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Virtual Testbeds for Community Resilience Analysis: Step-by-Step Development Procedure and Future Orientation

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A B S T R A C T

Virtual community resilience testbeds enable community-level inferences, convergence research, and serve as decision-making aids. Testbeds are critical for the verification and validation of emerging computational models and quantitative assessment frameworks of community-level disaster impacts, disruption, and recovery processes. This paper illuminates the significance of establishing a standardized approach for developing virtual community resilience testbeds and proposes a systematic schema for this purpose. The workflow facilitates testbed development by defining a series of steps, starting with specifying the testbed simulation scope. Arguing hazard and community modules are the principal components of a testbed, we present a generic structure for testbeds and introduce minimum requirements for initiating each module. The workflow dissects the testbed's architecture and different attributes of the components beneath these modules. The proposed steps outline existing relevant tools and resources for creating the building, infrastructure, population, organization, and governance inventories. The paper discusses challenges testbed developers may encounter in procuring, cleaning, and merging required data and offers the initiatives and potential remedies, developed either by the authors or other researchers, to address these issues. The workflow concludes by describing how the testbed will be verified, visualized, published, and reused. The paper demonstrates the application of the proposed workflow by developing a testbed based on Onslow County, North Carolina using publicly available data. To foster sharing and reusing of developed testbeds by other researchers, all supporting documents, metadata, template algorithms, computer codes, and inventories of the Onslow Testbed are available at the DesignSafe-CI. The procedure proposed here can be used by other researchers to guide and standardize testbed development processes, and open access to virtual testbeds to the broader research community.

1. Introduction

Interest in the development and application of virtual testbeds for community resilience analysis has gained momentum along with rapid advances in computational science, tools, and technologies over the past few years. The application of virtual testbeds is being popularized among researchers as a means of verification and validation (V&V) of emerging community resilience models and frameworks [1–8]. Community resilience is a community's ability to prepare and plan for, absorb, recover from, and more successfully adapt to adverse events such as natural hazards [9–11]. Thus, the underlying structure of a community resilience testbed should be capable of incorporating and integrating data and models which support the full scope of resilience analyses. Testbeds enable community-level inferences, often through model chaining, and promote convergence through providing a means for community input and aiding in community-based decisions. Testbeds are being used to serve the needs of training and educational purposes as well as provide better support for risk-informed decision-making by communities to optimize public and private investments.

Despite their increasing popularity, testbeds are almost always indirectly presented in the literature. Enderami, et al. [12] performed a systematic literature review and identified 22 testbeds used for community resilience analysis. The review used specific inclusion/exclusion criteria and presented a comprehensive list of identified testbeds, and their metadata, including geographical location, spatial resolution, size, demographics, incorporated hazards, building and infrastructure inventory, socioeconomic systems, development timeline, associated publications inventory, and V&V [12]. Findings from reviewing 103 publications associated with 22 testbeds coupled with an expert survey revealed several gaps in testbed development knowledge, starting with confusion on what a testbed actually is [12]. Other gaps identified include, for example, that there is no standardized workflow for testbed development, and testbed publication is quite limited, leading to major challenges in access and reuse. The development of virtual testbeds is

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time-consuming and labor-intensive. When testbeds are not published, their use becomes out of reach for smaller research teams and projects. Standardizing the workflow of testbed development, including testbed publication, can open access more equitably across the research community. The goal of this paper is to fill these gaps by introducing a workflow for testbed development and demonstrating its application, including the testbed publication process. The paper contributes new knowledge through proposing a novel workflow for testbed development, and supports researchers' endeavors to create more reliable, comprehensive, and realistic models and frameworks for assessing the resilience of communities.

1.1. Defining a testbed

"A 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" [12]. In the context of community resilience, testbeds enable researchers to test, verify, and validate their community resilience algorithms at different scales and spatial resolutions.

For decades, researchers have studied disasters through field studies and case studies. While both field studies and case studies can aid in the development of a testbed, they are distinctly different from a testbed. Field studies are performed in real communities, often after disasters, and are used to collect data on specific topics, often about impacts and experiences after disasters. Field studies play an important role in testbed development; field study data can feed into modeling assumptions, and aid in model validation [13]. Case studies, on the other hand, require a detailed consideration of the development of a particular situation. Case studies also play an important role in testbed development; case studies often have very context-specific data and/or understandings which can aid in model assumptions and model validation. A popular trend in the literature is to develop a virtual testbed based on a real community where field studies and case studies have been performed in the past (see [13–16] as examples).

Similarly, for decades, disaster researchers have used classic risk assessment tools (e.g., Hazus [17]) and more recently used modern high-tech simulation instruments such as a Digital Twin, and agent-based models of infrastructure systems at the community level. While each of these is a valuable asset to researchers studying community resilience, risk assessment tools, Digital Twins, and agent-based models are distinct from virtual testbeds. All four have virtual and visualization components, but none of them provide the required architecture or metadata that accompany testbeds. For example, Hazus users, even when utilizing the Advanced Data and Models option, cannot examine models that include social and economic aspects of the community, nor can users characterize and propagate uncertainties in their models. Digital Twins are virtual environments that represent the physical characteristics of a community, without simulating its other dimensions. Agent-based models are models that can be applied within a testbed but do not represent the testbed itself. It is possible that future advancements in virtual testbeds, risk assessment tools, and Digital Twins will feed into the development of something new that utilizes the best of all three.

1.2. Motivation

The availability of existing testbeds for use by the research community has profound implications for advancing community resilience knowledge since each next researcher will not have to develop a new testbed from scratch. Developing a community resilience testbed is time-consuming and likely too labor-intensive for most research teams, particularly those without previous testbed development experience and project timelines shorter than three years. The lack of standard guidance to provide consistent instructions for testbed creation, validation, and publication, results in an uneven distribution of testbeds with different hazard and system types. The vast majority of existing testbeds focus on seismic-related hazards and physical infrastructure systems [6,7,18,19] exclusively and overlook modeling other hazard types and a community's social and economic systems. To reuse a testbed, only providing access to the testbed's datasets and chained algorithms is not enough. The testbed users should also be aware of data procurement and processing procedures, modeling assumptions in testbed creation, approaches applied for testbed verification and validation, and V&V results.

This paper proposes a systematic workflow for *initiating* community resilience testbeds. The next section begins by introducing a standard structure for community resilience testbeds based on the authors' analysis of existing testbeds and introduces the minimum components needed to initiate a testbed using findings from a systematic literature review and an expert survey [12,20]. The paper, then, presents the workflow, which begins with defining a testbed's initial simulation scope alongside designing its architecture and ends with testbed publication for reuse. Existing approaches and data sources for implementing the workflow and modeling testbed components are explained alongside possible challenges developers may encounter. The application of this workflow is demonstrated by establishing a testbed based on Onslow County, North Carolina, using publicly available data in the United States. The paper concludes with a discussion of potential remedies for addressing challenges in establishing a virtual community resilience testbed and areas for future testbed research.

2. Generic structure of community resilience testbeds

In line with the testbed definition stated in Section 1, we propose a generic high-level structure for community resilience testbeds, illustrated in Fig. 1. Ideally, a fully developed testbed consists of all components illustrated in Fig. 1. However, in practice, testbeds evolve gradually as they are being used. Thus, logic gates are borrowed from event-tree modeling to demonstrate the *minimum* components and hierarchy required for *initiating* a testbed. The minimum requirements for the testbed were determined based on our synthesis of the testbed literature and the result of a survey administered to testbed experts [20]. The survey data are available at DesignSafe-CI [21]. In Fig. 1, the "AND" gate is used to show that the output component exists only if all input components are available; conversely, the output of an "OR" gate develops even if only one input component exists. The proposed structure is constructed using primarily "OR" gates to minimize constraints for beginning the testbed development process. As evident in Fig. 1, community resilience testbeds must have both a hazard module and a community module. Ideally, the community module includes physical, social, and economic systems; however, only one of the three is sufficient to *initiate* a testbed. This means, despite the common perception, testbed development can begin with creating social or economic systems rather than physical ones; challenging the conventional engineering-centric approach to testbed development. The proposed structure in Fig. 1 is such that the availability of either of the community's infrastructure assets or building inventory is adequate to establish the physical system of the community module. The community's social and economic systems can be simulated using social and economic models or closely resembled by indices representing their capacity. A hazard module consists of one or more probabilistic or deterministic hazard numerical models. The details of the systems and subsystems beneath community and hazard modules depend on the testbed's purpose and the availability of needed data; such details as well as the required architecture for establishing a testbed are discussed in the next sections.

The proposed generic structure was applied to the 22 community resilience testbeds identified in [12] for validation. Table 1 presents a summary of the main features of the reviewed testbeds' systems and subsystems. The structure proposed in Fig. 1 is compatible with the structure of the identified testbeds. Table 1 also depicts where there are strengths and where there are gaps in the testbed development literature, further discussed herein.

Table 1
Summary of main components of the existing testbeds.

Testbed	Imaginary	Community Module									Hazard Module								
		Physical System							Social System	Economic System	Natural Hazard					Man-made Hazard			
		Building Inventory	Infrastructure Asset Inventory																
			Water	Power	Gas	Transportation	Communication	Wastewater and Drainage			Earthquake	Wind	Flood	Tornado	Tsunami	Urban Fire	Cyber-physical	Pandemic	Contamination
CLARC	●	●	●	●	●	●		●	●			●	●					●	
Centerville	●	●	●	●		●			●	●	●	●		●					
Benchmark City (China)	●	●	●	●	●	●		●			●								
Shelby County		●	●	●	●	●			●	●	●								
Seaside		●	●	●		●			●		●				●				
Galveston		●		●		●			●			●	●						
Gotham City	●	●	●	●		●	●		●	●									
Harris County				●	●	●						●	●						
Gilroy		●	●			●			●		●								
psuedo-Norman		●	●	●					●					●					
Joplin		●		●					●	●				●					
ASCE First Generation Testbed	●	●	●								●								
Lumberton		●							●				●						
Atlantic County		●										●	●						
San Francisco Bay Area		●				●					●								
Micropolis	●		●	●												●			●
Turin Virtual City		●									●								
Anytown	●		●								●								
The unnamed Water Network	●		●								●								
UW Power Systems Test Case Archive				●							●								
C-Town	●		●														●		
Mesopolis	●		●																●

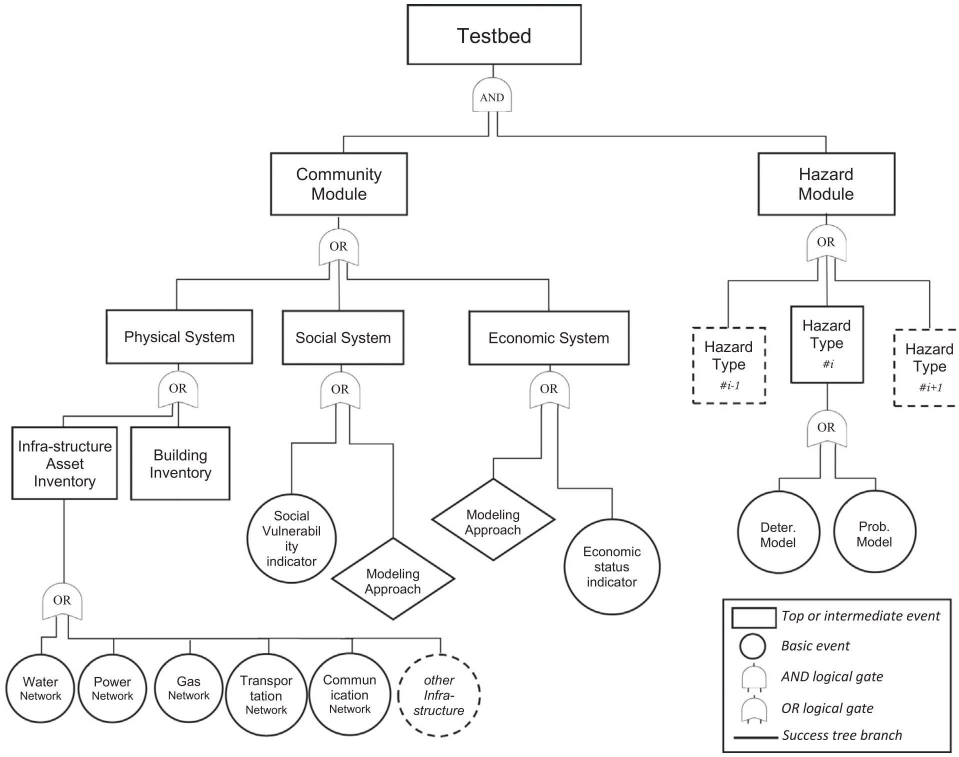

Fig. 1. Generic structure of a community resilience testbed where logic gates present requirements for initiating a new testbed.

3. Testbed development methodology

This section presents the methodology and workflow we established for developing a community resilience testbed. A community resilience testbed can represent either an imaginary or a real community [12]. The methodology elaborated herein can be applied to both imaginary and real testbeds; however, there are certain details on data collection and processing that perhaps are only applicable to testbeds that represent real-world communities.

3.1. Testbed preliminary simulation *scope and architecture*

Testbeds can have significant capability and modeling scope; achieving all components listed in Fig. 1, most likely, will occur over a significant time. Thus, creating a testbed requires a continuous development approach which starts with developers defining a preliminary simulation scope and establishing the hazard and community modules accordingly. Defining the testbed preliminary simulation scope includes determining the type, modeling approach, and spatial resolution of the hazard and community modules in alignment with its first users' needs. The availability of data needed for modeling hazard and community modules, as well as the skill of the researchers involved in initiating the testbed, are the other determining factors that may govern the preliminary simulation scope. Scope definition should be done in parallel with the development of the testbed's back-end architecture so that the testbed can continuously evolve using the output of the front-end users' models; this concept is illustrated in Fig. 2.

In Fig. 2, the cloud icon represents the testbed's virtual environment, which is divided into front- and back-ends and sits on a deck that contains external datasets. The puzzle pieces in Fig. 2 represent the components of the community module which are accessible from the front-end and can be utilized by the users as input to their models. The community module is continuously updated based on the output of users' models and community partners' input, as appropriate. This new contribution to testbed development is conceptually illustrated with a purple piece that is being added to the existing puzzle pieces in Fig. 2. Using the puzzle piece symbol to display the community module, we underline the significance of the back-end architecture in testbed development. While existing components of the community, including building inventory, infrastructure inventory, population inventory, organization inventory, and governance inventory, are linked together as pieces of a puzzle, the new component must also be properly chained. To chain, testbed developers need to determine how data libraries are transformed, stored, and consumed within the backend, and design appropriate pre- and post-processors to facilitate data transfer and linkage between them. Sections 3.2 and 3.3 discuss the details of the hazard module and the community module, shown in Fig. 2.

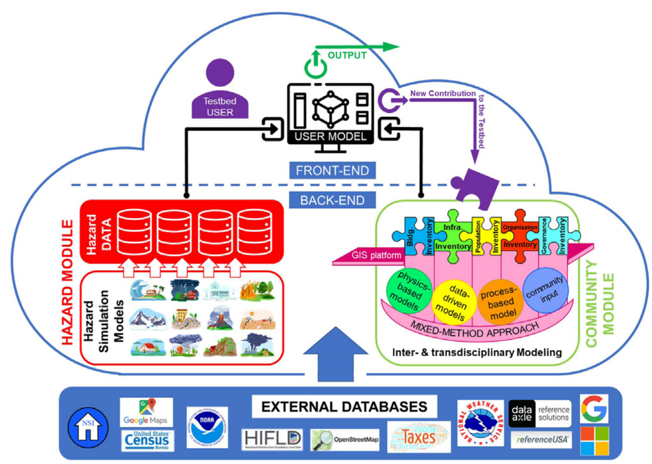

Fig. 2. Conceptual illustration of a community resilience testbed architecture.

3.2. *Hazard module*

The hazard module of a testbed can include characteristics of either natural or man-made (e.g., contamination, cyber-physical attacks, urban fires, and disease pandemics) hazards or both. Natural hazards are typically classified under two primary categories, 1) geologic hazards (which cover strong ground motions, liquefaction , tsunamis, landslides, and volcanic eruptions); and 2) climatic hazards (which include floods, hurricanes, storm surges, tornados, drought, and wildfire). The hazard module quantifies the hazard and provides an estimate of its characteristics (such as power, magnitude, intensity, velocity, etc.) at any location of interest over the entire area of the testbed. As shown in Fig. 2, these estimates are stored in a set of datasets and are accessible from the front-end. Several methods and multiple software programs and tools can be found in the literature for hazard simulation [22–32]. Of note, the regional quantification of a hazard raises additional challenges, such as the necessity to consider spatial variability and correlation in hazard simulation [33–36]. While considering the spatial correlation of hazards may significantly increase the computational complexity and cost, ignoring it may result in an overestimation of risk in the case of frequent hazards and an underestimation of risk in the case of rare hazards [37]. The "State of the Art in Computational Simulation for Natural Hazards Engineering" report [38] comprehensively reviewed simulation methods, data sources, and software tools that are typically used in engineering disciplines to characterize earthquake, hurricane, and tsunami hazards. As hazard modeling is much further along in testbed development than the community module, it is outside the scope of this paper to discuss various hazard modeling techniques and tools. Instead, this section discusses the significant principles of hazard modeling methods and refers readers to other studies that have provided detailed reviews of the modeling processes.

A hazard simulation model can be deterministic or probabilistic, while both are plausible for testbed development. Probabilistic models tend to consider all possible scenarios along with their likelihood of occurrence, whereas deterministic models simulate a specific example of a scenario, often the most adverse one, and do not have a stochastic basis. The probabilistic approach typically applies ensemble modeling to account for uncertainties in events' intensity, location, and time of occurrence. The output of a probabilistic approach is the exceedance probability of the hazard intensity that may be observed at the desired location in a given period. Natural hazards (particularly climatic hazards) are often complex adaptive phenomena, and their characteristics change significantly with any variations in the current condition. This means with unavoidable errors in data measuring, it is impossible to precisely forecast a future event using deterministic approaches [39]. Therefore, probabilistic methods can better estimate the characteristics of future natural events (especially climatic hazards) as climate change is happening. A major challenge with using probabilistic approaches is the presence of significant uncertainties in all components of the hazard model [28]. Uncertainty is commonly divided into epistemic and aleatory uncertainty [39]. Epistemic uncertainty originates from incomplete knowledge of a phenomenon or process that influences the event. Aleatory uncertainty derives from the inherent variations in a random event and the chaotic nature of natural hazards. Aleatory uncertainty cannot be reduced with new knowledge [40]. The aleatory uncertainty can be captured through multiple runs of the synthetic models with slight changes in initial and boundary conditions [41]. Epistemic uncertainties are often quantified by employing statistical models (e.g., Monte Carlo simulation) and ensemble modeling, even still ensemble models may not capture all possible future scenarios [42].

To better serve the purpose of V&V, testbed developers often tend to use deterministic models to hindcast past events when establishing the hazard module at the initial phases of testbed development. The application of scenario-based analyses is relatively straightforward and their results, compared to probabilistic-based assessments, are easier to interpret for decision-makers [43–45]. The National Institute of Standards and Technology (NIST) Community Resilience Planning Guide [46] also recommends establishing scenario analyses for more general resilience plans or when the hazard levels are not defined by code.

3.3. Community module

The community module of a fully developed testbed is ideally a complex geospatial model of multiple interconnected social, economic, and physical systems. Aside from the complexity of modeling these systems individually, simulating a community requires collaborative, inter-, and transdisciplinary modeling efforts and community input, which can both be challenging. To address the first challenge, it is imperative to determine how the output of models from different disciplines will be linked together, as they may be at different spatial resolutions, temporal scales, or measurement units. Rosenheim, et al. [47] proposed a workflow that links high-resolution spatial data on household characteristics to residential buildings that are linked to infrastructure. The workflow utilizes a stochastic model to transform Census demographic data aggregated at areal unit into disaggregated housing unit data that includes household-level characteristics. Accordingly, we propose using a similar approach to link the outputs of models from various disciplines. For this purpose, as illustrated in Fig. 2, the output of each model should be incorporated into a set of chained inventories, namely, building, infrastructure, population, organization, and governance. Each inventory is a collection of datasets that are linked through keys. For example, school datasets (organization inventory) can be linked to residential property datasets (building inventory) through the students and staff living in the housing units (keys); i.e., connecting the social system to the physical system.

As can be seen in Fig. 2, a mixed-method simulation approach should be employed to create community inventories. This means developers may use physics-based, data-driven, or process-based (e.g., Leontief input-output model) models depending on their needs. For the second challenge, the development of a community-level testbed requires input from community partners, both in the ideation of the initial scope of work and in the development of the community inventories [48]. This participation, labeled as Community Input in Fig. 2, can take different forms, such as surveys, interviews, focus groups, workshops, discussion panels, roundtables, etc., spanning the engagement continuum [49].

In this section, in addition to introducing the available data sources and modeling techniques for creating community inventories, we discuss several common challenges in establishing them and present conducive recommendations to address such challenges.

3.3.1. Building inventory

The building inventory typically consists of multiple datasets that include information about the main attributes of existing buildings, along with corresponding damage functions and/or functionality models. Table 2 presents a set of the most common building characteristics that were used for building inventory development in the community resilience literature [1,2,5,7,50-58]. The identified features are categorized into five overarching attributes, namely general, geotechnical, structural, architectural, and property-level, as shown in Table 2.

Table 2
Most applicable characteristics of buildings in community resilience models.

Attribute	Characteristics	
1 General	• Location • Height • Year built	• Building boundary • Square footage • Land-use class
2 Geotechnical	• Soil type	• Foundation type
3 Structural	• Vertical load system • Lateral load system	• Structural Integrity • Vertical and lateral irregularity
4 Architectural	• Roof system • Floor system	• Exterior walls • External components (*chimney, parapets, roof overhang, etc.*)
5 Property-level	• Value *(building/content)* • Ownership structure *(private/public)*	• Occupancy • Tenure

It is becoming increasingly common for local and county governments to store a great deal of information about the buildings within their jurisdiction in digital repositories that are accessible to the public or that can be obtained upon reasonable request. This information typically includes the building's location, area, boundary, land-use class, year built, structural system material, building and contents value, occupancy, ownership, and tenure status. However, this data does not suffice for common community resilience models, and more building or property-level information is needed to estimate damage and loss at the community level. Private data may somewhat address such data needs, at least sometimes. National Structure Inventory (NSI) [59], ReferenceUSA [60], ATTOM [61], and Microsoft Building Footprint [62], to name only a few, are databases that provide detailed building and property-level data in the United States.

Private data can be too expensive for academic researchers and often cannot be published to be reused by the research community due to copyrights. More importantly, private data do not necessarily provide all essential information. For example, existing datasets often do not include information about a building's first-floor elevation and roof shape, whereas, both of which are important for estimating flood- and wind-induced damage, respectively. An alternative solution to fill this type of data gap is employing Artificial Intelligence (AI) techniques and computer vision algorithms to extract such visible attributes by processing the images. Wang, et al. [63] have developed an AI-enabled tool, termed BRAILS,[1] for creating community-level building inventory. BRAILS is an open-source framework comprised of individual applications that are stitched together and use machine learning, particularly deep learning algorithms, to gather and process data from online resources such as Open Street Maps (OSM), Google Maps, Google satellite images, and street views. Although BRAILS was designed primarily for creating new building inventories in urban areas and has been used for this purpose since its inception [57,64,65], its modules can also be used individually to fill in gaps in an existing building inventory, as the authors did in Section 4.3.1 of the present paper. Although using private data and AI tools may fill some of the gaps in public data, there are still more details (e.g., lateral load system, foundation type, etc.) that should be included for community-level damage and loss analysis. In such cases, it is possible to simplify the building inventory based on some rational assumptions and use a suite of archetypes to represent all buildings in a community [58].

Merging multiple datasets with different spatial and temporal resolutions is a common challenge in the testbed development process. Different datasets use dissimilar identifiers and diverse geographical reference units (e.g., individual building, map block number, parcel number, etc.) and deal with any missing data differently. For example, McKenna, et al. [57] reported that Microsoft Footprint Database sometimes lumps the footprints of closely spaced buildings together. Thus, it is required to verify the accuracy of data being used for the development of the testbed's components, particularly secondary data assembled by someone outside of the research team. A practical way to perform data verification is cross-referencing and comparing the mutual attributes across datasets from different resources. Due to using various sources for data procurement, various datasets may contain uneven or even contrary information. To address such probable conflicts, the testbed developer should apply a set of solid and transparent principles based on their judgment.

3.3.2. Infrastructure inventory

Infrastructure inventories typically include information about water, electric power, transportation, gas and oil transmission, communication, wastewater, and drainage networks. As evident from Table 1, the first three types of aforementioned infrastructure have been of greater interest to testbed developers, whereas communication infrastructure has received the least attention from developers, despite being very common in reality. As the autonomous vehicle market is growing significantly and Internet of Things products [66] are becoming common, the data transfer and communications infrastructure should be appended to the testbeds' infrastructure inventories in the future.

Security concerns often prevent detailed information about a community's infrastructure assets from being made public. Restricted access to infrastructure data is often a common worldwide challenge among testbed developers that have been reported by several researchers from other fields as well [50,67-71]. This issue has been slightly resolved in the United States after establishing Homeland Infrastructure Foundation-Level Data (HIFLD) platform [DHS, 72]. The HIFLD data inventory comprised three categories of geospatial datasets, namely HIFLD Open, HIFLD Secure, and HIFLD Licensed Data. The HIFLD Open Data category contains national foundation-level geospatial critical infrastructure data within the public domain that are provided to support community preparedness, response, recovery, and resilience research. The HIFLD Secure data category, formerly known as Homeland Security Infrastructure Program (HSIP) Gold, is a for-official-use-only compilation of over 125 data layers characterizing domestic infrastructure and base map features. The HIFLD Licensed data is commodity data that is available upon a request in compliance with a set of predefined requirements [DHS, 72]. Even still, publishing that piece of the testbed for reuse by others may not be permitted. In these cases, testbed developers resort to publishing a coarse replica of the community's infrastructure network(s) containing only a few key aspects of the real system, e.g., pseudo-Norman testbed by Masoomi and van de Lindt [73]. We, herein, present our findings on a few existing resources that provide conducive data for simulating road, power, and water networks in testbed development.

Road networks are the backbone of a community's transportation network. Some road network attributes, such as route footprint, speed limit, and traffic direction, are often publicly accessible and can be procured from OpenSteetMaps [OSM, 74] or the local government's Department of Transportation (DOT). Other attributes of road networks, such as real-time traffic data, might be obtainable from private companies that provide location-based data in the testbed's geographic scope, such as Google Maps, INIRIX,[2] Waze,[3] Uber,[4] etc. Additionally, Boeing [75] developed a code for modeling road networks for every urban area in the world using OSMnx, an open-source Python tool. The code is available for public reuse at (https://github.com/gboeing/street-network-models).

An electric power network, in general, consists of three major components: (1) power stations to generate electricity, (2) a transmission system to carry the generated electricity to substations, and (3) a distribution system to provide end-users with power. The UW Power System Test Case Archive (https://labs.ece.uw.edu/pstca/) is a website that provides required datasets for modeling common 1960s power distribution systems in the Midwestern US. Also, the researchers at Texas A&M University have launched a repository named Texas A&M University Electric Grid Datasets (https://electricgrids.engr.tamu.edu/) that contains a collection of electric grid datasets. The S&P Global Commodity Insights, also known as Platts, is a private company that provides data on the global energy and commodities markets and offers spatial data on electric power, natural gas, and oil transmission network features in North America and Europe (https://www.spglobal.com/commodity-insights/en).

Water distribution systems typically consist of a water main, distribution pipelines, elevated water tanks, reservoirs, valves, pumps, and pumping stations. In the U.S., Kentucky Water Resources Research Institute developed a database (http://www.uky.edu/WDST/database.html)

[1] Building Recognition using Artificial Intelligence at Large Scale

[2] https://inrix.com/

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

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

that provides a collection of datasets for 40 different water distribution networks. The datasets consist of information on the networks' physical layout, geometry data, GIS maps, hydraulic models, and water demands [76].

3.3.3. Population, organization, and governance inventory

Social and economic systems are more often discussed within case studies and theoretical works, and incorporating such systems and phenomena into community resilience testbeds is uncommon, as can be observed in Table 1. Ideally, social and economic systems in a testbed's community module include multiple interconnected predictive models along with high-resolution population, organization, and governance inventories. However, in practice, only a few predictive social science and economic models have been created for this purpose. Population evacuation [77], population dislocation [52,78], housing unit allocation [79], and household housing recovery [80] are the few predictive social models that have been used in testbeds; albeit they only focus on the population, ignoring other aspects of the social system, including c For assessing the regional impact of natural hazards on a community's economy, Computable General Equilibrium (CGE), business interruption loss, and recovery models are the few predictive models available in the literature [2,52,81-86]. Instead, testbed developers, particularly those who have an engineering background, have mostly used static indices to characterize a community's social and economic capacity, Gotham City and CLARC in Table 1, for example. Indeed, these indices are easy to apply and interpret for non-experts. They also do not need a high-resolution population inventory, which predictive models often require.

Population inventory provides demographic information (e.g., population estimates, age, sex, race, ethnicity, disability, etc.) about the people living in the testbed area. The U.S. Census Bureau is the leading source of statistical information about the U.S. population, which collects and provides detailed demographic data at multiple spatial resolutions ranging from the National Level down to Census Blocks. Data come from decennial censuses, which count the entire U.S. population every ten years, as well as multiple other annual surveys such as American Community Survey (ACS), which is the largest household survey [87]. In addition to unavoidable statistical errors, biases, and uncertainties associated with working with data, doing samplings, and surveys, census counts face a few other obstacles. Census has historically underestimated populations that are more challenging to contact through surveys, phone calls, and door-to-door outreach, such as rural communities, poor urban communities, and undocumented immigrants [88]. Although U.S. Census Bureau Post-Enumeration Surveys may show no statistically significant error at the state and national levels, it still matters for testbeds as they represent communities smaller than an entire state. This highlights the importance of engaging local communities in testbed development since such errors are rarely discovered without community input.

Census data cannot be applied directly for creating a high-resolution population inventory since Census Block is the finest spatial resolution of census data, which still does not cover all variables. For example, ACS five-year surveys do not provide reliable data at spatial scales smaller than the census tract level for several demographic variables [89]. Thus, an alternative way for creating high-resolution household-level population inventories is applying stochastic processes on the census data and generating high-fidelity population inventory; see Rosenheim, et al. [47] as an example. Although there are private companies (e.g., DirectMail[5] and REGRID[6]) that provide rich data at the parcel or household level, publishing these data will bring up both ethical and copy-right issues.

Organization inventory includes data about businesses and social institutions that are designated to provide goods and services for community members. Social institutions are any entity within the community that meet people's social needs, such as education, family, healthcare, and religion, whereas businesses offer other necessary products and services, such as grocery stores, crucial for a community to function and recover after a disaster. There are multiple resources (e.g., ReferenceUSA, Directmail.com, Placer.ai, etc.) that offer the information needed for building the organizational inventory.

Governance inventory includes information on all governmental agencies that contribute to a community's resilience through making policies, taking action, or providing goods and services. These data typically come from community input.

Here, population, organization, and governance inventories are discussed together, but not to symbolize any less importance relative to building and infrastructure inventories. As interdisciplinary collaborations increase and more community resilience testbeds are being developed and reused, social and economic models are becoming more important, and high-resolution population, organization, and governance inventories will become more critical.

3.4. Testbed verification and validation

Testbeds are primarily used for verification and validation (V&V) of community resilience algorithms. Testbeds themselves must also go through V&V processes to be able to apply results from a testbed analysis to the real world. Verification, in general, is the process of determining that model's implementation represents the developer's conceptual description and specifications of the model. Validation is the process of determining the degree to which a model is an accurate representation of the real world from the perspective of the intended uses of the model (CFDC 1998). Testbed verification involves evaluating the accuracy of employed datasets and modeling approaches individually. See Section 3.3.1 for more information about how to perform the verification. Testbed validation ensures the reliability of the whole environment as it assesses if chained models, integrated modules, and systems still accurately represent the target community when stitched together. To validate a complex computational environment of connected models and data, such as a community resilience testbed, post-disaster data collection and longitudinal studies are needed. As a result, it has become common to develop testbeds of communities that are rich in case studies and post-disaster data. Joplin and Lumberton are two examples of testbeds from Table 1 that have been validated using post-disaster data. To validate the Joplin testbed, estimates obtained from the processing of collected data and reviewing existing government documentation, archived literature, and case studies on Joplin after the EF-5 tornado on May 22, 2011, were used [2]. Lumberton Testbed was validated using post-event data from an ongoing longitudinal research study after the 2016 catastrophic flooding in the city of Lumberton, North Carolina, due to Hurricane Matthew [15].

A few years after a disaster, the population, demographic texture, built environment, and economy of the harmed community are likely to change significantly. Hence, for the V&V of a testbed, the datasets need to be modified to resemble the community at the time of the event. This modification would be very challenging if the event occurred before the digital age. If so, connecting results to existing theories, ground truthing, using expert panels, and comparing the results with other published research in the testbed scope are the alternative techniques for the second phase of testbed V&V [90,91]. While no approach will provide a perfect validation check, the ones described here fairly verify the reliability of systems and modules, either separately or together.

3.5. Testbed visualization, publication, and reuse

In addition to facilitating testbed reuse, testbed visualization can be remarkably effective when discussing analysis results with the decision- and policy-makers. Any geographic information system (GIS) software can be used for this purpose. The GIS environment not only provides the

[5] https://www.directmail.com/

[6] https://regrid.com/

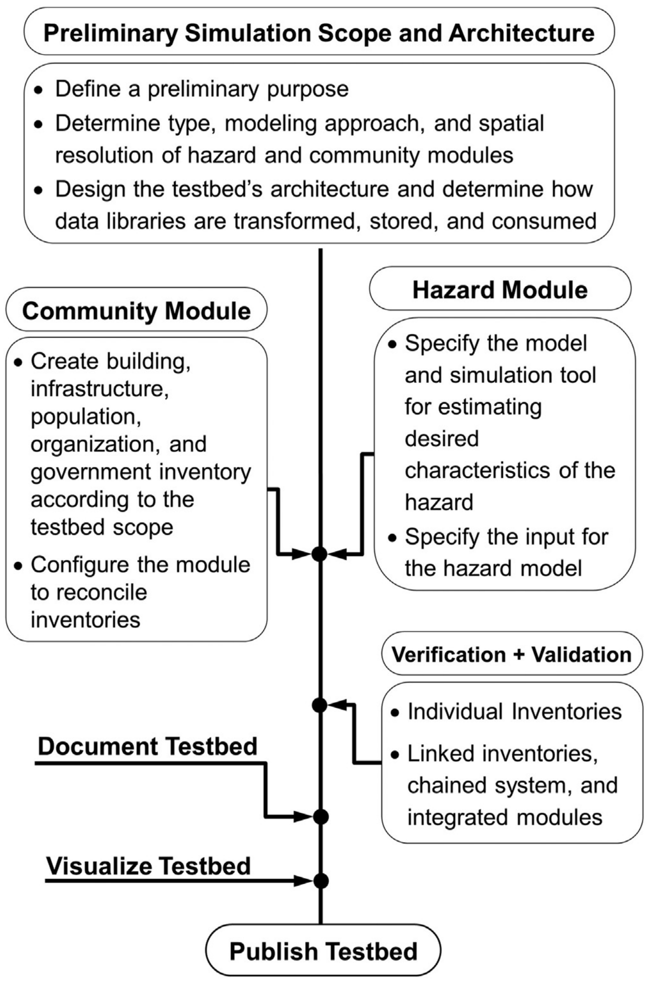

Fig. 3. Testbed development workflow.

opportunity to integrate both the attribute and spatial data for all of the components in a testbed's community module to be stored in a single database but also can be applied to map the community resilience analysis results. ESRI ArcGIS and Q-GIS are conducive software for testbed visualization, however, they require additional software to chain algorithms and simulate disasters. Open-source libraries, such as Leaflet and Folium, are also available to visualize testbed interactively in the Python environment.

Testbed publishing is another imperative step in the testbed development process that cannot be skipped. The creation and validation of testbeds require a great deal of time and effort. Thus, it is not trivial to share a verified and validated testbed to be reused by researchers other than those who created them. Publishing a testbed involves more than sharing the datasets and algorithms that form the testbed components. Documentation of data sources, data cleaning and merging procedures, modeling assumptions, verification and validation process, and contact information for the developer (team) are also required to be published along with testbed components. Platforms such as DesignSafe-CI and IN–CORE are appropriate environments for publishing testbeds.

Fig. 3 presents the step-by-step workflow of the methodology described in Section 3.

4. Step-by-step example to initiate a testbed

To demonstrate the implementation of the workflow shown in Fig. 3, the authors developed a testbed based on Onslow County, North Carolina, using publicly available data in the United States. All testbed documents, datasets, and algorithms (Python scripts and Jupyter notebooks) used for the creation of the testbed's modules are open source and are available on DesignSafe-CI [92] to support an interdisciplinary collaboration for establishing a fully-developed testbed using the proposed workflow.

Onslow County is a coastal community in the State of North Carolina in the United States with a history of experiencing major hurricanes. The county comprises the City of Jacksonville, which is the County seat, and multiple towns. As of the American Community Survey (ACS) 2015–2020, 198,377 people, including 66,131 households with a median income of $69,717 resided in the county. In terms of age, over two-thirds of the total population are between 18 and 65 years old. The racial composition of the county is 74.72% White, 13.99% African American, 0.55% Native American, 2.16% Asian, 0.15% Pacific Islander, 1.46% from other races, and 6.98% from two or more races. About 12.58% of the population is Hispanic or Latino of any race [U.S. Census, 93]. As a hurricane-prone area with a demographic similar to the national average, Onslow County is of interest to community resilience researchers. Onslow County has been used multiple times as a case study in the community resilience literature [8,41,94-100], which makes it a proper community for developing a virtual testbed. The following subsections describe the testbed simulation scope and apply the proposed workflow step by step to develop its components.

4.1. Onslow testbed preliminary simulation scope and architecture

The primary objective of this example is to showcase the application of the proposed workflow. As such, there are no established user needs and demands. Thus, in this particular example, we focus on hazard modeling and evaluating initial impacts. In this context, for the hazard module, the data on (i) wind speed induced by a scenario hurricane and (ii) inundation depth due to a 500-year flood event is estimated across the testbed area and will be available to the testbeds' front-end users. For the community module, the front-end users will have access to the (i) building inventory (including residential properties and grocery stores), (ii) infrastructure inventory (including road network only), and (iii) population inventory (including household-level demographic data and social vulnerability estimates), all linked together geospatially.

The focus of this example is placed on demonstrating how the proposed workflow can be implemented and utilized effectively. The specified simulation scope represents an example starting point. By publishing the testbed and making it publicly available, other researchers and experts are able to collaborate and further develop each module based on their needs and expertise.

4.2. Onslow testbed hazard module

According to the National Oceanic and Atmospheric Administration [NOAA, 101] historical hurricane tracks database, Onslow County has never been hit by a Category 5 hurricane, but three Category 4 hurricanes, including Helene (1958), Diana (1984), and Hazel (1954), were recorded within 100 km of the county between 1857 and 2020. To simulate hurricane-induced winds, Hurricane Helene (1958), the most powerful one of those three Category 4 hurricanes, was chosen as the scenario event [8]. The data needed for simulating the intended scenario event, including information on its track, maximum wind speed, and the central pressure of the hurricane eye, were retrieved from the Atlantic hurricane database [AOML 102]. The wind field model, proposed by Holland [103], was employed to estimate the maximum gradient wind speed at the location of interest. Despite its simple form, the model is highly efficient computationally and has been widely used in the literature for this purpose [e.g., 104,105-108].

$$V_G = \left[\left(\frac{R_{max}}{r}\right)^B \cdot \left(\frac{B \times \Delta p \times \exp\left[-\left(\frac{R_{max}}{r}\right)^B\right]}{\rho} \right) + \frac{r^2 f^2}{4} \right]^{0.5} - \frac{r \times f}{2} \quad (1)$$

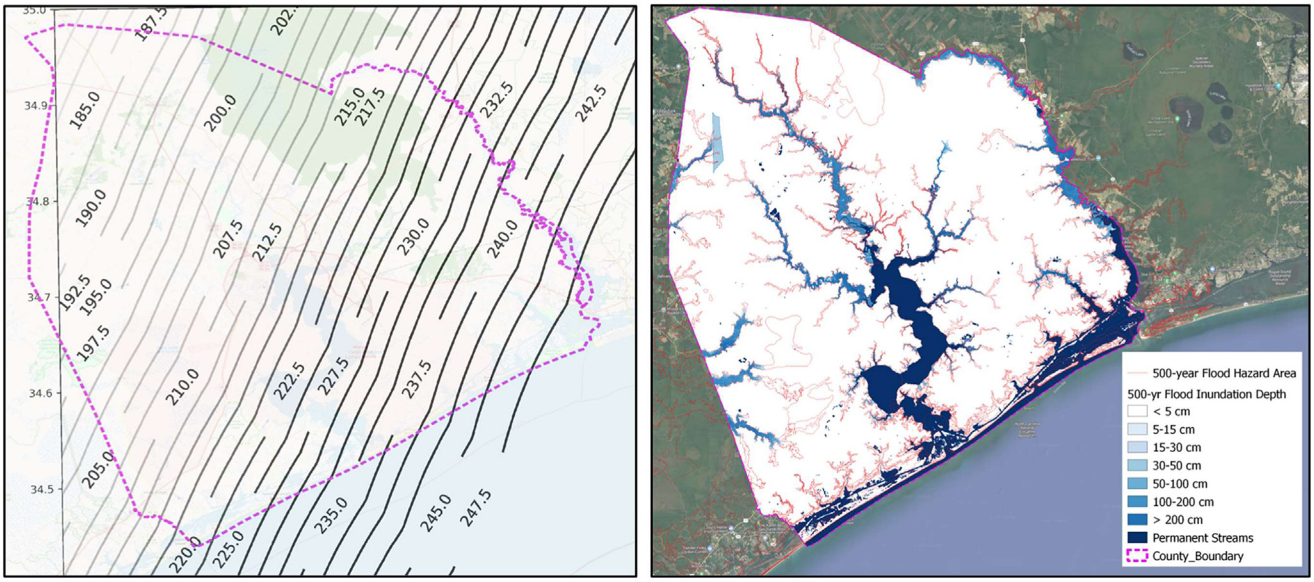

Fig. 4. Onslow Testbed hazard module: a) Hurricane Helene (1958)-induced 3-s gust wind speeds (km/h); b)500-year flood map.

where R_{max} is the radius of the maximum wind, r indicates the distance from the hurricane eye to the desired location, B is the pressure profile parameter, f is the Coriolis parameter, Δ_p is the difference between the central pressure of the hurricane eye and atmospheric pressure, and ρ is the air density. The values of R_{max}, B, and f were determined using Eqs. (2), (3), and (4), respectively.

$$R_{max} = 2.556 - 0.000050255\ \Delta p^2 + 0.042243032\ \psi \tag{2}$$

$$B = 1.881 - 0.00557 R_{max} - 0.01097\psi \tag{3}$$

$$f = 2\Omega \cdot sin\varphi \tag{4}$$

where φ is the local latitude and Ω represents the average angular velocity of the earth. In the end, Gradient wind speed (V_G) is converted into 3-s gust wind speed using conversion factors to yield the surface wind value at the location of interest [105,108–111]. A Python script, executable on Jupyter Notebook and other computing platforms, is developed for simulating the wind field model and is publicly available on DesignSafe-CI [92]. It should be mentioned that the testbed's hazard module currently does not account for the spatial correlation of the hurricane wind fields, however, it can be updated as the testbed is further developed over time. An illustrative example of a methodology for quantifying the spatial correlation of wind speed uncertainties can be found in the work of Fang, et al. [112].

The National Flood Insurance Program (NFIP) is a federal-level program managed by Federal Emergency Management Agency (FEMA) that enables homeowners, business owners, and renters in participating communities in the United States to purchase federally-backed flood insurance. NFIP publicly offers a wide range of digital resources for free download. The National Flood Hazard Layer (NFHL) database is one of those digital resources that provides geospatial data for floods with a 0.2% annual risk [FEMA, 113]. For Onslow Testbed, NFHL data for Onslow County in a GIS file format and incorporated into the hazard module [FEMA, 114]. Fig. 4 shows a screenshot of the hazard maps included in the hazard module of Onslow Testbed.

4.3. Onslow testbed community module

4.3.1. Building inventory

The building inventory in this example consists of geospatial data on physical characteristics, market values, and associated fragility-based vulnerability functions of intended buildings within the testbed area. This information was mostly obtained from the open-to-public datasets provided by Onslow County's government.[7] The tax records were used to identify each building's occupancy and dwelling type, the number of stories, exterior wall material, year built, square footage, and market value. The information retrieved from tax records is then spatially joined with the building footprint dataset to establish the testbed's base map. Microsoft Building Footprint data was used for cleaning and V&V of the building footprint dataset. The accuracy of the tax records data was verified through cross-referencing and comparing the mutual attributes with ReferenceUSA datasets. In addition to providing information on businesses in the United States, ReferenceUSA has a "U.S. New Movers/ Homeowners" dataset that includes proper data about single and multi-family dwellings. To determine the buildings' roof shapes, we used "RoofTypeClassifier" module of BRAILS [115] and Google satellite images. Approximately one percent of the buildings in the testbed inventory were randomly selected, and the predicted shape for their roofs was visually validated using OSM and Google street views and images. Table 3 summarizes the features included in the building inventory of Onslow Testbed besides their data sources and verification procedures.

To lower computation costs, we would rather use reduced-order vulnerability functions for developing the testbed's building inventory. An appropriate Hazus hurricane fragility model [FEMA, 109] was assigned to each building in the inventory using the concept of the building portfolio. A building portfolio is a collection of building archetypes with different attributes that represent a community's building stock [58]. The building inventory was simplified to 22 archetypes, including one commercial archetype and 21 residential.

An F.16 Hazus damage model was assigned to all grocery stores within the testbed area. Residential buildings were mapped using the algorithm shown in Table 4. The mapping algorithm, first, categorizes residential buildings based on their dwelling type into four groups as defined in Table 4. Next, the algorithm determines the corresponding archetype for each building based on the (1) type of external wall, the number of stories, and roof shape for buildings in groups I and II; or (2) construction year for buildings in group III; or (3) the number of stories for buildings in group IV. Then, the algorithm maps associated Hazus

[7] https://onslowcountync.gov/

Table 3
Onslow Testbed building inventory features.

Building Attribute	Data Source
Location and footprint info	The building's location and footprint information was obtained from the building footprint dataset of the local government and were verified using the Microsoft Building Footprint data. This geospatial data was used to create the testbed's base map.
Occupancy and Dwelling type	The building occupancy and dwelling type was obtained from the local government's tax records and validated using the U.S. Homeowners and U.S. Business datasets, publicly available on ReferenceUSA.
Number of stories	The number of stories for each building was achieved from the local government's tax record database and was visually validated for a group of randomly selected buildings.
Exterior wall type	The information on the exterior walls of the buildings was obtained from the local government's tax record database.
Roof shape	The building roof shapes were determined using the BRAILS *RoofTypeClassifier* module and Google satellite images and were visually validated for a group of randomly selected buildings.
Market value	The market value of the buildings was fetched from the local government's tax records and was verified using the U.S. Homeowners and U.S. Business datasets, publicly available on ReferenceUSA.

fragility functions to the buildings. As can be seen in Table 4, more than one fragility function can be assigned to most of the residential archetypes. This is due to the fact that to assign the exact corresponding Hazus fragility function more data is needed, including information on the buildings' roof cover, sheathing, roof-wall connection type, window shutters, glazing coverage, missile environment, and terrain surface roughness. Procuring such types of data is almost impossible, even for a mid-size community such as Onslow County. In this example, a "0.35 m" terrain surface roughness and "A" missile environment are assumed according to Onslow County's topography. For roof cover, window shutters, and glazing coverage, the mapping algorithm randomly

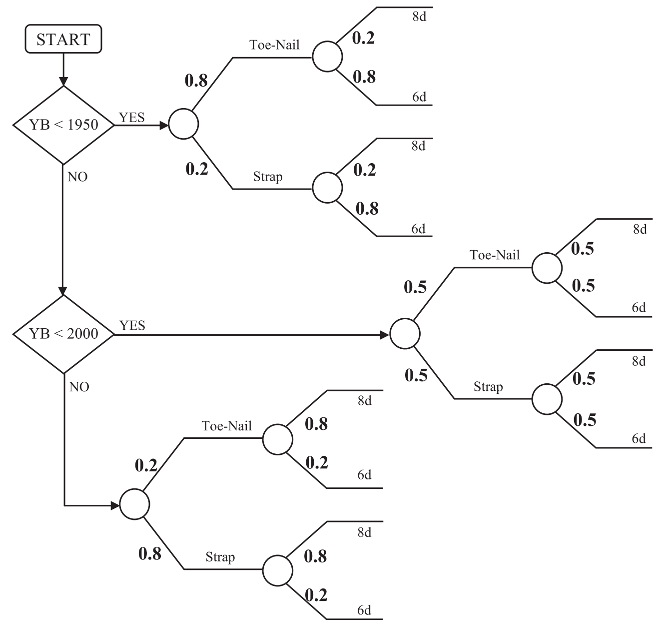

Fig. 5. Algorithm for assigning roof-wall connection and sheathing type in Onslow Testbed.

assigns possible options with equal likelihood to each building. For example, it is presumably as likely for an Archetype-1 building to have window shutters or not. To allocate roof-wall connection and sheathing type, the mapping algorithm applies the binomial probability rule, illustrated in Fig. 5. The criteria in Fig. 5 were selected due to the significant evolution in building codes in those periods such that more recent building codes comply with more strict requirements. For instance, the probability of using a strap for connecting the building's roof and wall increases from 20% to 50%, and 80% as the year built changes from periods before, between, and after 1950 and 2000. The Python script developed for executing the applied mapping algorithm is available on DesignSafe-CI [92].

Table 4
Mapping testbed's residential building inventory to Hazus damage functions.

Archetype Group	Dwelling Type	Archetype †		Mapped Hazus Damage Functions *
I	Beach House, Single-Family	1	URM wall, 1-STY, Gable roof	A.2; A.10; A.50; A.58; A.66; A.74; A.82; A.90; A.98; A.106
		2	URM wall, 1-STY, Hip roof	A.6; A.14; A.54; A.62; A.70; A.78; A.86; A.94; A.102; A.110
		3	URM wall, 2-STY, Gable roof	A.34; A.42
		4	URM wall, 2-STY, Hip roof	A.38; A.46
		5	WFR wall, 2-STY, Gable roof	A.18; A.26
		6	WFR wall, 2-STY, Hip roof	A.22; A.30
II	Beach Townhome, Beach Duplex, Beach Condo, Town Home, Duplex, Condominium, Multi-Family, Apartment	7	URM wall, 1-STY, Gable roof	C.22; A.2; A.10; A.50; A.58; A.66; A.74; A.82; A.90; A.98; A.106
		8	URM wall, 1-STY, Hip roof	A.6; A.14; A.54; A.62; A.70; A.78; A.86; A.94; A.102; A.110
		9	URM wall, 2-STY, Gable roof	A.34; A.42
		10	URM wall, 2-STY, Hip roof	A.38; A.46
		11	WFR wall, 1-STY, Gable roof	C.14; C.20; C.21
		12	WFR wall, 1-STY, Hip roof	C.15
		13	WFR wall, 2-STY, Gable roof	C.24; A.18; A.26
		14	WFR wall, 2-STY, Hip roof	A.22; A.30
		15	WFR wall, 3-STY, Gable roof	C.25
		16	WFR wall, 4-STY, Gable roof	C.26
III	Multi-Section MH, Singlewide M/H	17	YB < 1976	B.3 (pre-HUD, Tied Down); B.3 (pre-HUD, NOT Tied Down)
		18	1976 < YB < 1994	B.3 (HUD, Tied Down); B.3 (HUD, NOT Tied Down)
		19	YB > 1994	B.3 (1994 HUD - Wind Zone II, Tied Down)
IV	Mixed-Use Res/Com	20	≤ 2-STY	F.9; F.10; F.11; F.12
		21	2 ~ 5-STY	F.27; F.28; F.29; F.30
		22	≥ 5-STY	F.45; F.46; F.47; F.48

† URM = unreinforced masonry; WFR = wood frame; STY = story; YB = year built.
* The notations used to introduce the damage functions match the notations in Hazus Technical Manual [FEMA, 109].

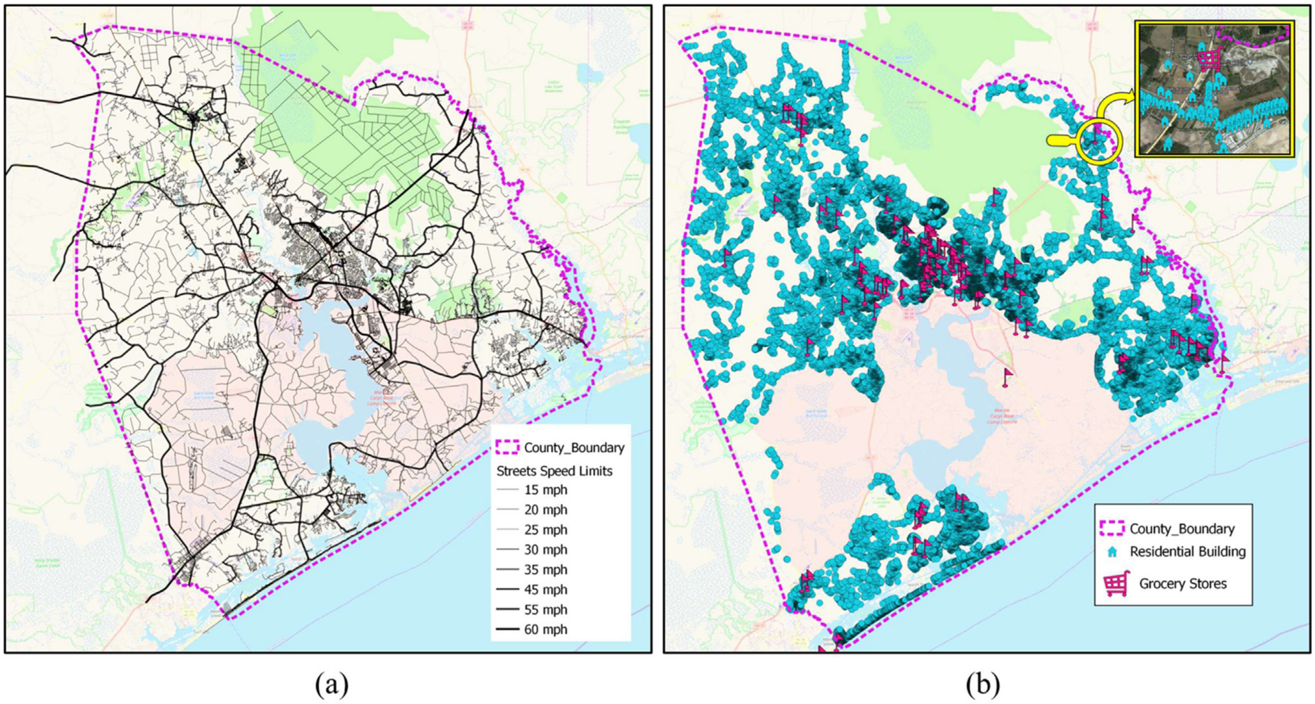

Fig. 6. Physical components of Onslow Testbed: a) road network; b) residential buildings and grocery stores spatial distribution.

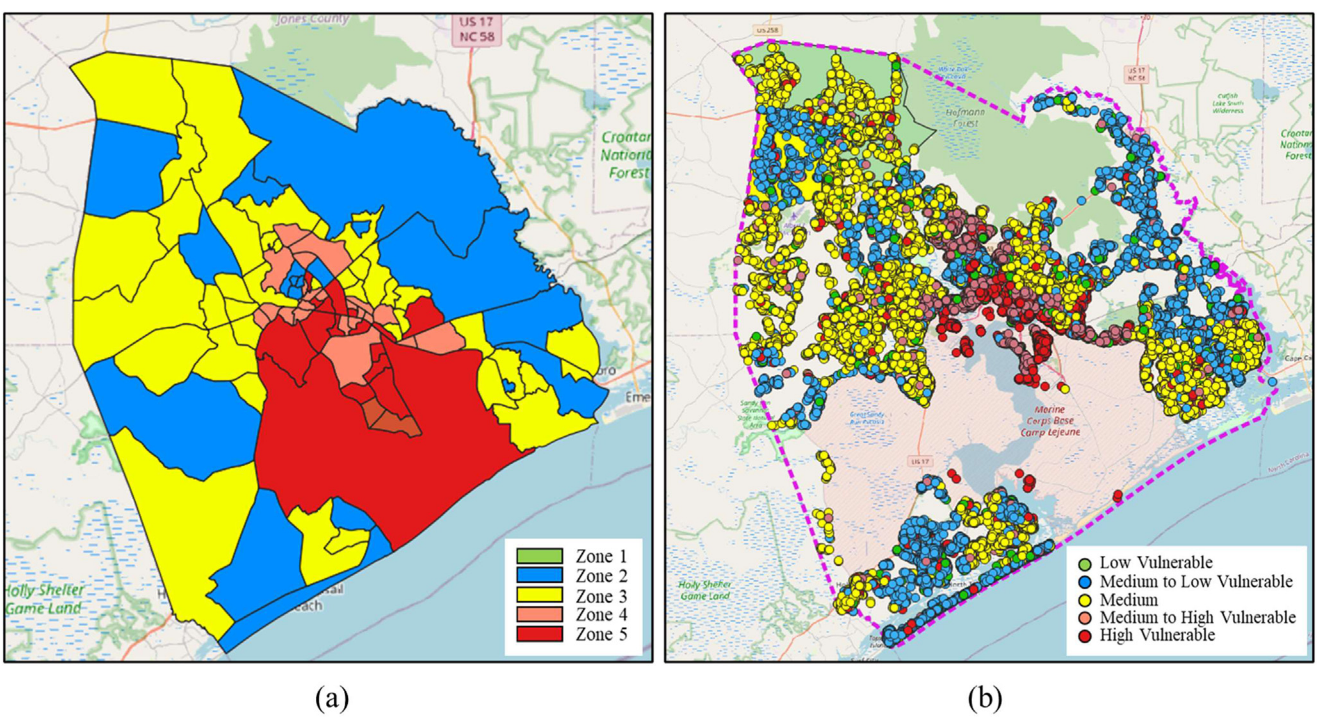

Fig. 7. Mapped (a) SVS zones at the census block group level, (b) households-level social vulnerability in Onslow Testbed.

4.3.2. Infrastructure inventory

Onslow road network model includes geospatial data about the speed limit, traffic direction, and routes footprint within the testbed area. These data were taken from OSM and the North Carolina Department of Transportation (NCDOT) open data. We used Graph theory for the mathematical simulation of the road network [116]. Graphs are collections of nodes connected by edges. The nodes represent the locations where route footprints intersect, while the edges depict the routes that connect these intersections. Other attributes of the road network including streets' name, type, speed, and traffic data were assigned to the edges. The free-flow speed was estimated for streets located in urban areas by 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 (such as bad weather). Finally, the developed datasets based on the road network were spatially merged and incorporated into the testbed's base map. Fig. 6 illustrates the main physical components incorporated into the community module of Onslow Testbed.

In summary, to replicate a similar physical system for another testbed, the testbed developer should go through the following procedure step-by-step:

Step 1 Fetch the most updated geospatial data of building footprints from the local government and Microsoft Building Footprint databases; clean and cross-check the retrieved data.

Step 2 Download the tax record information from the local government's website; clean the data; keep the required attributes, including occupancy, dwelling type, number of stories, exterior wall material, year built, and square footage, and delete the extra information; verify the information using the U.S. Homeowners and U.S. Business datasets, publicly available on ReferenceUSA.

Step 3 Merge the datasets resulting from Steps 1 and 2; keep an eye out for differences between the spatial units of the building footprint and the tax record dataset. For example, a condominium that often contains multiple individually owned apartments is represented by one single footprint record that is associated with multiple tax parcels. In such cases, aggregate the information of tax parcels into a single record.

Step 4 Determine the building roof shape using the “RoofTypeClassifier” module of BRAILS and Google satellite images and add it to the building attribute dataset. BRAILS is an open-source Python package that has multiple modules with different capabilities and was developed by SimCenter to populate the building inventory of a community [115]. In this example, we modified BRAILS to fetch the footprint data locally from the clean and verified dataset created in Step 1. By default, BRAILS reads the footprint data from OSM and Microsoft Building Footprint databases.

Step 5 Use expert knowledge and engineering judgment to develop a proper mapping algorithm for assigning Hazus fragility functions to their corresponding buildings in the inventory.

Step 6 Obtain data on the speed limit, traffic direction, and routes footprint from OSM and the State DOT; estimate the free-flow speed of urban streets using Google Maps data; create a graph model of the road network; assign the attributes of each street to the corresponding edge.

Step 7 Spatially join the road network model with the base map from Step 3.

4.3.3. Population inventory

The population inventory in Onslow Testbed includes household-level demographic data and social vulnerability estimates. In this example, we estimated households' characteristics using the stochastic algorithm developed by developed by Rosenheim [117]. On the other hand, the Social Vulnerability Score (SVS) developed by Enderami and Sutley [118] to serve the purpose of testbed development. The SVS is a scalable composite index that overcomes two important limitations of existing place-based social vulnerability indices: it is constructed using an approach that does not decrease in validity with changing spatial resolution, and it only needs to be calculated for the geographic area of interest, instead of for the entire country thereby significantly reducing computational effort for testbed developers and users. The SVS synthesizes a set of demographics from the U.S. Census database at the desired location and yields a number, called a score, that represents the relative social vulnerability with respect to its national average. The resulting scores are mapped into five zones, ranging from very low vulnerability (zone 1) to very high (zone 5). Details on SVS development and verification can be found at [118]. The open-source code published by Enderami and Sutley [119] was used to map the social vulnerability of census block groups in the testbed area using ACS 2015–2020 data [U.S. Census, 93]; results are shown in Fig. 7(a). Every household within Onslow County is randomly assigned a social vulnerability value, displayed in Fig. 7(b), according to the SVS zone assigned to their corresponding block group and pre-defined ranges. The details of this stochastic algorithm are available in [118].

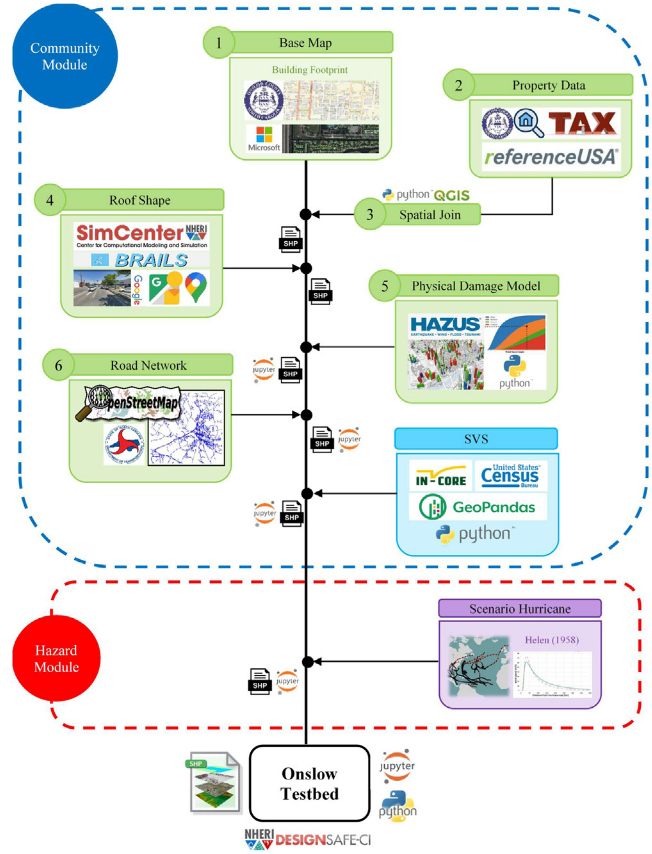

Fig. 8. Onslow Testbed development workflow.

4.4. Onslow testbed verification and validation

The wind model in the hazard module was validated by comparing the estimated peak gust wind speed with data recorded during Hurricane Helene. For example, the peak gust wind speed recorded during Hurricane Helen was identical to the value estimated by the incorporated wind model, almost 240 km/h. No further V&V for using the FEMA flood hazard map is needed since we only use the simulation results of a validated flood model in the hazard module. The validity of data used for developing the testbed's physical system was verified, as explained in Section 4.3.1. Similar to the FEMA flood hazard maps, using the SVS to represent the testbed's social capacity does not need any additional V&V. A detailed description of evaluating the external validity and internal robustness of the SVS can be found in Enderami and Sutley [118].

To verify and validate the testbed as an integrated system, we require damage survey results after Hurricane Helene, which we were not able to find. Importantly, the building inventory and population data used in testbed development are modern, while Hurricane Helene is 70 years old. Thus, even if this historical data were available, it could not validate damage analysis outcomes since the population and building inventory have significantly evolved over time. Thus, in this example, the reliability of each testbed's components was independently verified by comparing the outcomes to published similar research results and relying on the authors' engineering judgment.

4.5. Onslow testbed visualization and publication

In the end, all testbed components, including the Python scripts, Jupyter Notebooks, GIS files, hazard models, inventory datasets, and geographical data files were integrated into a package to constitute the Onslow Testbed. The package and the testbed's supporting documents (e.g., data cleaning process) are available on DesignSafe-CI for re-use and further development. Such re-use and further development are open to other researchers, where their contributions can also be publish on the DesignSafe platform under their own name.

Fig. 8 illustrates an overview of how the proposed testbed development workflow was implemented to establish the Onslow Testbed.

5. Conclusion

The guideline proposed in this paper systematizes the development of virtual testbeds and facilitates the reuse of a testbed by researchers other than those who primarily established it. Expanded accessibility of testbeds will result in advances in the state of knowledge on community resilience. Community resilience cuts across different stressors (natural, man-made), scales (national, state, local), and community dimensions (physical, natural, cultural, human, social, financial, political), and a community resilience testbed should be aligned with all these considerations. As shown in Table 1, more research is needed to incorporate climatic, particularly slow-onset, and man-made hazards and more social and economic models into testbed analyses. Our proposed testbed development process focuses on civil infrastructure networks and population-focused social and economic systems, pointing to a need for more development and inclusion of critical systems such as education, public safety, governance, and healthcare. However, the introduced approach boosts multi-, inter-, and transdisciplinary collaborations on community resilience research and provides ample opportunity to incorporate more fitting social and economic phenomena and theories into testbeds. This contribution leads to developing testbeds with more evenly evolved community modules which are needed to accommodate next-generation numerical models of community resilience, particularly ones that account for equity.

Aside from introducing the current data resources to testbed developers, a secondary outcome of this study is to aid researchers in understanding the existing shortages of high-resolution data on social, economic, and infrastructure systems, and identifying research needs and future directions in this field. As is showcased in the paper, machine learning-based predictive models can be applied to address data gaps in testbed development. On the other hand, the rapid growth of Artificial Intelligence (AI) opens up new research areas in automating the development of testbed components and high-fidelity simulation using AI tools. In addition, more longitudinal studies are needed to establish diverse testbeds representing a variety of communities under different circumstances and hazards. This also leads to the opportunity of developing a uniform community-level taxonomy for data collection for post-disaster reconnaissance and advance current practices. Future research also may need to focus on developing ethical guidelines to ensure the responsible use of data and protect the privacy of individuals and communities involved in the testbeds. Perhaps the biggest direction for testbed developers and users is to adopt community engagement practices to inform testbed development and use, and implementation of the simulation findings.

Data availability statement

Some or all data, models, or code generated or used during the study are available in a repository or online in accordance with funder data retention policies. The datasets, shapefiles, and the Jupyter Notebook that are referred to in this study are available in the DesignSafe-CI data repository at https://doi.org/10.17603/ds2–8h8f-xe60.

Relevance to resilience

This paper provides a step-by-step development procedure for virtual testbeds that enable community-level resilience assessment. Testbeds are an important tool for cross-disciplinary and convergent research on community resilience. The proposed development procedure advances the state of knowledge on the basic components of a testbed, the development process, available data inventories, and other key considerations. The work will be of interest to researchers who study resilience-based design of structures and infrastructures and seek their intersection with social and economic systems within a community. Eq. (1)

Declaration of Competing Interest

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

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Maps in this study were created using the Free and Open Source QGIS.

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