Case Study

Scenario Generation for Built Environment Decision Support under Uncertainty: Case Studies of Airflow Modeling and Climate-Resilient Infrastructure System Design

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Abstract: When confronted with unforeseen challenges, practicing informed decision making is crucial for enhancing resilience in the built environment. While scan-to-building information modeling (BIM) is a well-established approach for creating detailed digital representations of physical assets, its application in assessing and improving infrastructure resilience remains underexplored. This study addresses this gap by proposing a novel application of scan-to-BIM, namely, scan-to-BIM-to-digital twin (S-BIM-DT) workflow. By integrating reality capture and digital twin technologies, this workflow creates continuously updated and accurate digital representations of physical assets, enabling the generation of various scenarios. Unlike traditional methods, the S-BIM-DT workflow facilitates continuous model refinement, supporting informed resilience strategies. By combining these technologies into a cohesive process, the workflow facilitates decision making under uncertainty, enabling stakeholders to evaluate and respond to various scenarios effectively. We demonstrate the implementation of the S-BIM-DT workflow through two use cases that highlight its capability to enhance resilience at different scales. The first use case involves the Combined Transportation, Emergency, and Communications Center (CTECC) in Austin, Texas. BIM-enriched computational fluid dynamics (CFD) modeling simulates airflow and develops alternative scenarios for optimizing the heating, ventilation, and air conditioning (HVAC) systems. This approach enhances resilience against airborne health threats in a postCOVID context. The second use case focuses on designated areas within Beaumont, Texas, as part of the Southeast Texas Urban Integrated Field Laboratory (SETx-UIFL) research. By developing inundation maps to assess extreme weather events, this modeling aids in preparedness efforts and informs the development of climate-resilient infrastructure in vulnerable neighborhoods. Results indicate that the S-BIM-DT workflow effectively generates scenarios that enhance resilience in the built environment by facilitating informed decision making. This study serves as a bridge between advanced scan-to-BIM methodologies and the practical strategies needed to improve built infrastructure resilience. **DOI: 10.1061/JCCEE5.CPENG-6253.**

Author keywords: Urban resilience; Built environment; Scan-to-building information modeling (BIM); Scenario generation; Reality capture; Decision making process.

Introduction

Although an increasing number of infrastructures are being built every day to meet evolving societal needs (Hargaden et al. 2019), the vulnerability of built infrastructure to a spectrum of challenges, such as natural hazards and unforeseen disruptions, has never been more apparent (Ogie et al. 2018). Texas, for example, has endured a series of severe droughts and intense flooding events over the years as a result of the state's susceptibility to climate variability (Merem et al. 2021; Stott et al. 2016), as well as significant impacts from the COVID-19 pandemic, which is an unforeseen global health challenge that occurred in the past few years (Clark-Ginsberg et al. 2021). These events expose a critical vulnerability: existing methods for infrastructure management are often unable to effectively anticipate or mitigate unforeseen challenges, increasing concerns about the resilience of built infrastructure (Shakou et al. 2019; Lee et al. 2023). An instance of this internal limitation is the lack of as-built and as-is information (Wang and Yin 2022). This growing awareness highlights the urgent need for innovative approaches that address the resilience of built environments to face evolving regional and global threats.

Scan-to-building information modeling (BIM), an active research area, has emerged as a promising tool in the construction

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industry, offering precise measurements and comprehensive virtual representations of the built environment (Castañeda et al. 2021). The rise of digitalization and Industry 4.0 has further enabled the adoption of these technological innovations, enhancing the industry's capacity to respond to unforeseen challenges (Chen et al. 2022; Elghaish et al. 2022; Liu et al. 2022; Maqbool et al. 2023). A key innovation, the digital twin, integrates real-time data with virtual representations of physical assets, offering substantial potential benefits and gaining prominence (Bousdekis et al. 2021). However, despite these advancements, current practices typically deploy these technologies independently, limiting their potential to generate scenarios essential for informed decision making under uncertainty. This disconnect presents a critical research gap: the lack of integrated workflows combining scan-to-BIM and digital twin technologies to support scenario generation for infrastructure resilience. Previous studies, such as Banfi et al. (2022), have begun integrating these technologies for building management, focusing on aspects like thermal transmittance and environmental condition analysis. Yet, there remains a need for a workflow that facilitates the generation and management of scenarios specifically aimed at improving infrastructure resilience in the face of unforeseen events.

To bridge this gap, our study proposes a novel application of the scan-to-BIM-to-digital twin (S-BIM-DT) workflow to support scenario generation for informed decision making under uncertainty. We focus on the postconstruction phase, specifically, renovations and upgrades of those built infrastructures that were not initially designed with these advanced technologies in mind. Our study seeks to explore and address the following key research question: "How can scenarios be generated to support decision making under uncertainty to improve resilience in the built environment?" Through the adoption of the S-BIM-DT workflow in the built infrastructure buildings and systems, our intent is to bridge the gap between traditional and modern construction methods and promote proactive preparedness for unforeseen challenges through an integrated workflow. While our initial emphasis lies on addressing natural disasters and health crises, the framework is adaptable to a wide array of unforeseen events that may affect built environments.

The implementation of digital twins, despite their potential, comes with considerable complexity and cost implications (Güngör 2019). The necessity for real-time data integration in construction projects varies significantly depending on the specific requirements of each use case (Ding et al. 2023). Dynamic environments benefit from real-time scenario generation to quickly adapt to changing conditions (Yan et al. 2021), whereas stable contexts can rely on static models refreshed with up-to-date data sets (Osadcha et al. 2023). Our study demonstrates that focusing on the scan-to-BIM phase can effectively support scenario generation without the need for real-time data integration. We validate our approach's ability to generate useful scenarios for stakeholder decision making through the successes of actual infrastructure use cases. We also discuss the potential advantages and challenges of incorporating the full digital twin workflow in future applications, grounded in two use cases. Through this exploration, we aim to advance the construction industry toward a more informed, proactive, and effective development paradigm that enhances resilience in the built environment.

Background Research

Scenario Generation

Scenario generation is crucial for enhancing infrastructure resilience by exploring potential situations to support decision making, especially in renovation and urban planning (Erdogan et al. 2019; Kamari et al. 2021; Knies and Diermeyer 2020). Effective scenario generation considers various factors and uncertainties, such as disaster types and magnitudes, to assess and design adaptable infrastructure for current requirements and withstand future challenges (Kim and Newman 2020). This approach minimizes disaster consequences and avoids extensive renovations and reconstructions, thereby strengthening the resilience of the built environment (Fang et al. 2020; Rouhanizadeh and Kermanshachi 2020). For instance, scenario generation enhances the effectiveness of emergency response plans and contributes to community safety and well-being (Giuliani et al. 2020; Lemaitre et al. 2021; Clark-Ginsberg et al. 2021; Mohamed et al. 2019; Shah et al. 2020). However, traditional scenario generation methods often lack accurate data sources and the ability to reflect 'as-is' conditions, limiting their effectiveness in resilience planning (Wang and Yin 2022). For example, Tabata et al. (2017) assessed disaster waste management strategies in Minami-Ise, Japan, but their scenarios were constrained by insufficient inventory and incoming data, affecting the reliability of their resilience efforts. Our proposed workflow addresses this gap by leveraging enhanced data sources to produce more accurate and comprehensive scenarios.

Reality Capture: A Paradigm Shift through Scan-to-BIM

Developing reliable scenarios to enhance infrastructure resilience requires collecting and processing substantial amounts of data that are precise, exhaustive, and up-to-date to ensure dependable simulations (Deng et al. 2021). Reality capture is an emerging approach that is revolutionizing the design, construction, and management of construction projects by optimizing data collection quality (Fobiri et al. 2022; Ibrahim et al. 2022). Techniques like light detection and ranging (LiDAR) and photogrammetry capture current field conditions and convert the physical world into accurate digital formats (Bravo et al. 2021; Xie et al. 2022). The data create precise 3D models, maps, and other digital assets that support projects in different phases (Alizadehsalehi and Yitmen 2021). Reality capture offers significant benefits over traditional surveying and mapping methods in the context of enhancing infrastructure resilience. It enables fast, accurate data collection, providing a reliable baseline for scenario generation and analysis of infrastructure vulnerabilities (Fobiri et al. 2022). In contrast to traditional LiDAR setups, unmanned aerial vehicles (UAVs) have become popular tools in support of recent research, such as UAV-based photogrammetry and UAV-LiDAR that is used for much more precise 3D topographic data (Li et al. 2021). The scan-to-BIM process advances reality capture from data collection to constructing accurate BIMs (Zhao et al. 2021). This approach overcomes issues with outdated or inaccurate digital models based on traditional design drawings, ensuring that digital representations present the true state of the infrastructure (Boje et al. 2020).

Building Information Modeling

In the scan-to-BIM workflow, BIM serves as the integration hub, ensuring seamless data transition into digital models. This integration solves data fragmentation, enabling comprehensive, accurate digital representations (Sepasgozar et al. 2023). The architecture, engineering, and construction (AEC) industry studies see BIM as an essential part of the digital twin and a source of data that includes computer-aided designs (CADs) and other relevant information and files (Singh et al. 2021). BIM has traditionally been viewed as a key data repository, aiding in the development of digital models (Boje et al. 2020). The BIM-enhanced method improves scenario generation by integrating precise data, resulting in more accurate predictions. For example, Zheng et al. (2023) demonstrated BIM-CFD integration for simulating outdoor environments, providing valuable decision making information. However, integrating various engineering models poses challenges due to the need for specific algorithms and data transfer mechanisms (Gilbert et al. 2021). There has been an advancement toward the development of more open data standards and the adoption of BIM. Recently, efforts to develop open data standards, such as Industry Foundation Classes (IFC), have promoted interoperability across systems and stakeholders (Justo et al. 2021; Ostárek 2023; Zhao et al. 2022). For large projects, time-series data can be stored in a well-structured relational database for BIM, allowing effective querying using structured query language (SQL) (Lu et al. 2020; Tang et al. 2019). The recognition of the importance of data integration has stimulated developments in standards and technologies to support integrated practices.

Digital Twins

This study explores extending digital twins beyond static modeling by integrating internet of things (IoT) data for live updates and immediate feedback loops for scenario testing. This advanced approach meets the need for sophisticated decision making tools in handling complex, dynamic challenges. Kritzinger et al. (2018) categorized digital forms into models, shadows, and twins based on integration levels. From the perspective of data flows, a digital model represents built assets that exist in the physical world and is characterized by manual data flow between real and digital entities (Sawhney et al. 2020). A digital shadow has a one-way automated data flow from the physical entity to the digital entity and is typically defined as an emulation of a physical asset or process (Ladj et al. 2021). Digital twins feature automated bidirectional data flow, allowing physical and digital entities to interact intelligently (Sepasgozar 2021). In construction engineering, digital twins synchronize information to enhance design, construction, and operational phases, enabling real-time convergence between physical and virtual states (The Future Factory 2019). In advancing automated data flow, IoT plays a crucial role. In the built environment, IoT devices have numerous applications, collecting real-time data about status indicators such as temperature, air quality, and other environmental factors (Al-Obaidi et al. 2022; Dallasega et al. 2017). Despite that, interoperability issues and a lack of standardized protocols hinder IoT integration in the construction industry (Khurshid et al. 2023; Tang et al. 2019). Recent research suggests that integrating BIM, semantic web technologies, and relational databases can address these challenges, enabling IoT deployment (Merino et al. 2023; Qiang et al. 2024). Digital twins help construction professionals understand the risks and benefits of different scenarios by simulating designs, performance, and impacts in a virtual environment (Yitmen and Alizadehsalehi 2021; Ye et al. 2023). However, no widely accepted digital twin definition exists in architecture, engineering, construction, operations, and management (AECOM) (Chang-Richards et al. 2022). Adoption barriers include expenses, legal considerations, and human factors.

Comparative Review of Scenario Generation Approaches

Building upon the core concepts of scan-to-BIM with digital twins (S-BIM-DT), it is imperative to compare current scenario generation approaches within the context of infrastructure resilience. A comparative analysis offers insights into their efficacy, adaptability, and application scope. Existing methodologies ranging from traditional approaches to advanced S-BIM and S-BIM-DT techniques vary considerably in terms of procedural complexity, integration capability, and end-use scenarios. Table 1 summarizes various scenario generation approaches, highlighting method attributes, practical applications, and references to literature.

Research Approach

Based on the background research section, scenario generation processes frequently struggle with a lack of data sources and an inability to effectively represent the existing conditions. Additionally, the current approach to employing technologies in the AEC industry is fragmented, hindered by a lack of comprehensive and integrated methods. To bridge these gaps, this paper leverages the S-BIM-DT workflow to support scenario generation for unforeseen challenges in the built environment. The workflow will be presented in detail, with each stage adaptable to the user's specific purpose. Given that this study aims to assess the capability of the S-BIM-DT workflow in facilitating scenario generation, the breakdown of the process of turning BIM into a digital twin and IoT implementation are presented more in general. By employing scan-to-BIM and BIM-integrated models, it is achievable to effectively develop preparedness scenarios. The S-BIM-DT workflow also allows for fully achieving a digital twin model, if necessary,

Table 1. Summary of differences between different scenario generation approaches

Methods	Highlights	Applications	Citations
Traditional methods	Static modeling techniques with a manual calculation.	Structural analysis and design feasibility.	Hibbeler (2006)
	Reliance on historical data for environmental impact assessments.	Environmental impact studies and regulatory compliance.	Lallawmzuali and Pal (2023)
	Predominant use of manual drafting and two-dimensional CAD analysis.	Urban planning and land use optimization.	Wood (2013)
Scan-to-BIM (S-BIM)	Integration of multidisciplinary data for the comprehensive model.	Advanced simulations for structural resilience and resource efficiency.	Badenko et al. (2019)
	Accuracy and precision.	Accurate 3D data to maintain and restore the built environment.	Rocha et al. (2020)
Scan-to-BIM-to-digital twin (S-BIM-DT)	Real-time data analysis.	Smart infrastructure management and automation.	Banfi et al. (2022)
	Predictive analysis.	Anticipate potential failures, optimize resource allocation, and improve long-term planning.	Fahim et al. (2022)
	Dynamic simulations incorporating projections and patterns.	Predictive maintenance and adaptive solutions.	Wagg et al. (2020)

by continuously incorporating new data into future implementations. The benefits of using digital twins in support of dynamic scenario generation include enhanced accuracy and adaptability but come with higher expenses in terms of setup and computational resources.

Fig. 1 presents an IDEF-0 diagram illustrating the five main steps in the S-BIM-DT workflow. These steps are: reality capture, data acquisition, integration of information into a digital representation, performing simulations and scenario generation, and the decision making process. Detailed introductions to these steps are provided in the following sections:

Step 1: Reality Capture

The initial phase of the S-BIM-DT workflow involves the capture of as-built or as-is geospatial information from the built environment, employing advanced and popular technologies and techniques such as LiDAR, UAVs, and photogrammetry (Khanal et al. 2020). The most common output from reality capture is a point cloud, providing a precise 3D representation of the environment, capturing geometric intricacies and spatial arrangements crucial for subsequent digital model generation (Xu et al. 2022). Once the built environment has been captured, raw point clouds are registered in a common coordinate system and merged into a single point cloud. While automated registration methods are available, the process often remains semiautomated (Neri et al. 2023). Specialized software tools are used for noise reduction, scan alignment, and optimization to ensure data quality. This merged data set then serves as the input for modeling procedures. It is crucial to acknowledge that raw point cloud files, especially for large areas, can be voluminous and require significant computational resources. This substantial size may present challenges with data transfer, particularly in cloud-based or collaborative work applications, necessitating fast internet connections and effective data management procedures. Sometimes, the process involves meshing and transforming the point cloud into a 3D mesh model to facilitate manipulation and understanding before importing it into BIM software (Momeni Rad et al. 2024). The time required for this process varies with scanning complexity and the desired level of detail in the BIM model. As the initial stage of the workflow, this refinement ensures the model's accuracy, laying a solid foundation for subsequent phases.

Step 2: Data Acquisition

Incorporating sufficient data is crucial in the S-BIM-DT workflow. This phase involves extracting data and storing it in an organized database. Key tasks include extracting, structuring, and transferring data from collection points to the database, ensuring data integrity and consistency to prevent errors and data loss. Sufficient data in this context means having enough quantity, high quality, accuracy, completeness, consistency, and interoperability for its intended purpose (Fadlallah et al. 2023). This process requires strategically deploying manual data collection methods, IoT devices, or both throughout the built environment to collect data. Data collected in this step are essential for the subsequent steps, requiring data cleaning and regulation criteria to control this process. Both manual and automated data filtering are necessary to eliminate extraneous data, such as that resulting from moving objects, reflections, or sensor artifacts, ensuring data integrity and quality control (Wen et al. 2024). Efficient data storage is essential, serving as a secure repository for valuable data sets from diverse sources. A cloud-based database is recommended to ensure synchronization of the most recent changes and historical data, allowing for accurate generation of back-and-forth scenarios (Tao et al. 2021). Because cloud databases are equipped with tools for enhancing performance, automated backups, and data protection (Akhtar et al. 2021), the potential for integration with other cloud services and application programming interfaces (APIs) further enhances real-time data acquisition capabilities. For example, we can extract real-time data using public and IoT platform APIs (Markert et al. 2024; Vítor et al. 2021). The scalability and adaptability of the cloud-based database accommodate evolving data volumes and formats, enhancing the BIM's abilities to effectively store and leverage valuable information from the dynamic built environment.

Step 3: Integrating Information into Digital Representations

Within the S-BIM-DT workflow, creating an augmented BIM model is pivotal for expediting scenario generation. The process

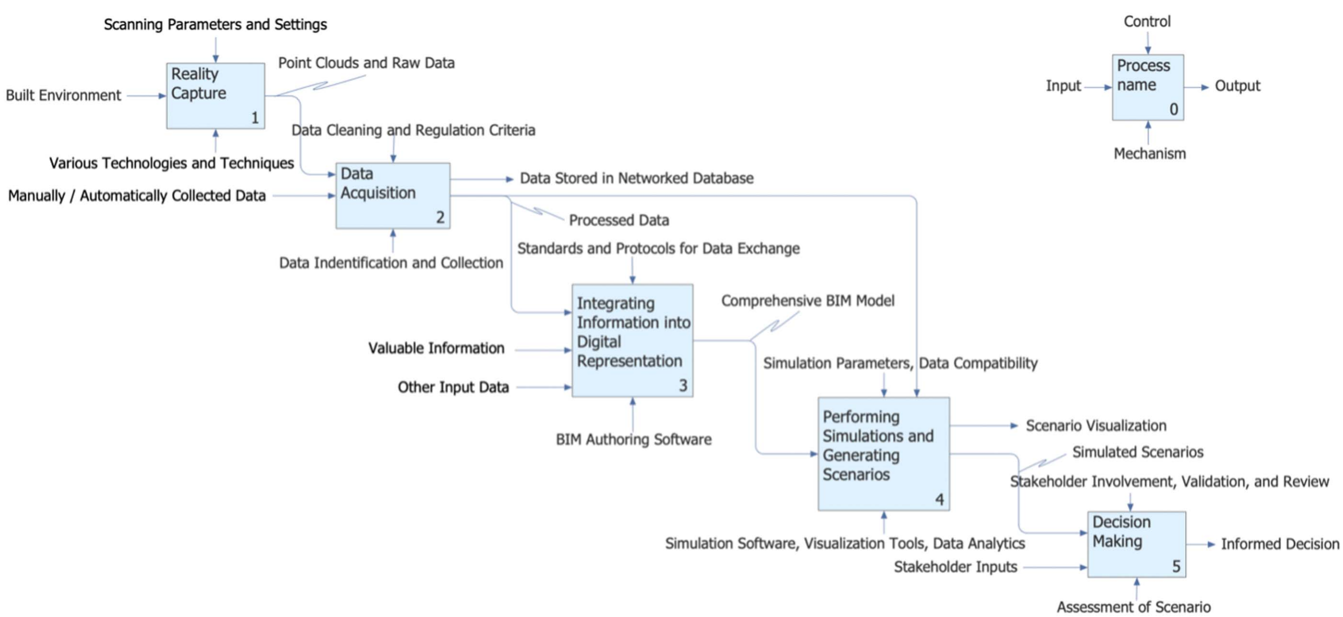

Fig. 1. IDEF0 diagram depicting the S-BIM-DT workflow.

begins by selecting a model-authoring tool that meets research requirements and facilitates data exchange among multidisciplinary stakeholders, including architects and engineers. Before integrating data into the BIM model, meticulous data mapping and conversion are crucial to ensuring alignment with the BIM software's format and structural requirements (Wefki et al. 2024). Therefore, the S-BIM-DT workflow necessitates the seamless integration of diverse data sets, organizing them in a manner consistent with corresponding BIM elements. This integration addresses potential issues such as data compatibility, handling large data quantities, and ensuring data correctness and precision through specialized tools and procedures. Interoperability is enhanced by using standards such as IFC when necessary, facilitating effective data exchange among various software applications (Shehzad et al. 2021). The framework also aims to incorporate real-time data systems to synchronize BIM models with digital twin platforms, preparing them for potential future implementations. This comprehensive modeling effort is instrumental in shaping the digital twin of the built environment, thereby strengthening the foundations for scenario generation.

Step 4: Performing Simulations and Scenario Generations

The S-BIM-DT workflow employs various types of software and tools to simulate and generate different scenarios based on user-specific objectives. Even in the absence of a complete digital twin model, BIM-based or BIM-enhanced platforms retain significant value (Akbarieh et al. 2020). Additionally, other platforms are available for specialized purposes, such as the geographic information system (GIS) platform for landscape and urban planning. In the workflow sequence, a comprehensive BIM incorporated into a modeling platform provides precise data for simulations. A crucial aspect involves implementing middleware or utilizing APIs to streamline data transmission for scenario generation, ensuring compliance with standards such as IFC when handling BIM data (Schonhowd et al. 2023). Advanced platforms integrate powerful analytics and simulation technologies to generate scenarios under controlled variables and parameters (de los Campos et al. 2020). Data visualization is also integral, offering a comprehensive and actionable view of the built environment and potential scenarios. This enables stakeholders to understand complex scenarios and outcomes through sophisticated graphical representations, enhancing decision making and planning in the following phase (Bakhtiari et al. 2024).

Step 5: Decision Making Process

Data-driven and comprehensive scenarios serve as the foundation for strategic thinking and decision making (Bokolo 2023). Determining which scenarios to pursue and how to expand them involves a thorough review process considering multiple aspects. This enhancement includes performing 'what-if' analyses to understand the consequences of adjusting variables and their magnitudes (Ciorna et al. 2024). The process begins with a comprehensive evaluation of each scenario based on criteria such as feasibility, potential impact, compliance with regulatory standards, and alignment with long-term goals. Stakeholder engagement is essential during this phase to ensure that the scenarios meet the requirements and expectations of the community, designers, and engineers (Prebanić and Vukomanović 2023). Chosen scenarios are further developed by incorporating detailed elements such as infrastructure requirements and resilience considerations. This development identifies infrastructure vulnerabilities, enabling resilience strategies to improve the built environment's ability to withstand and recover from unforeseen challenges, such as extreme weather events.

Implementation of the S-BIM-DT Workflow in Use Cases

This section validates the S-BIM-DT workflow for scenario generation through two real-world case studies, summarized in Table 2, including the attributes and features of the tools used. In Use Case A, the S-BIM-DT workflow was utilized by incorporating a BIM-CFD integrated platform with simulated airflow models. This integration aimed to improve the CTECC's HVAC system, enhancing overall efficiency and performance. Use case B, supported by the Southeast Texas Urban Integrated Field Laboratory (SETx-UIFL), leverages S-BIM-DT workflow by incorporating BIM with inundation simulations. This approach assessed the built environment, aided in the renovation of the built infrastructure, and aimed to design new climate-resilient infrastructure. The authors also explore the workflow's real-time data capabilities.

The CTECC Research—(Use Case A)

Background and Objectives

Use Case A leverages a combined transportation, emergency, and communications (CTECC) research being developed by a municipality in the Southern United States. This is a high-density, 24/7 call center used to dispatch first responders, manage transportation, and conduct emergency management at the city and county levels. Call centers, due to their high-density nature, pose mental and physical health challenges for workers (Lin et al. 2009), which have been exacerbated by the COVID-19 pandemic. To promote the well-being and productivity of operators, the CTECC management department looked toward holistic frameworks that assess the existing HVAC system and design a postCOVID-19 HVAC system. This system aims to support occupant health and ensure sustainability against future airborne diseases. Key areas considered included indoor air quality (IAQ), workstation layout, and thermal control (Ceylan 2021; Chaiklieng and Poochada 2021). However, The CTECC building manager faced challenges addressing dispatcher complaints due to difficulties in identifying problematic floor vents. The visualization of temperature and airflow direction was not possible with outdated 2D drawings, and the building layout had changed due to workstation relocations. The goal of this

Table 2. Summary of differences between two use cases

Use case	Reality capture approach	Collection method	Capture resolution	Output from point clouds	Performance goal	Use case scenario	Scale
Use Case A: CTECC	LiDAR	Manual	Millimeters (mm)-level	Interior intricate models	PostCOIVD airflow optimization	Building management	Project (single infrastructure)
Use Case B: SETx-UIFL	UAV photogrammetry	Manual/ automatic	Centimeters (cm)-level	Digital elevation model	Flood resilience plan	Urban planning	Neighborhood (infrastructure system)

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use case is to develop a BIM-enhanced CFD model that integrates spatial data from the existing built environment with airflow simulations. This integration aims to identify and address indoor airflow and thermal comfort issues. Additionally, we aim to explore the feasibility of enabling dynamic scenarios. These scenarios will help identify indoor airflow issues and design changes to reduce person-to-person airborne transmission of infectious pathogens.

Approaches

The S-BIM-DT workflow adapted to Use Case A is illustrated in the IDEF-0 diagram in Fig. 2. Note that the unique features of this specific use case are shown in red. Use Case A implements a combination of LiDAR, a thermal imager, a cloud-based database, model-authoring technologies, BIM, and a CFD engine.

STEP 1: Reality Capture

The main call center was captured and documented using a terrestrial LiDAR scanner [see Fig. 3(a)]. The raw data [see Fig. 3(b)] produced are the departure point of the digital model. We selected 36 scanning locations for comprehensive coverage, where locations were strategically chosen around the call center room's perimeter, exits, walkway intersections, and any changes in floor level. Special attention was given to features such as HVAC vents, cantilevered steel display walls, and the ceiling in an irregular shape through the precise placement of the LiDAR scanner. Then, the 3D point cloud was processed using a commercial tool, as shown in Fig. 4. The model was refined by eliminating erroneous points that obscured surface views, accurately documenting the room's dimensions and features (see Fig. 5).

STEP 2: Data Acquisition

Following dispatcher reports of inconsistencies in the HVAC system, we assessed ventilation and heat sources. During the design of the postCOVID-19 HVAC system, we obtained airflow parameters, such as supply flow rate and temperatures, from the CTECC manager, incorporating IoT sensors when real-time analysis was necessary. We used a thermal imager to capture temperature data from floor and wall vents, as well as internal thermal loads such as monitors [see Figs. 6(a and b)], to identify thermal imbalances. Infrared and visible light images were fused for a comprehensive engineering assessment. We reshaped and converted temperature and airflow data into compatible formats, such as comma-separated values (CSV) or network common data format (NetCDF). The captured and processed data were stored on a cloud-based drive on the University of Texas server and can be extracted to Step 3.

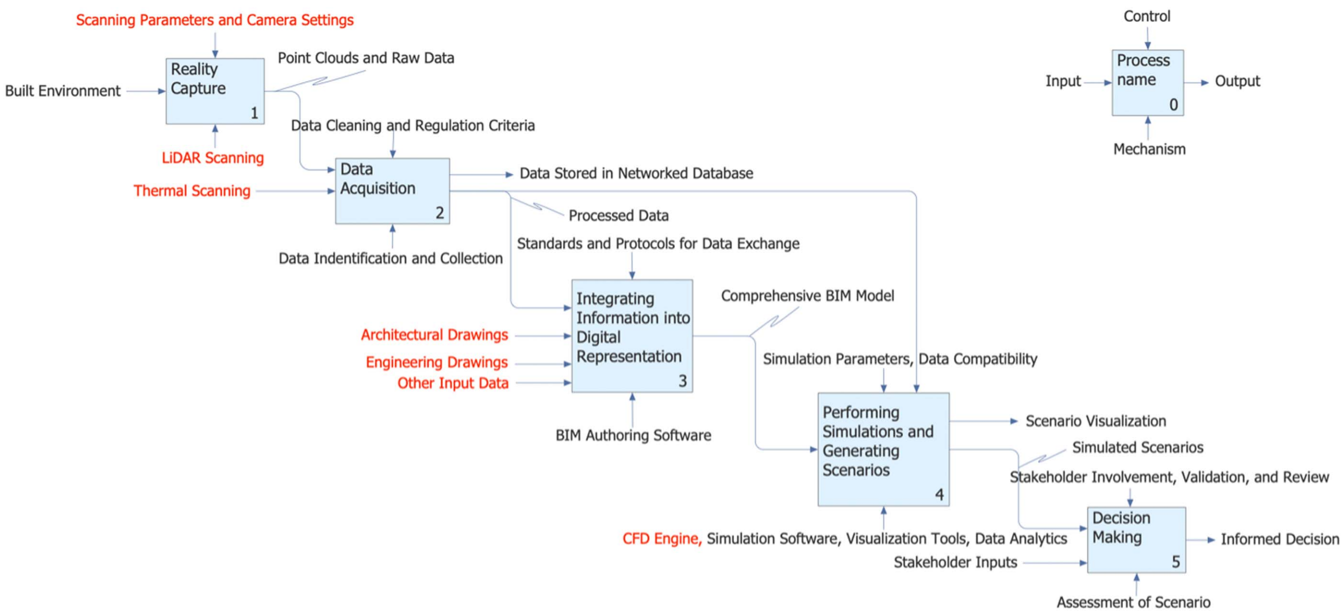


Fig. 2. IDEF0 diagram of S-BIM-DT workflow in Use Case A.

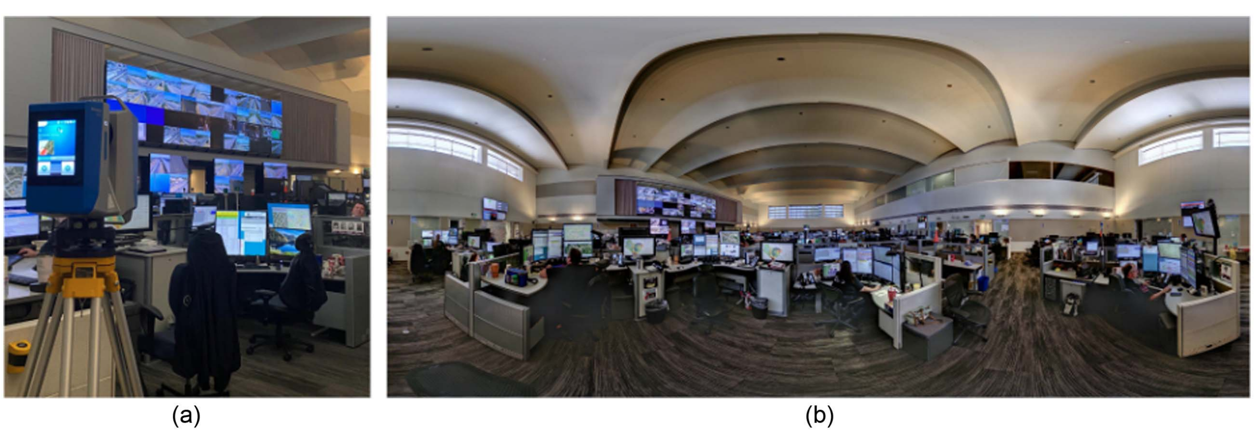


Fig. 3. LiDAR scanning conducted at CTECC: (a) terrestrial LiDAR scanner; and (b) an example of 360 image at CTECC.

STEP 3: Integrating Information into Digital Representation

We integrated the 3D point cloud generated from Step 1 into the BIM environment [see Fig. 7(a)], providing a precise digital representation of the physical and functional characteristics of CTECC's room. The BIM was further developed using captured geospatial data in a model-authoring tool as the modeling platform [see Figs. 7(b and c)]. The model produced in the commercially available model-authoring software system is shown in Fig. 8. In addition to geospatial data, the BIM integrates temperature readings and other relevant data sources, such as HVAC parameters and occupancy information. This comprehensive data integration is crucial for supporting the subsequent steps.

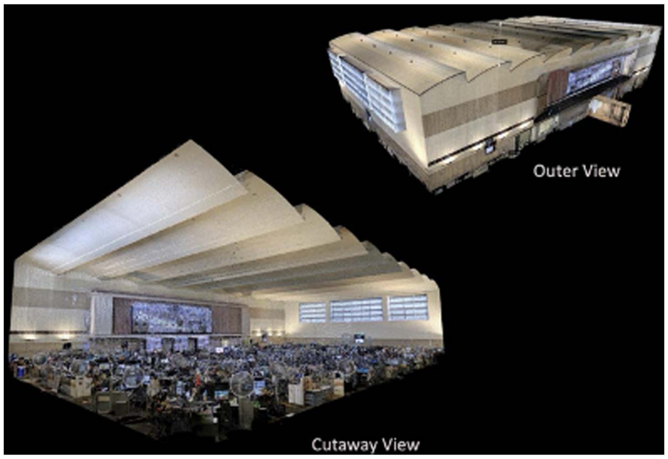


Fig. 4. Axonometric images were generated via a LiDAR scanner.

STEP 4: Performing Simulations and Generating Scenario

Through thorough assessment, it was determined that two air handling units (AHUs) provide ventilation, with floor vents evenly dispersed across the area. Based on the data obtained from the steps before, including HVAC documentation, site investigation, and the generated digital model, CFD modeling is ready to be simulated. Before the simulation, we segmented the model into a section view that shows the workstation layout and the vents on both the wall and the ground. After running a sample simulation, Fig. 9 illustrates the airflow originating from the wall and floor vents, showing the temperature, direction, and distribution of air to the workstations.

Outcomes and Discussions

The CFD modeled various scenarios considering pathogen source position, partition geometry, and airflow characteristics based on

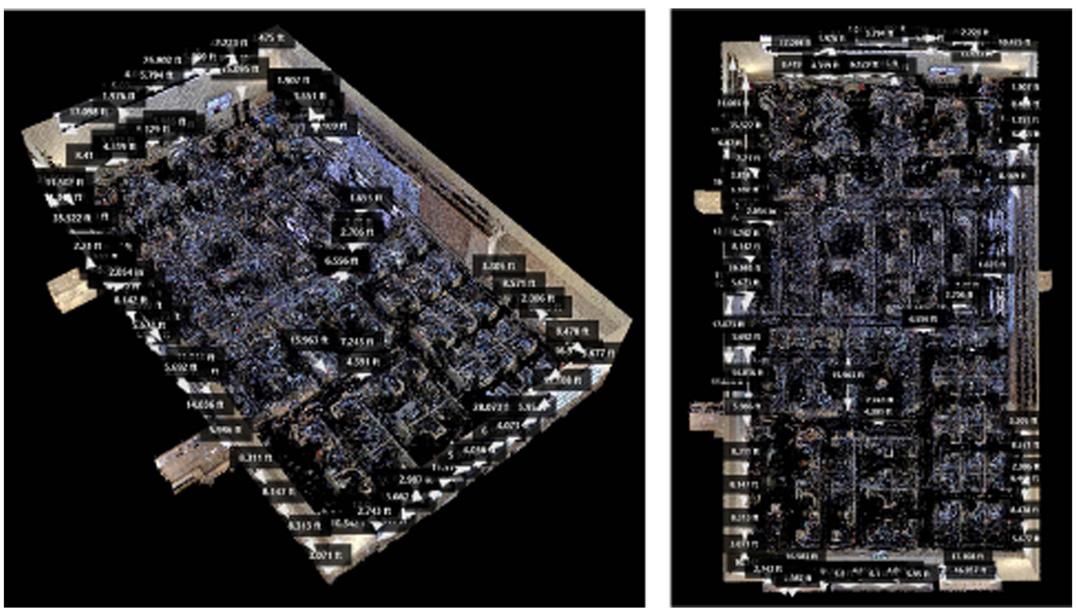
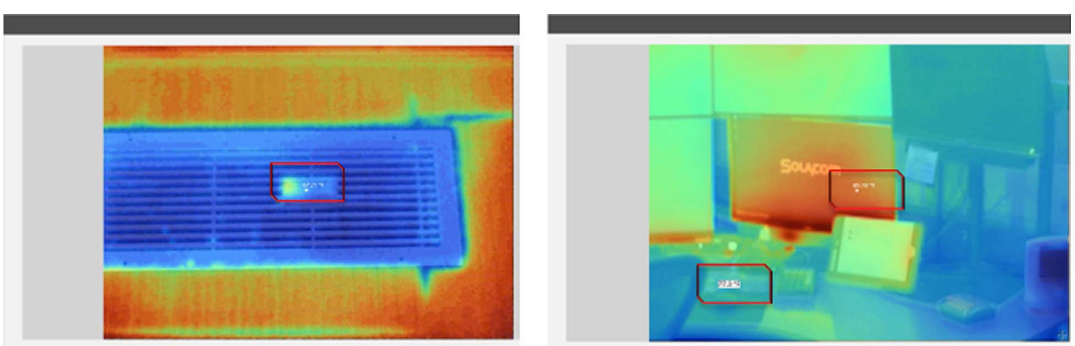


Fig. 5. Dimension measurements of the CTECC.



(a) (b)

Fig. 6. Temperature readings from thermal scanning: (a) temperature of a ground vent; and (b) temperature of a monitor.

Fig. 7. Model-authoring software system integrates with point cloud data: (a) modeling based on point cloud; (b) detailed BIM model; and (c) section views.

Fig. 8. Visualize the model generated from the model-authoring tool.

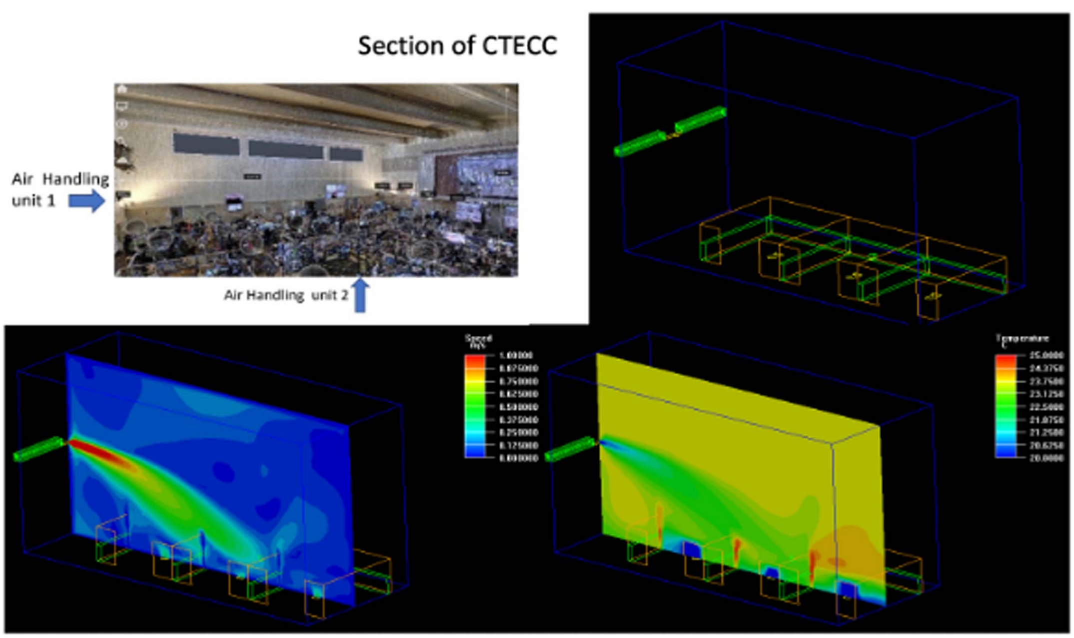


Fig. 9. An example of airspeed and temperature from the CFD model.

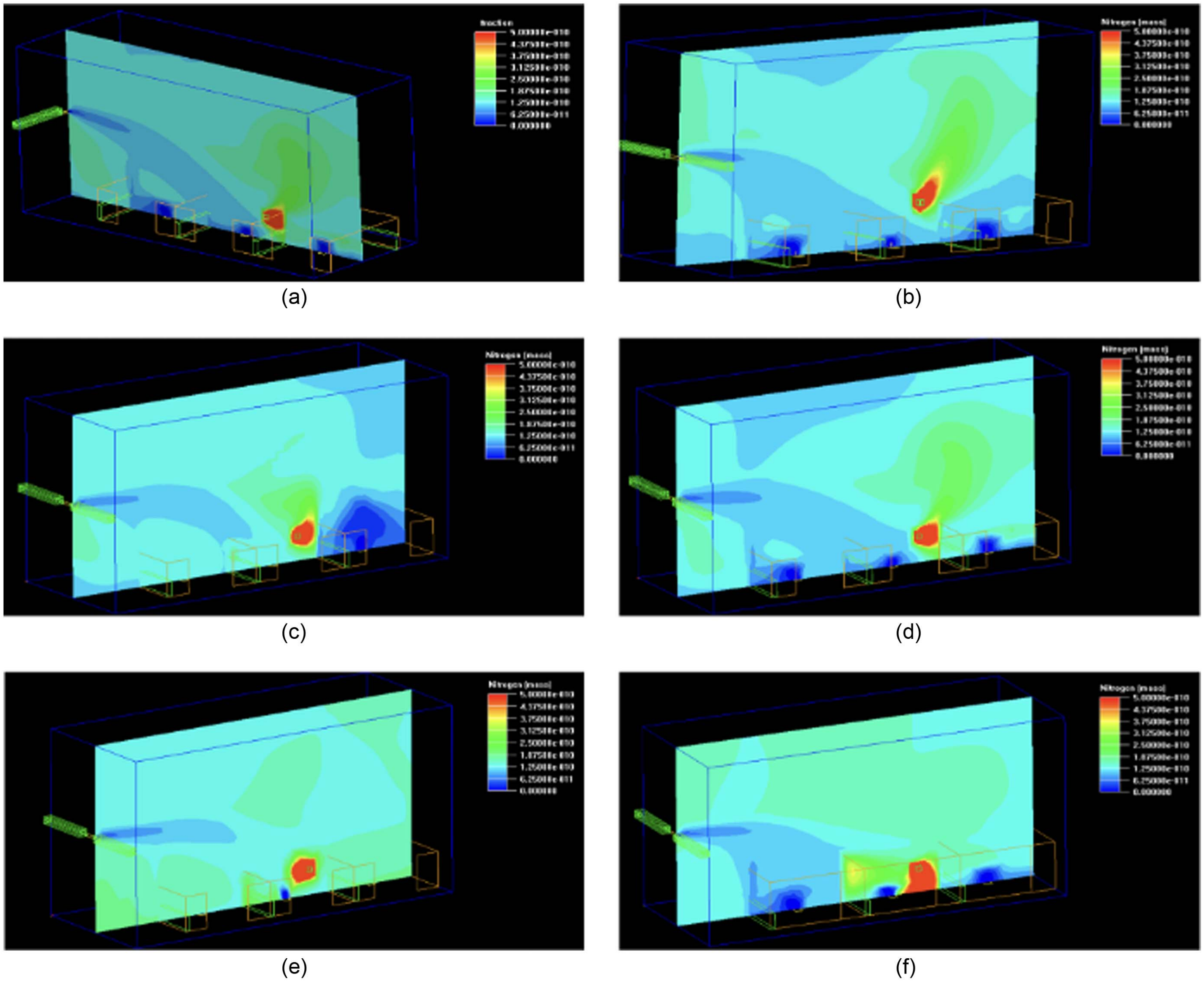


Fig. 10. The pathogen concentration distribution shown in the CFD model: (a) an example of pathogens concentration (red is a source); (b) concentration of pathogens with standing infector; (c) concentration of pathogens with seating infector; (d) concentration with diffuser in each partition; (e) diffuser and infector in the same partition; and (f) high partition and diffuser in each partition.

actual spatial locations [see Fig. 10(a)]. For CTECC's interior renovations to prevent future infections and outbreaks, the authors investigated several factors:

1. Pathogen Source Location: Evaluated how a dispatcher's position (standing versus seated) affects airflow [see Fig. 10(b) versus Fig. 10(c)].
2. Diffuser Position Relative to Infector: Compared scenarios where the supply diffuser and infector are in different partitions versus the same partition [see Fig. 10(c) versus Fig. 10(e)] to assess the capability of preventing infectious propagation by housing the infector and supply diffuser in the same partition.
3. Floor Diffuser Position: Examined airflow changes with one diffuser per three cubicles versus a diffuser positioned in each cubicle [see Fig. 10(c) versus Fig. 10(d)].
4. Partition Design: Investigated the impact of partition height and type, suggesting that raising partition height and adding sliding doors for individual workstations could decrease person-to-person exposure [see Fig. 10(d) versus Fig. 10(f)].

While the highest level of precision required for modeling airflow in our CFD simulations was in the centimeter (cm) range, using millimeter (mm) precision from the reality capture step becomes valuable when selecting specific retrofit solution details. Leveraging this insight, we analyzed the CFD to develop a functional retrofit solution using displacement ventilation, which supplies outdoor air near occupants. This approach provides better air quality compared to mixing ventilation, while achieving the same exposure reduction with mixing ventilation would require more fresh air and cause more energy for air conditioning. An additional energy-saving benefit of displacement ventilation is its focus on cooling the occupied space while allowing the area above 3 meters to remain warmer. The large temperature stratification created by displacement ventilation cools the occupied zone to the setpoint temperature, reducing the energy required for cooling the upper part of the room. We identified measures aligning with desired outcomes and proposed these to the building manager and stakeholders to enhance IAQ through improved ventilation efficiency and reduced person-to-person exposure, as determined by CFD scenarios. For example, we recommended increasing the height of space partitions and using sliding doors for cubicles. Additionally, we suggested assessing the retrofit of AHUs to operate with high-efficiency particulate air (HEPA) filters and adjusting the underfloor AHU to supply 100% fresh air. This capability enhances air quality within the facility and ensures compliance with health and safety standards by continuously monitoring and adjusting the air supply based on environmental conditions and occupancy levels. As part of the overall IAQ and ventilation improvement strategy for Use Case A, our research team also recommended repositioning the return grilles and ducts and decreasing occupant density. In the end, the CTECC management group has decided to follow our recommendation of replacing floor diffusers to achieve an underfloor AHU that can provide 100% fresh air. This research use case demonstrates that the S-BIM-DT workflow facilitates the decision making on reconfiguring the workstation layout and designing the ventilation system for an optimal airflow solution. Our findings support the literature emphasizing the need for accurate, up-to-date data and advanced modeling techniques in enhancing infrastructure resilience (Deng et al. 2021; Sepasgozar 2021). This approach simplifies identifying potential problems and presenting effective solutions, especially in the absence of detailed drawings for interiors with intricate designs. Traditional methods, which rely on physical plans or less integrated digital approaches, would likely struggle with such complexity, particularly when updates or changes are not reflected in existing documentation (Abdullahi et al. 2023). In contrast, scenarios visualized in CFD, generated from integrated information, assist stakeholders in comprehending and making decisions more effectively than relying on tedious technical reports. The outcomes persuasively demonstrate the practical utility and benefits that the scan-to-BIM phase of the S-BIM-DT workflow provides to the building management domain. We generated scenarios using a cycles per instruction (CPI) computer with two processors that includes a 16-core CPU and 68GB of RAM. The average simulation time was approximately 30 min. We set up a robust data management and transmission workflow, termed S-BIM-DT, to ensure the efficient handling of collected data. The workflow allows continuous data entry into the simulation, enabling fast fluid dynamics simulation on the GPUs (Choi and Sung 2024; Lyu et al. 2024). Consequently, CFD depicts airflow patterns and behavior in dynamic scenes, such as detecting abnormal airflow and temperature imbalances. This highlights the potential to implement real-time features.

Limitations and Future Work

One of the challenges was the lack of detailed architectural plans for intricate interiors, making it difficult to interpret LiDAR data. We recommend incorporating geospatial references in future reality capture processes to improve precision and spatial understanding. In addition, scanning occupied spaces was also challenging due to dense workstations and office supplies, resulting in slightly blurry point clouds in two corners. However, this did not affect the research team's ability to create models and alternative scenarios. The duration of the scans and the number of scan points were limited to minimize the impact on facility operations, balancing detail with operational impact. Public acceptance and concerns about privacy, noise, and intrusion need to be addressed when conducting LiDAR scanning in an occupied environment. Due to the special nature of the CTECC, all data, regardless of sensitivity, must comply with stringent cybersecurity protocols. This regulation may cause delays or restrict the implementation of advanced technological solutions. In contrast, traditional methods, where data security concerns are generally less pronounced due to the offline nature of data handling, do not face such constraints (Krempl et al. 2014). Data synchronization and the complexity of calibrating CFD models to accurately present physical environments can become cumbersome and error-prone with continuous data updates. Future research opportunities include leveraging machine learning to effectively detect abnormal airflow and temperature imbalances. This approach could enable the system to identify specific airflow scenarios, alert users, and pinpoint the most critical vents responsible for the issues, thereby saving time by obviating the need for manual inspections of each vent or AHU individually. Future research also has the potential to identify optimal solutions for managing these imbalances, further enhancing the efficiency and resilience of infrastructure systems.

Contributions

This experiment is an enlightening reference for those infrastructures with a similar working environment to Use Case A, operating 24/7 and performing essential and high-stress work. It informs stakeholders about approaches to accurately assessing building performance and facilitates the decision making process by planning various scenarios. Solutions such as improved postCOVID HVAC systems and adjustments to workstation layout provide dispatchers with a healthier workplace to face unforeseen challenges. The study particularly demonstrates the benefit of the S-BIM-DT workflow for scenario generation in a built environment, contributing both to theory and practice in the domain of infrastructure resilience. For instance, the CTECC has replaced its floor diffusers, doubling their number and halving the flow per diffuser. The new layout included one diffuser per cubicle. These renovations enhance resilience, ensure the facility remains operational, promote adaptability, and integrate a long-term outlook on community service and resource utilization, prioritizing the uninterrupted operation of essential services during unexpected events.

The Southeast Texas Urban Integrated Field Laboratory Supported Research—(Use Case B)

Background and Objectives

Southeast Texas is home to the world's largest oil refinery, a key asset to the global energy industry. This region faces multiple environmental challenges, including the risk of flooding and air pollution. As the region's population continues to increase, understanding the potential consequences of these hazards, especially regarding the local economy and climate dynamics, becomes crucial. The SETx-UIFL supports the research, which seeks to explore how environmental hazards may impact communities in Beaumont-Port Arthur and aims to find equitable and effective climate solutions for communities caught between floods and air pollution. An integrated workflow for scenario generation is critical in the strategy codesign process, where codesign is a collaborative process that involves various stakeholders in the creation of solutions. The workflow is tasked with assisting stakeholders in envisioning and understanding the physical and social implications of codesigned strategies. In Use Case B, the authors experiment with the S-BIM-DT workflow in urban planning at the neighborhood scale to facilitate the scenario generation process, foster equitable adaptation strategies, design new infrastructure, and promote the resilience of existing infrastructure. In particular, the authors selected an area in the region that currently houses a pump station as a flood infrastructure system. The S-BIM-DT workflow is expected to enhance the understanding of hazards and their implications for pump station operation through various scenarios. These might include the expansion of pump stations and the enlargement of buffer zones such as green areas, consideration of various flood levels, and investigation into the feasibility of constructing more residential buildings.

Approaches

The S-BIM-DT workflow adapted to Use Case B is illustrated in the IDEF-0 diagram in Fig. 11, with the unique features of this specific

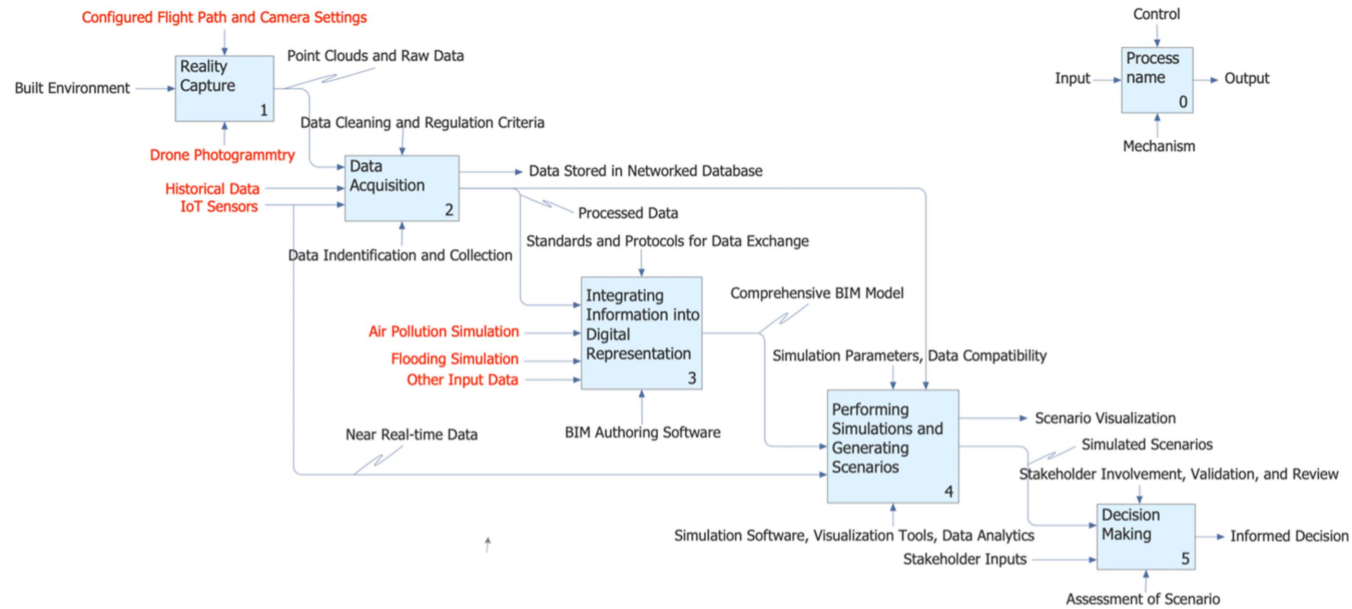


Fig. 11. IDEF-0 diagram of S-BIM-DT workflow in Use Case B.

use case highlighted in red. The tool implemented in Use Case B for the purpose of scanning and modeling the space was a combination of drone aerial photogrammetry and a cloud-based and relational database that stores aerial images, processed maps, and prerequisite data for simulating inundation maps.

STEP 1: Reality Capture

Prior to conducting reality capture, the drone flight path was planned using commercial drone mapping software to enable autonomous flight and the capture of aerial photographs. A total of 3,445 aerial photos were collected and uploaded to a drone mapping and data analysis platform, as shown in Fig. 12. Fig. 13(a) presents one of the captured aerial images. These aerial photos are ideal data sources for photogrammetry due to their geotagging capabilities. The latitude, longitude, and altitude from the drone's global positioning system (GPS) and onboard sensors are embedded within the metadata of each aerial image as it is captured.

A point cloud generated from aerial imagery is an indispensable output of reality capture, as visualized in Fig. 13(b). The point cloud is a collection of three-dimensional points representing the surface of the mapped area and serves as the foundation for creating precise and detailed 3D models, as shown in Fig. 13(c). In this use case, the generated point cloud enables the extraction of elevation information from the Halbouty pump station and its surrounding area, as shown in Fig. 13(d). Finally, a highly accurate topographic map embedded with contour lines, as shown in Fig. 13(e), provides a direct visualization valuable for land surveying tasks.

STEP 2: Data Acquisition

We acquired data in support of our inundation simulations including digital elevation models (DEMs), catchment data, flowlines, and water discharge data. Regional DEMs are sourced from the United States Geological Survey (USGS) (Iii et al. 2024). We acquired higher-resolution DEMs through processed point clouds

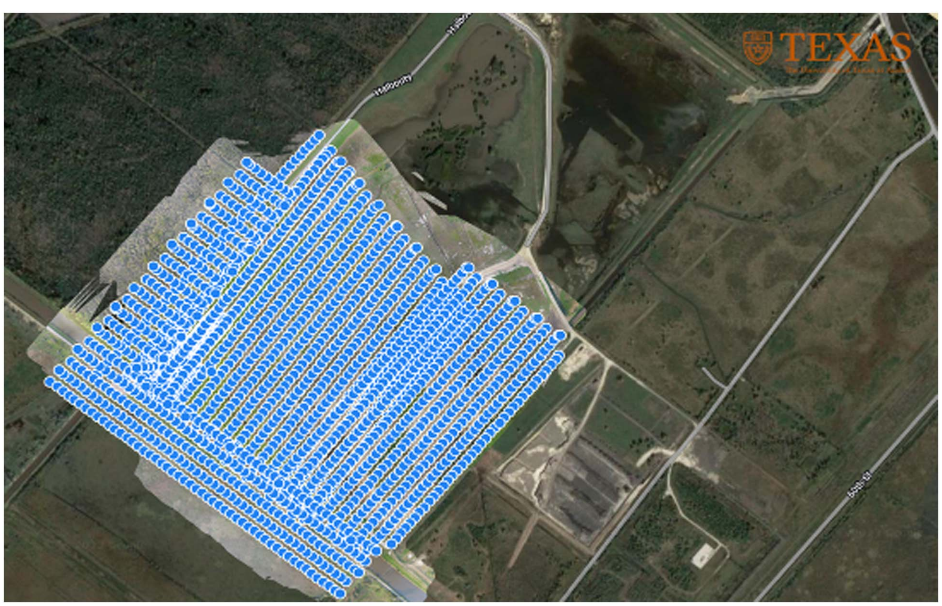


Fig. 12. Annotations for aerial photos via drone mapping software. (Image by Linchao Luo.)

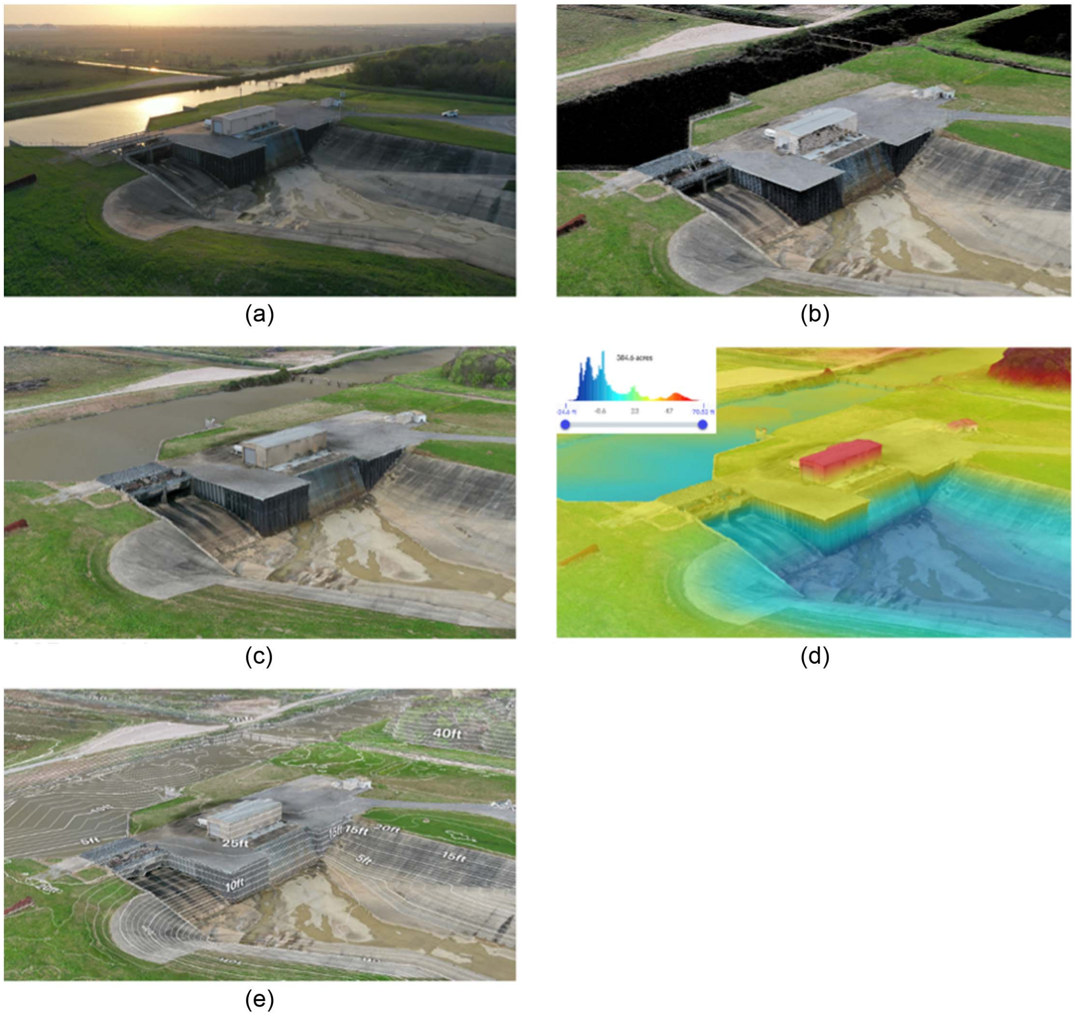


Fig. 13. Drone-captured aerial imagery and processed models of the Halbouty pump station: (a) aerial imagery; (b) generated point clouds; (c) 3D model; (d) 3D model with elevation data; and (e) 3D model with contour lines. (Images by Linchao Luo.)

in Step 1 to enhance the precision of our simulations for the specific target area. Additionally, flowline and catchment data are also acquired from the USGS. We utilized the one-hour interval water discharge data and historical records from the National Oceanic and Atmospheric Administration (NOAA) and converted the National Water Model (NWM) discharge data into NetCDF format to ensure data compatibility. All the data mentioned ensure precise simulation of flood inundation scenarios by combining high-resolution topographic data with reliable hydrological network information.

STEP 3: Integrating Information into Digital Representations

We effectively transferred and integrated data from previous steps to expedite the inundation simulations in collaboration with the Texas Advanced Computer Center (TACC). This integration streamlines the development of multiple scenarios. Additionally, we visualized the integrated data using GIS (see Fig. 14). This visualization supports stakeholders in understanding the built environment of the target area within its urban context. In the next step, we will also visualize inundation scenarios on the GIS platform.

STEP 4: Performing Simulations and Generating Scenarios

We leveraged GeoFlood, a computationally efficient flood inundation mapping tool to generate inundation scenarios. GeoFlood computes flood inundation extent and depth under uniform conditions along river segments, including channel and floodplains, and delineated from flow directions, by combining two methods, GeoNet, an advanced method for terrain data analysis (Passalacqua et al. 2010; Sangireddy et al. 2016), and height above nearest drainage (HAND) (Zheng et al. 2018). Finally, we delineated a flood map by using input discharge from NOAA as peak flow distributed along the river network. Detailed information and usage instructions for GeoFlood are available in Zheng et al. (2018). For example, the inundation scenarios, based on weighted water discharge data from historical Hurricane Harvey and a smaller rain event in 2023, help stakeholders see how the built environment appears on a street map and where inundation is to extend (see Fig. 15).

Outcomes and Discussions

Our research group generated inundation scenarios representing different levels of flooding caused by Hurricane Harvey. Fig. 16(a) illustrates the full extent of Hurricane Harvey's impact, while Figs. 16(b and c) depict scenarios with 50% and 25% of the flood severity, respectively. Stakeholders and local communities evaluated whether the existing urban landscape could support the development of new neighborhoods while assessing the effects of severe climate events on local communities. This included examining the resilience of the current infrastructure. The inundation scenarios provided critical insights, revealing that building new neighborhoods on the current landscape is not feasible unless the capacity of existing flood-blocking infrastructure is improved (see Fig. 16).

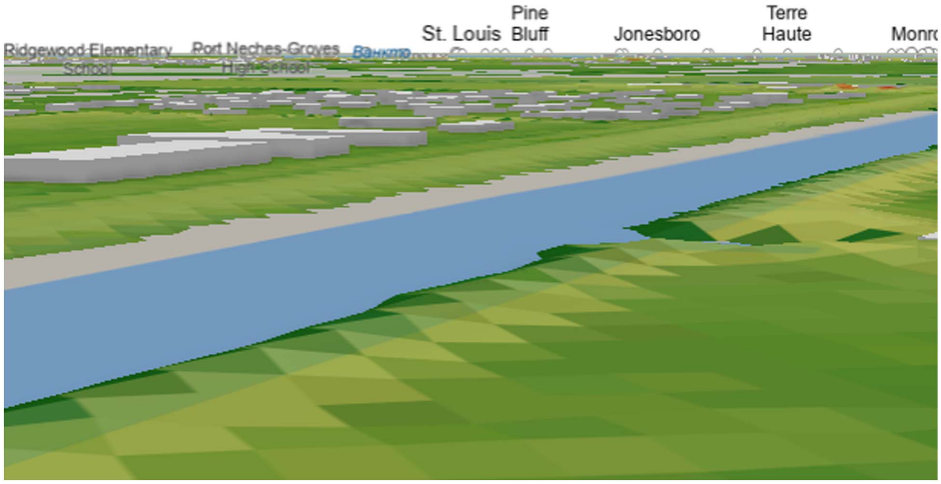


Fig. 14. Integrated data visualization.

Fig. 15. Visualization of an inundation scenario.

Fig. 16. Inundation scenarios from different levels of Hurricane Harvey impact: (a) Hurricane Harvey inundation scenario; (b) 50% of Harvey impact inundation scenario; and (c) 25% of Harvey impact inundation scenario.

Stakeholders then decide whether to extend the Halbouty pump station or expand the detention pond across the area to ensure that the planned new neighborhoods are not severely affected by flooding events.

GeoFlood creates inundation extents and water depth grids at multiple stage levels, making it a promising flood mapping strategy for future applications. Inundation generated from GeoFlood extents overlaps between 60% and 90% with those of the Federal Emergency Management Agency (FEMA) floodplain coverage (Zheng et al. 2018). When the GeoFlood area is compared to the FEMA-flooded area by local drainage catchment for each river segment, the results indicate a high level of accuracy, suggesting that overall, the flood extent generated by the GeoFlood method closely matches the FEMA benchmark. This accuracy represents an ideal tradeoff between speed and precision, as GeoFlood was designed to capture inundation patterns to guide real-time flood disaster preparedness and response. This capability is significantly faster than traditional hydraulic modeling methods. We generated scenarios on an Intel i9-9900 3.10 GHz 8-core CPU, 32GB RAM, and NVIDIA Quadro RTX 4000 GPU. We utilized consecutive data from NOAA-measured discharge and achieved near real-time inundation simulation. The average inundation simulation time is approximately 10 min, which we define as near real-time based on recent publications (Brown et al. 2022; Dai et al. 2024; Joseph et al. 2023; Ming et al. 2024; Nielsen et al. 2024; Overeem et al. 2024).

In this use case, we shifted focus to the realm of decision making within the larger context of infrastructure resilience, particularly under the influence of uncertainty. Our current achievements provide a solid foundation for future endeavors in data integration and visualization. It is worth noting that the S-BIM phase provides a distinct advantage over ground surveys by capturing extensive data across large regions. Unlike traditional ground surveys, which can be hindered by physical obstacles and property restrictions, drones can easily access and gather data from otherwise inaccessible environments (Emimi et al. 2023). Since the HAND was evaluated over the continental United States using a 10 m/pixel DEM (Liu et al. 2018), it may cause the inundation simulations to be less accurate in a specific area, particularly concerning infrastructure and neighborhood surroundings. By implementing our proposed workflow, drone photogrammetry allows us to generate DEMs with resolutions of a few inches per pixel. These high-resolution DEMs and elevation data refine the inundation simulations by acting as detailed surface layers, resulting in more accurate presentations of inundation scenarios. This enhanced accuracy enables stakeholders to determine, for example, the percentage of the neighborhood that will be impacted and the volume of stormwater the infrastructure must manage. Such precise visualizations support stakeholders in making more informed decisions regarding resilience planning in the built environment under uncertainty. We published our collected data in the Environmental System Science Data Infrastructure for a Virtual Ecosystem (ESS-DIVE) (Luo et al. 2023), providing sufficient geometric data and the status of the land surface to researchers.

Limitations and Future Work

Despite advancements, drone-based photogrammetry may pose limitations for broader urban planning applications. Battery life constraints require multiple flights, leading to time-consuming recharging and potential data inconsistencies. Urban drone flight regulations regularly limit altitudes, paths, and proximity to buildings and people. For instance, the flight path near the Halbouty pump station was restricted due to its proximity to an airport, affecting airspace access which caused us to narrow down the area. However, even with these limitations, achieving resolutions of a few inches is still much better than the 1-meter DEMs offered by the Texas Natural Resources Information System (TNRIS). Neighborhood-scale urban areas often feature complex buildings, trees, and other obstacles that can block the drone's line of sight to target objects. Shadows, reflections, and occlusions can also impact data quality and precision in outdoor urban environments. The S-BIM-DT workflow introduces complexities not seen in traditional methods, such as integrating massive volumes of data in diverse formats and structures, which requires significantly more computational resources. For example, simulating high-resolution DEMs in modeling tools demands more computing power. These insights motivate us to continuously refine the S-BIM-DT workflow to better support complex scenario analysis. For instance, we are exploring the use of optimization algorithms to obtain optimal design solutions to enhance infrastructure resilience under uncertainty.

Contributions

By innovatively integrating drone-based photogrammetry with the GeoFlood inundation modeling tool, we generated high-resolution DEMs, thereby advancing flood modeling by demonstrating that high-resolution terrain data significantly enhances simulation precision. We adapted the S-BIM-DT workflow for neighborhood-level urban planning and integrated diverse data sources such as drone imagery, USGS data, and NOAA data into a unified workflow, demonstrating its flexibility and applicability beyond building-scale infrastructures and extending its utility to larger, more complex urban environments. The multiple detailed scenarios we generated enhance the theoretical framework for scenario generation under uncertainty, providing stakeholders with methodologies to assess various strategies for improving infrastructure resilience. The rapid inundation simulations offer precise visualizations of potential flood impacts, empowering stakeholders to make informed decisions regarding infrastructure resilience planning and emergency preparedness. We achieved near real-time inundation simulations using one-hour interval water discharge data from NOAA, proving the potential for immediate flood disaster preparedness and response, directly impacting community safety and resource allocation during flood events. Research findings in Southeast Texas are expected to be generalizable to other regions and improve the resilience of vulnerable communities across the globe.

Conclusions

The development of an informed decision making process is essential to the resilience of our built environment. This study presented a workflow that encompasses a scan-to-BIM-to-digital twin (S-BIM-DT) that supports scenario generation to enhance this process. By bridging the scan-to-BIM applications with the practical needs of infrastructure resilience, our research advances both theoretical understanding and practical application in this domain. The paper also explores the benefits and feasibility of implementing the entire S-BIM-DT workflow to enhance the use of digital twins in scenario generation. The effectiveness of the S-BIM-DT workflow was demonstrated through two real-world use cases. The first, the CTECC research in Austin, Texas, integrated a digital model with simulated airflow models to create alternative scenarios to address operational challenges. This research improves IAQ and reduces the risk of airborne disease transmission by reconfiguring the HVAC system and workstation layout. The second use case, the SETx-UIFL-supported research, combined digital models and environmental simulations to assist in designing and maintaining climate-resilient infrastructures, focusing on flood infrastructure and climate impact analysis. These applications illustrate how the workflow aids stakeholders in making informed decisions that strengthen infrastructure resilience. However, several challenges were identified, such as integrating massive volumes of data in diverse formats and structures, requiring significantly more computational resources. Addressing these issues is crucial for fully realizing the S-BIM-DT workflow's potential. Future research could focus on leveraging machine learning and optimization techniques to generate scenarios more effectively, conserve computational resources, and manage large data sets efficiently. These advancements would help stakeholders identify optimal solutions quickly, thereby enhancing the workflow's effectiveness in resilience planning. The S-BIM-DT serves as an empowering tool that bridges technological advancements and practical application needs, contributing substantially to developing a resilient built environment to navigate unforeseen challenges. The S-BIM-DT workflow allows stakeholders to generate and evaluate a vast array of scenarios, and promote a decision making process imbued with wisdom. This contributes substantially to developing a resilient built environment, providing valuable insights and strategic approaches for future research.

Data Availability Statement

All data and models that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments

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