].

During the 2016 flood in Lumberton, three schools (West Lumberton Elementary, W.H. Knuckles Elementary, and Lumberton Junior High School) were directly impacted as they were situated within the inundated area [33]. West Lumberton Elementary School was completely flooded; W.H. Knuckles Elementary and Lumberton Junior High School experienced partial flood damage. However, all Lumberton schools, whether damaged or not, remained closed for at least three weeks due to incidents such as road closures, loss of power, and water outages, with many schools still needing bottled water for a while after reopening [33]. As documented in Wave 1 and 2, Lumberton Junior High School and W.H. Knuckles Elementary School reopened after three weeks while repairs were ongoing for over a year in W.H. Knuckles Elementary School. The West Lumberton Elementary School was permanently closed after the flood, resulting in the displacement of students and staff to a temporary location; eventually, students were transferred to other functioning schools as a long-term solution. Figure 7 shows a hypothetical algorithm we used in this study to simulate the student admission and transfer process after the 2016 flood in Lumberton. The algorithm simplifies the student transfer and enrollment process by including a set of assumptions about the factors that would affect the process: 1) admission to a new school is solely based on the grade level of the student and the availability of a vacant desk, 2) proximity is the primary factor in prioritizing transfers, 3) only public schools are taken into account, so affordability is not a concern, and 4) free and safe transportation is always secured for all students.

The algorithm shown in Fig. 7 takes the student's grade level, home address (or coordinates), and pre-disaster school as input and attempts to find a new school admission at the same grade level for every student

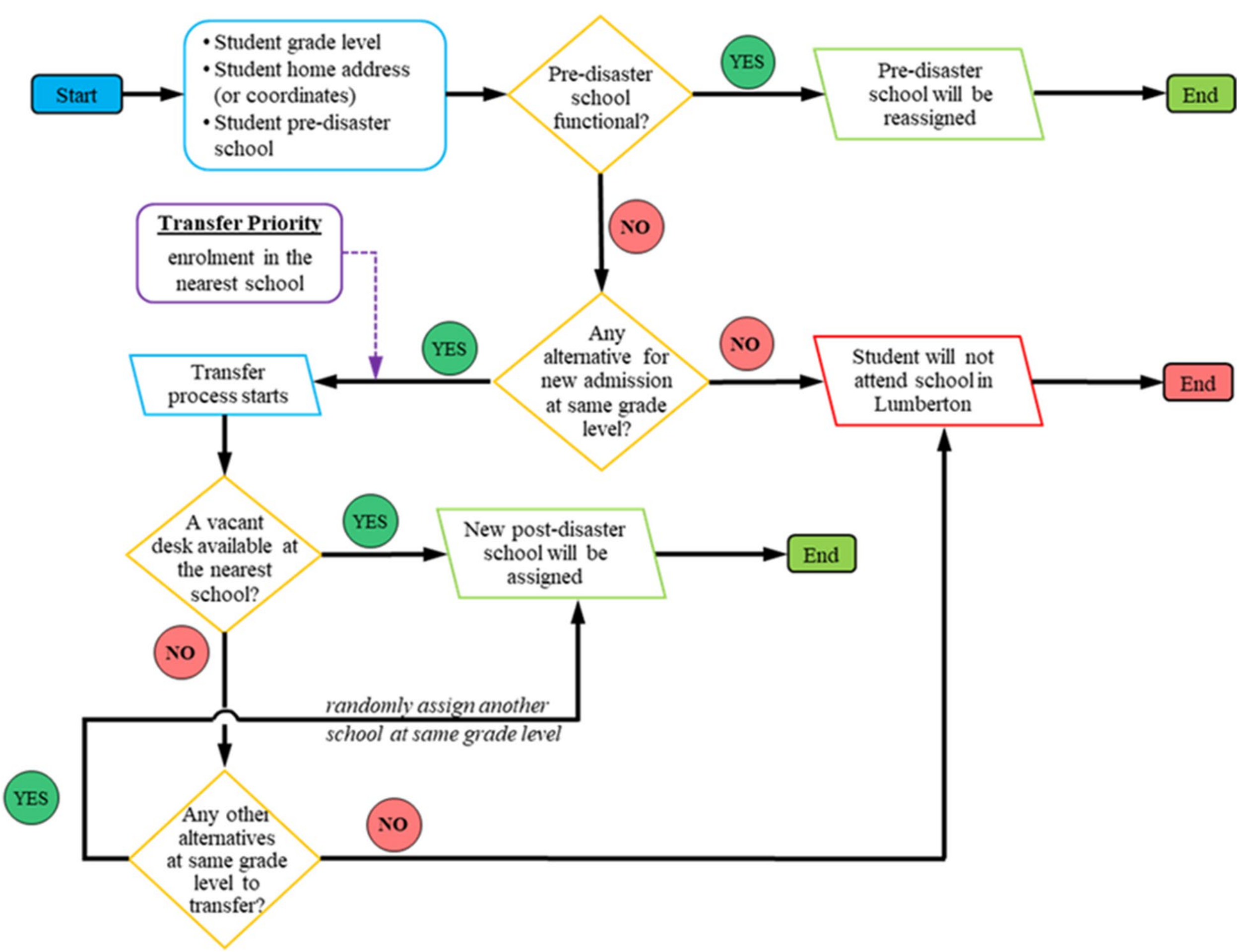

Fig. 7 Hypothetical algorithm for simulation of student enrollment and transfer

in need. If the attempt succeeds, a new post-disaster school will be assigned to the student; otherwise, the student will not be able to attend school in Lumberton and might be transferred to other schools within or outside of the district. The transfer process begins by assessing the availability of a vacant desk at the nearest school. This assessment involves estimating a maximum post-disaster enrollment capacity for each functional school within Lumberton. To do so, we first approximated the maximum pre-disaster enrollment capacity for each school using the maximum student–teacher ratio across the Robeson County Public Schools district; $STR^{max} = 20.5$ as reported by NCES [53]. The calculated value was then adjusted using the school's post-disaster functionality to obtain the maximum post-disaster enrollment capacity. Of note, this process assumes that the number of teachers working at the school does not change after the disaster.

Table 3 and Fig. 8 present a summary of outputs from executing the students' post-disaster transfer algorithm, including post-disaster enrollment counts and *STR* values. In Table 3, the pre-disaster enrollment numbers and *STR* ratios were obtained from the NCES [53] database; the post-disaster functionality percentages were

Table 3 Pre- and post-disaster characteristics of Lumberton schools

School	† Grade level	Pre-disaster enrollment	* STR^b	** $\Omega^a(\%)$		max pre-disaster enrollment capacity	max post-disaster enrollment capacity	Post-disaster enrollment	§ STR^a
				3 weeks	*15 months*				
Janie C Hargrave	ES	208	11.6	90	100	369	332	234	13.0
Rowland Norment	ES	457	13.8	90	100	676	608	471	14.3
Tanglewood	ES	442	13.8	90	100	656	590	477	14.9
W H Knuckles	ES	274	15.2	85	100	369	313	313	17.4
West Lumberton	ES	114	10.8	0	0	216	0	0	-
L Gilbert Carroll	MS	579	14.5	90	100	820	738	579	14.5
Lumberton Junior High School	MS	588	14.0	90	100	861	774	588	14.0
Lumberton Senior High School	HS	1380	12.5	90	100	2263	2036	1380	12.5
	$\sum =$	**4042**					$\sum =$	**4042**	

† *ES* Elementary School, *MS* Middle School, *HS* High School

* Pre-disaster student–teacher ratio

** Post-disaster functionality level

§ Post-disaster student–teacher ratio

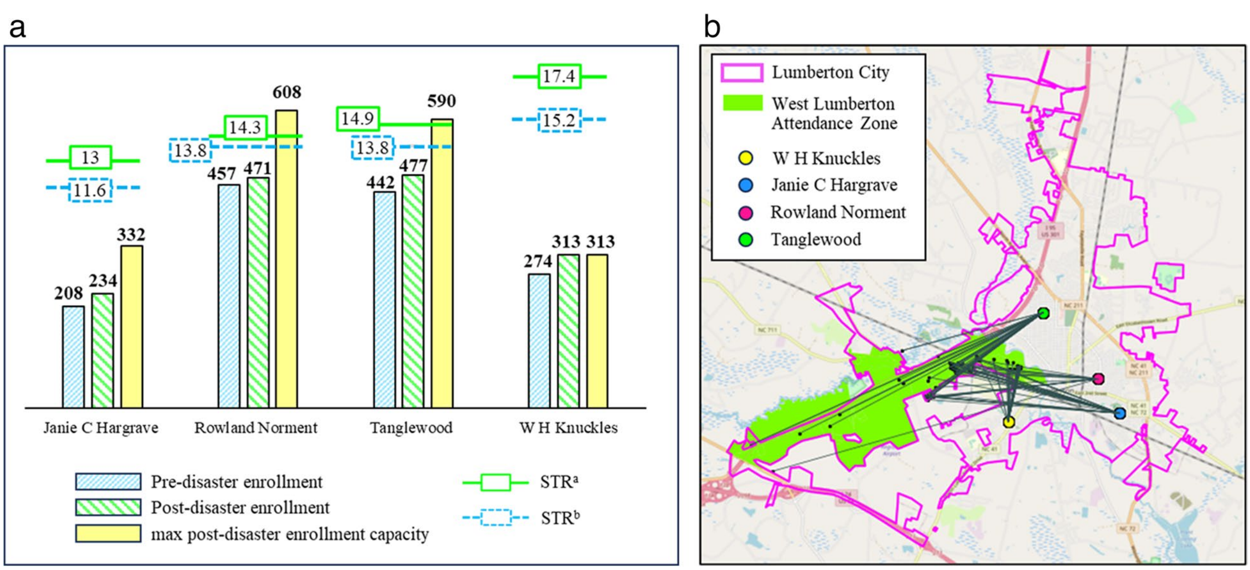

Fig. 8 **a** Post-disaster enrollment counts and STR ratios for functional elementary schools, (**b**) geospatial snapshot of new post-disaster enrollments

inferred from the summary of responses to qualitative interviews that are provided in Waves 1 and 2 of the longitudinal study reports [31, 33]. In this particular example, as evident in Table 3, there was enough capacity to support all of the West Lumberton Elementary School students. Since there was sufficient enrollment capacity after schools' reopening, we did not need to execute the algorithm at multiple points in post-disaster time and used the same outputs to calculate accessibility metrics at 3 weeks and 15 months after the flood. However, the algorithm is capable of being executed at various time points.

As can be seen in Fig. 8(a), post-disaster enrollments and *STR* ratios increased for the elementary schools after reopening because of the necessity of admitting West Lumberton Elementary School students. W.H. Knuckles is the nearest alternate school for most of the 114 students who used to go to West Lumberton School before the flood, but it can only admit 39 new students. Figure 8(b) displays the geospatial snapshot of post-disaster enrollment of West Lumberton Elementary School students. The nodes in Fig. 8(b) represent the post-disaster functional elementary schools and the links map West Lumberton School students to their post-disaster assigned schools.

To account for uncertainty, input variables, including ScT, T_{tr}^{b}, $T_{tr}^{a}(t)$, T_{tr}^{ave}, STR^{b}, $STR^{a}(t)$, STR^{max}, and $\Omega^{a}(t)$ were assumed to be random variables with statistical characteristics as presented in Table 4. The ScT, T_{tr}^{b}, $T_{tr}^{a}(t)$, T_{tr}^{ave}, STR^{b}, $STR^{a}(t)$, and STR^{max} variables were assumed to be lognormally distributed and the beta PDF was used to model $\Omega^{a}(t)$. The coefficient of variation was hypothetically assumed to be 0.05 for all random variables except for ScT, for which a coefficient of variation of 0.01 was assumed. This is because the school time is less uncertain than other random variables. The mean value of the random variables was determined as follows: (i) For T_{tr}^{b}, $T_{tr}^{a}(t)$, T_{tr}^{ave}, it was obtained from the travel time analysis model; (ii) For ScT, it was specified as 25,200 s (7 h) for elementary schools and 27,000 s (7.5 h) for middle and high schools [53]; (iii) For STR^{b}, $STR^{a}(t)$, and $\Omega^{a}(t)$, it was obtained from Table 3; and (iv) STR^{max} was taken as 20.5 [53], as explained earlier.

To determine a threshold for the expected value of accessibility corresponding to the same level of accessibility as pre-disaster, we followed the approach described in "Quantifying post-disaster accessibility to tangible pharmacy products" section. First, post-to-pre-disaster *STR*, school functionality, and travel time ratios were set to one to resemble the condition that all 4,402 Lumberton students have the same accessibility to intangible education services as pre-disaster. Then, we took the lower bound of 95% confidence interval of possible outcomes derived from a Monte Carlo simulation with 100k iterations to calculate the desired threshold, resulting in a value of 0.84. Figure 9 shows students expected accessibility to intangible education services in Lumberton at two different points in time: 3 weeks after the flood from Hurricane Matthew, and 15 months later.

As can be seen in Fig. 9(a), the accessibility to school is impacted for almost all students across the community. However, the level of impact was different based on where they lived before the flooding and the school they attended. For middle and high school students, this accessibility loss is primarily due to the increase in students' home-to-school travel time, while for elementary school students, the loss is due to an increase in travel time and a decrease in individual attention time. The accessibility to education improved significantly after 15 months, as shown in Fig. 9(b); even then, the expected value of the metric was less than 0.84 for 833 students. This means 20.6% of students, fifteen months after the disaster, still experienced decreased levels of accessibility to intangible education services, compared to pre-disaster time. The Wave 2 housing survey asked

Table 4 Statistical characteristics of input variables for the accessibility metric to intangible education services

Input variable	Unit	Lower bound	Upper bound	Mean-value source	Coefficient of variation	Distribution type
ScT	sec	0	$+\infty$	25,200 if elementary 27,000 if not elementary	0.01	Lognormal
T_{tr}^{b}	sec	0	$+\infty$	Computational model	0.05	Lognormal
$T_{tr}^{a}(t)$	sec	0	$+\infty$	Computational model	0.05	Lognormal
T_{tr}^{ave}	sec	0	$+\infty$	Computational model	0.05	Lognormal
STR^{b}	—	0	$+\infty$	Table 3	0.05	Lognormal
$STR^{a}(t)$	—	0	$+\infty$	Table 3	0.05	Lognormal
STR^{max}	—	0	$+\infty$	20.5	0.05	Lognormal
$\Omega^{a}(t)$	—	0	1	Table 3	0.05	Beta

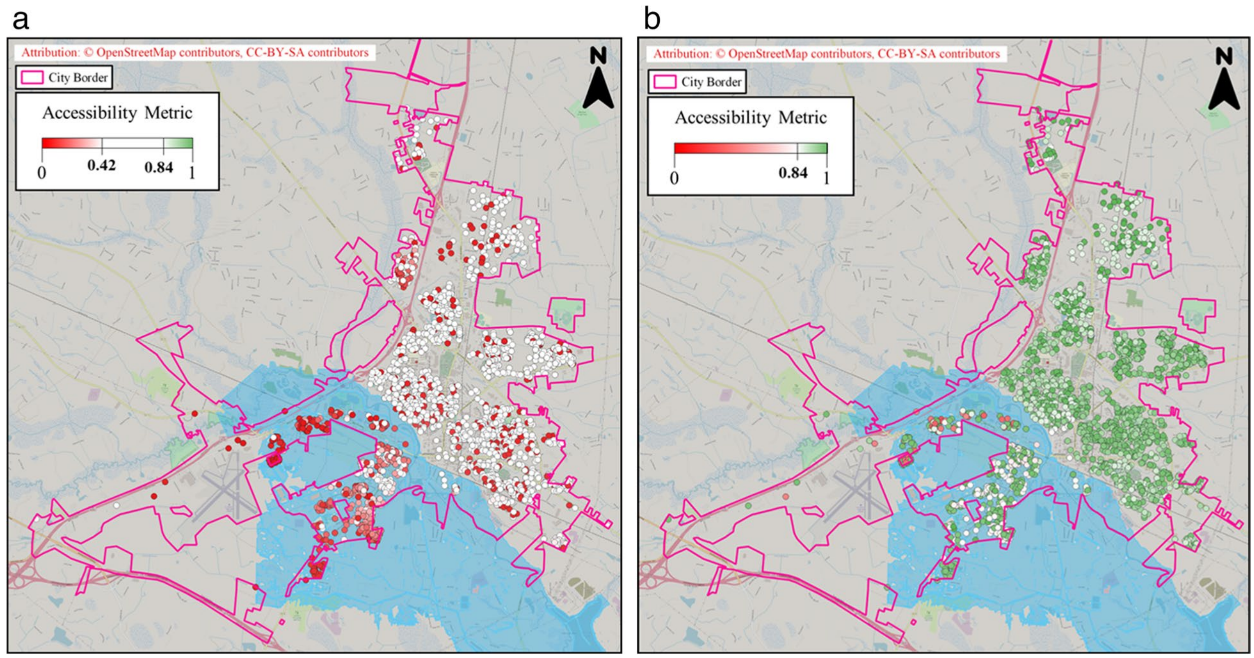

Fig. 9 Students expected accessibility to intangible education services in Lumberton at (**a**) three weeks and, (**b**) fifteen months after the 2016 flooding following Hurricane Matthew

two related questions, including Question #23 stated in "Quantifying post-disaster accessibility to tangible pharmacy products" subsection, where 24 households indicated that their access to 'school, work, grocery stores, and other essential needs' was still not the same as it was before the flood. The second related question (Question #23) was asked to respondents who indicated they had children enrolled in school at the time of the flooding, "When thinking about your child/ren's educational recovery following Hurricane Matthew, would you say that your child/ren's educational situation is (a) Better than it was before the flooding; (b) Back to where it was before the flooding; (c) Worse than it was before the flooding; or (d) Uncertain, things are still changing for my child/ren." Findings reported in the Wave 2 report indicate that 78 households responded to the question, where 60 households (77%) stated their child/ren's education recovery was the same or better than before the flood, 6 (8%) were worse, and 11 (14%) were uncertain. These findings from the field study support the validation of the computational results.

Discussion and conclusions

This study's contribution to advancing the state of knowledge in community resilience lies in addressing the ambiguity in defining and measuring accessibility. Post-disruption accessibility of community members to essential products is an important proxy for assessing the recovery trajectory of a community. To measure accessibility in the context of community resilience, analysts should employ metrics that: (1) include dimensions other than just physical access and proximity, and (2) concurrently consider factors influencing the characteristics of both product users and product providers. Accessibility metrics developed in this paper combine proximity, acceptability, adequacy, and availability dimensions, while acceptability and adequacy are addressed from both user and provider perspectives. The metrics also employ the organizational functionality of the product providers in measuring accessibility. This approach provides a more comprehensive and nuanced understanding of post-disruption access to essential products.

In addition to these advances, metrics operate at the household level and yield a unitless ratio between zero and one, which can be aggregated for that household across multiple products, if needed. For example, pharmacies offer both intangible products, such as consultation services with a pharmacist, and tangible products such as prescribed medications; accessibility to each of these products should be measured using their own specific metrics. Finally, the household's accessibility to the pharmacy can be estimated by calculating the weighted average or harmonic mean of the values computed by each metric, depending on how the user wants to reflect the importance of each product in the combined accessibility. For example, a weighted average enables the user to explicitly assign relative importance to each metric and is useful when there is a consensus and clear understanding of the significance of each product. Alternatively, the harmonic mean is more sensitive to lower values, so it is appropriate when the user is uncertain about the importance of each product and wants to ensure that lower values have a stronger impact.

The proposed metrics are a function of time, which makes them suitable for evaluating accessibility as a multi-dimensional temporally-varying concept. The metrics are also capable of being used as a predictive model for community decision-makers to gauge the effectiveness of their resilience plans and prioritize recovery actions under various "what if" scenarios. However, for the sake of the manuscript's length, this paper does not include examples of such types of analysis. Instead, it focuses on elaborating on the metrics and their underlying development rationale, employing the illustrative example as a means of demonstrating the proof of concept. While effective in many scenarios, the proposed metrics may lead to skewed accessibility assessments due to normalizing them by pre-disruption accessibility level. For instance, using pre-disruption access as the baseline can disproportionately favor those with initially high access levels in recovery prioritization. To mitigate this issue, we suggest applying of an acceptable threshold for the metrics according to the community's norms and expectations. This threshold would ensure that accessibility assessments are correctly interpreted in recovery scenarios. Acknowledging this as a limitation of our current methodology, we recommend it as an essential area for future research to refine and improve the accuracy and fairness of accessibility evaluations.

As random numbers are crucial for stochastic processes, we used the same seed number across different runs of the Monte Carlo simulation to ensure the reproducibility of the results. The seed number serves as an initial value for generating a sequence of random numbers. Using the same seed number produces the same sequence of random numbers and, consequently, identical simulation results. Controlling the seed allows for consistent testing within the same scenario and facilitates comparisons across different scenarios.

While the detailed computational outcomes of the proposed accessibility metrics have not been explicitly validated due to the lack of the required data, findings from the Lumberton field study in general support the validity of the computational results and simulation algorithms. These promising results, despite simplified assumptions in the development of metrics, open doors for future research explorations. Sensitivity analysis would reveal the impact of each simplification on the outcome, potentially enriching the model's generalizability and robustness. Further investigation into these areas could refine the model and expand its applicability to a wider range of scenarios.

Household dislocation is a common outcome following disasters, which happened after the 2016 flooding event in Lumberton as well. In this paper, household dislocation, and consequently, student and staff dislocation, were not considered due to a lack of data. However, the metrics and algorithms could accommodate this by adjusting the post-disaster travel time and student-to-teacher ratios when data is available. Also, affordability and awareness, as well as the effect of users' cultural and social considerations on their perception and preferences were not included in developing the accessibility metrics proposed in this paper and can be an area for future research. Importantly, the affordability and awareness of users are getting more critical as new visions for improving the resilience of communities emerge. For instance, the COVID-19 pandemic proved that there is a crucial need for community resilience frameworks to go beyond "resistance and returning to normal" to include adaptability and transformation along with mitigation, preparedness, robustness, and recovery. Communities can mobilize their adaptive capacity and reorganize to cope with their new situation after a disruption. Many organizations demonstrated such traits during the COVID-19 pandemic by transforming in-person products online. This adaptive capacity and transformation altered components contributing to organizational functionality, and consequently, reduced the risk of organizational functionality failure, which is a step toward resilience. However, this step will be taken only if the organization still remains accessible and community members are able to use its products. A reliable internet connection may be difficult to afford for the most socially vulnerable community members, for example. In that case, awareness and affordability are two accessibility dimensions that are more likely to be compromised which may lead to exacerbating existing inequity in access to resources in the communities if ignored in measuring accessibility.

Appendix

Table 5 List of variables used in this paper

Variable	Description
AT^{max}	Maximum threshold for reasonable access time to receive the tangible product
AT^{min}	Minimum threshold for reasonable access time to receive the intangible product
$AT_I^a(t)$	Access time to intangible products at time *t* after the disaster
AT_I^b	Access time to intangible products during the normal period before the disruption
$AT_T^a(t)$	Access time to tangible products at time *t* after the disaster
AT_T^b	Access time to tangible products during the normal period before the disruption
$C^a(t)$	Expected capacity of an organization at time *t* after a disruption
C^b	Pre-disruption capacity of an organization
$D^a(t)$	Product demand for an organization at time *t* after the disruption
D^b	pre-disruption product demand for an organization
$Q(t)$	Probability that the organizational functionality is equal to or greater than the MALF before time *t* after a disruption
$IAT^a(t)$	Individual attention time for intangible product at the time *t* after the disruption
IAT^b	Individual attention time for intangible product during the normal period before the disruption
IAT^{min}	Minimum threshold for reasonable individual attention time
L_2	Functionality percentage corresponding to an organization at the Fully Operable state
L_3	Functionality percentage corresponding to an organization at the MALF state
RT^b	Response time at the nearest MALF organization before the disruption
$RT^a(t)$	Response time at the nearest MALF organization at time *t* after the disaster
ST_0	Pre-disruption service time within an organization
$STR^a(t)$	Student–teacher ratio at time *t* after the disruption
STR^b	Student–teacher ratio before the disruption
STR^{max}	Maximum student–teacher ratio across the target school district
ScT	School time during a typical day
T_{tr}^{ave}	Mean of travel time to all organizations providing the intended product in the study area before the disruption
$T_{tr}^a(t)$	Travel time to the nearest MALF organization providing the desired product at time *t* after the disaster
T_{tr}^b	Travel time to the nearest MALF organization providing the desired product before the disruption
$\Delta A_I(t)$	Accessibility to intangible products at time *t* after the disruption
$\Delta A_T(t)$	Accessibility to tangible products at time *t* after the disruption
$\Omega^a(t)$	School's post-disaster functionality percentage at time *t* after the disaster

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All maps in this study are created using the QGIS as a free and open-source software program.

Authors' contributions
A.E. and E.S. conceived the presented idea, developed the computational model, and performed the analysis for the illustrative example. J.H. and M.W. contributed to the collection and analysis of the business data used in the verification process. L.D.O assisted in incorporating uncertainty into the model and provided critical feedback on the computational model. J.W.v.d.L supervised the findings of this work and played a leadership role in shaping the research and interpreting the results. All authors discussed the results and contributed to the final manuscript.

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Data availability
Some or all data used in this study are proprietary or confidential in nature and may only be provided with restrictions (e.g., anonymized data) upon a request from the second author, Dr. Elaina Sutley. This includes the following:
1. All damage data at a level of detail in which individual houses can be identified.
2. All household or business survey data at a level of detail in which individuals and their responses to any survey/interview questions can be identified. The data are not publicly available, and access is limited to project investigators within the Center for Risk-Based Community Resilience Planning at NIST who have completed Institutional Review Board (IRB) training and whose universities have signed the Interagency Agreement (IAA).

Declarations

Competing interests
The authors declare no competing interests.

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References

1. Williams TG, Logan TM, Zuo CT, Liberman KD, Guikema SD (2020) Parks and safety: a comparative study of green space access and inequity in five US cities. Landsc Urban Plan 201:103841. https://doi.org/10.1016/j.landurbplan.2020.103841
2. Wang Y, Liu Y, Xing L, Zhang Z (2021) An Improved Accessibility-Based Model to Evaluate Educational Equity: A Case Study in the City of Wuhan. ISPRS Int J Geo Inf 10(7):458
3. Thomson D, Cantrell E, Guerra G, Gooze R, Tout K (2020) Conceptualizing and measuring access to early care and education
4. Talen E, Anselin L (1998) Assessing spatial equity: an evaluation of measures of accessibility to public playgrounds. Environ Plan A 30(4):595–613
5. Talen E (2003) Neighborhoods as Service Providers: A Methodology for Evaluating Pedestrian Access. Environ Plann B Plann Des 30(2):181–200. https://doi.org/10.1068/b12977
6. Saurman E (2016) Improving access: modifying Penchansky and Thomas's theory of access. J Health Serv Res Policy 21(1):36–39
7. Penchansky R, Thomas JW (1981) The concept of access: definition and relationship to consumer satisfaction. Medical care. 19(2):127–40
8. Loreti S, Ser-Giacomi E, Zischg A, Keiler M, Barthelemy M (2022) Local impacts on road networks and access to critical locations during extreme floods. Sci Rep 12(1):1552. https://doi.org/10.1038/s41598-022-04927-3
9. Logan TM, Guikema SD (2020) Reframing Resilience: Equitable Access to Essential Services. Risk Anal 40(8):1538–1553. https://doi.org/10.1111/risa.13492
10. Dong S, Esmalian A, Farahmand H, Mostafavi A (2020) An integrated physical-social analysis of disrupted access to critical facilities and community service-loss tolerance in urban flooding. Comput Environ Urban Syst 80:101443. https://doi.org/10.1016/j.compenvurbsys.2019.101443
11. Docekala G, Tanga W, Eastina M, Lana Y, Delmelle E (2020) Space-time variation in shelter accessibility in Eastern North Carolina, following Hurricane Florence (2018). AutoCarto 2020, the 23rd International Research Symposium on Cartography and GIScience. Redlands, California: CaGIS
12. Dempsey N, Bramley G, Power S, Brown C (2011) The social dimension of sustainable development: Defining urban social sustainability. Sustain Dev 19(5):289–300
13. Vaughan KB, Kaczynski AT, Wilhelm Stanis SA, Besenyi GM, Bergstrom R, Heinrich KM (2013) Exploring the distribution of park availability, features, and quality across Kansas City, Missouri by income and race/ethnicity: an environmental justice investigation. Ann Behav Med 45(Suppl 1):S28–38. https://doi.org/10.1007/s12160-012-9425-y
14. Paschall K, Tout K, Fojut J (2022) Measuring Access to Early Care and Education with the 2019 NSECE. OPRE Report #2022–234. Washington, DC: Office of Planning, Research and Evaluation, Administration for Children and Families, U.S. Department of Health and Human Services
15. Logan TM, Williams T, Nisbet A, Liberman K, Zuo C, Guikema S (2019) Evaluating urban accessibility: leveraging open-source data and analytics to overcome existing limitations. Environment and Planning B: Urban Analytics and City Science 46(5):897–913
16. Contreras D, Blaschke T, Hodgson ME (2017) Lack of spatial resilience in a recovery process: Case L'Aquila. Italy Technological Forecasting and Social Change 121:76–88. https://doi.org/10.1016/j.techfore.2016.12.010
17. Enderami SA, Sutley EJ, Hofmeyer SL (2021) Defining organizational functionality for evaluation of post-disaster community resilience. Sustain Resilient Infrastruct. 1–18. https://doi.org/10.1080/23789689.2021.1980300
18. Verma H (2011) Services Marketing: Text and Cases (second edition). Pearson Education, India
19. Nofal O, Rosenheim N, Kameshwar S, Patil J, Zhou X, Van De Lindt JW et al (2024) Community-level post-hazard functionality methodology for buildings exposed to floods. Computer-Aided Civil and Infrastructure Engineering. https://doi.org/10.1111/mice.13135
20. Nofal OM, Amini K, Padgett JE, van de Lindt JW, Rosenheim N, Darestani YM et al (2023) Multi-hazard socio-physical resilience assessment of hurricane-induced hazards on coastal communities. Resilient Cities and Structures 2(2):67–81. https://doi.org/10.1016/j.rcns.2023.07.003
21. Sanderson D, Cox D, Barbosa AR, Bolte J (2022) Modeling Regional and Local Resilience of Infrastructure Networks Following Disruptions from Natural Hazards. J Infrastruct Syst 28(3):04022021. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000694
22. Amini K, Padgett JE (2023) Probabilistic risk assessment of hurricane-induced debris impacts on coastal transportation infrastructure. Reliab Eng Syst Saf 240:109579. https://doi.org/10.1016/j.ress.2023.109579
23. Khan AA, Bhardwaj SM (1994) Access to Health Care: A Conceptual Framework and its Relevance to Health Care Planning. Eval Health Prof 17(1):60–76. https://doi.org/10.1177/016327879401700104
24. Saxon J (2020) Empirical Measures of Park Use in American Cities, and the Demographic Biases of Spatial Models. Geographical Analysis. 53(4):665–85. https://doi.org/10.1111/gean.12265
25. Constas M, Frankenberger T, Hoddinott J (2014) Resilience measurement principles: Toward an agenda for measurement design. Resilience Measurement Technical Working Group, Technical Series, Food Security Information Network, p 1
26. Davis CA (2014) Water System Service Categories, Post-Earthquake Interaction, and Restoration Strategies. Earthq Spectra 30(4):1487–1509. https://doi.org/10.1193/022912eqs058m
27. Allen AO (1978) Chapter Five - QUEUEING THEORY. In: Allen AO (ed) Probability, Statistics, and Queueing Theory. Academic Press, pp 149–233
28. Kroese DP, Taimre T, Botev ZI (2013) Handbook of Monte Carlo Methods. John Wiley & Sons
29. Fishman GS (2006) A First Course in Monte Carlo. Thomson Brooks/cole
30. van de Lindt JW, Peacock WG, Mitrani-Reiser J, Rosenheim N, Deniz D, Dillard M et al (2020) Community Resilience-Focused Technical Investigation of the 2016 Lumberton, North Carolina, Flood: An Interdisciplinary Approach. Nat Hazard Rev 21(3):04020029. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000387
31. Sutley EJ, Dillard MK, van de Lindt JW (2021) Community Resilience-Focused Technical Investigation of the 2016 Lumberton, North Carolina Flood: Community Recovery One Year Later. NIST Special Publication. 1230(2). https://doi.org/10.6028/NIST.SP.1230-2
32. Helgeson J, Hamidah S, Sutley E (2021) The Lumberton, North Carolina Flood of 2016, Wave 3: A Community Impact and Recovery-Focused Technical Investigation Following Successive Flood Events. NIST Special Publication. 1230(3). https://doi.org/10.6028/NIST.SP.1230-3
33. van de Lindt J, Peacock W, Mitrani-Reiser J, Rosenheim N, Deniz D, Dillard M, Fung J. The Lumberton, North Carolina Flood of 2016: A community resilience focused technical investigation. NIST Special Publication. 2018;1230(1). https://doi.org/10.6028/NIST.SP.1230.
34. Enderami SA, Mazumder RK, Dumler M, Sutley EJ (2022) Virtual Testbeds for Community Resilience Analysis: State-of-the-Art Review, Consensus Study, and Recommendations. Nat Hazard Rev 23(4):03122001. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000582
35. Infogroup I (2016) ReferenceUSA database
36. Watson M, Crawford S, Sutley E, Loerzel J (2022) The Lumberton, North Carolina Flood of 2016, Wave 4: Occupancy and Operational Status During the COVID-19 Global Pandemic. NIST Special Publication. Gaithersburg, MD: National Institute of Standards and Technology
37. Xiao Y, Watson M, Helgeson J, Farokhnia K, van de Lindt J, Mitrani-Reiser J, Instrument BS, January 19, et al (2018) Wave 2. Designsafe-C I:2020
38. van de Lindt JW, Kruse J, Cox DT, Gardoni P, Lee JS, Padgett J et al (2023) The interdependent networked community resilience modeling environment (IN-CORE). Resilient Cities and Structures 2(2):57–66. https://doi.org/10.1016/j.rcns.2023.07.004
39. Nofal OM, van de Lindt JW (2020) High-resolution approach to quantify the impact of building-level flood risk mitigation and adaptation measures on flood losses at the community-level. International Journal of Disaster Risk Reduction 51:101903. https://doi.org/10.1016/j.ijdrr.2020.101903
40. Nofal OM, van de Lindt JW (2020) Probabilistic Flood Loss Assessment at the Community Scale: Case Study of 2016 Flooding in Lumberton, North Carolina. ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering 6(2):05020001. https://doi.org/10.1061/AJRUA6.0001060

41. Nofal OM, van de Lindt JW (2020) Minimal Building Flood Fragility and Loss Function Portfolio for Resilience Analysis at the Community Level. Water 12(8):2277
42. Nofal OM, van de Lindt JW (2021) High-resolution flood risk approach to quantify the impact of policy change on flood losses at community-level. International Journal of Disaster Risk Reduction 62:102429. https://doi.org/10.1016/j.ijdrr.2021.102429
43. Nofal OM, van de Lindt JW, Do TQ (2020) Multi-variate and single-variable flood fragility and loss approaches for buildings. Reliab Eng Syst Saf 202:106971. https://doi.org/10.1016/j.ress.2020.106971
44. Rosenheim N, Guidotti R, Gardoni P, Peacock WG (2021) Integration of detailed household and housing unit characteristic data with critical infrastructure for post-hazard resilience modeling. Sustain Resilient Infrastruct 6(6):385–401. https://doi.org/10.1080/23789689.2019.1681821
45. Rosenheim N (2021)Detailed Household and Housing Unit Characteristics: Data Replication and Code. DesignSafe-CI. https://doi.org/10.17603/ds2-jwf6-s535 v2
46. OpenStreetMap contributors: Planet dump. https://planet.openstreetmap.org (2015). Accessed April 2022.
47. Boeing G (2017) OSMnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks. Comput Environ Urban Syst 65:126–139
48. Trudeau RJ (1993) Introduction to graph theory. Dover Pub, New York City, NY
49. Brown S, Dawson R (2016) Building network-level resilience to resource disruption from flooding: case studies from the Shetland Islands and Hurricane Sandy. E3S Web Conf 7:04008
50. Pregnolato M, Ford A, Wilkinson SM, Dawson RJ (2017) The impact of flooding on road transport: A depth-disruption function. Transp Res Part D: Transp Environ 55:67–81. https://doi.org/10.1016/j.trd.2017.06.020
51. Krishnamoorthy K (2016) Handbook of statistical distributions with applications second edition. second ed. Chapman and Hall/CRC
52. Great Schools Partnership, Education Writers Association, Nellie Mae Education Foundationcite: Glossary of Education Reform. https://www.edglossary.org/ (2014). Accessed Oct 2022.
53. National Center for Education Statistics (NCES): School Attendance Boundary Survey (SABS). https://nces.ed.gov/programs/edge/SABS (2016). Accessed Oct 2022.

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