International Journal of Disaster Risk Reduction 80 (2022) 103215

Contents lists available at ScienceDirect

International Journal of Disaster Risk Reduction

journal homepage: www.elsevier.com/locate/ijdrr

# An integrated framework for temporary disaster debris management sites selection and debris collection logistics planning using geographic information systems and agent-based modeling

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A R T I C L E I N F O

*Keywords:*
Temporary debris management site (TDMS)
Site selection
Disaster debris management
Geographic information systems (GIS)
Agent-based modeling (ABM)
Disaster recovery

A B S T R A C T

Effective temporary debris management sites (TDMS) planning requires the consideration of its subsequent impact on debris collection logistics. This study establishes an integrated framework to determine the optimal locations for TDMSs that meet geographic requirements while minimizing the social and economic impacts imposed on the community due to uncollected debris. A geographic information system (GIS) was used to locate candidate TDMSs based on geographic parameters set forth by governing agencies. To consider the subsequent impact of TDMSs on debris collection, an agent-based model was constructed to evaluate post-disaster debris removal performance with varying TDMSs planning scenarios. Using the AnyLogic Optimization engine, the selection of TDMSs locations was optimized to minimize both overall debris collection time and subsequent negative impacts of uncollected debris on the public. The validity of the proposed framework was demonstrated through its application for determining optimal TDMSs locations in Liberty County, Florida, in response to Hurricane Michael where vegetative debris (i.e., potential fire hazards) and the debris within the urban areas are prioritized for collection. Compared to the actual debris collection time, the selected near-optimal TDMS locations resulted in a decrease in the total debris collection time from 156 to 112 days, with vegetative debris and debris located within the urban areas being collected within 60 and 70 days, respectively. The proposed framework will enable planners to (i) evaluate different TDMS planning scenarios in order to inform debris resource planning and management and (ii) prioritize the collection of specific types of debris based on their emergency/recovery preferences.

## 1. Introduction

The frequency of disaster events has increased by a factor of five over the past 50 years [1] and is expected to continue increasing in light of climate change and changes in weather patterns [2]. Aside from the substantial immediate human and physical damage, an inevitable by-product of disasters is the generated debris, with amounts considerably exceeding annual waste generation rates in some cases [3]. In the immediate aftermath of a disaster, substantial amounts of debris can impede emergency response and rescue efforts by obstructing transportation networks [4,5]. Disaster debris places a substantial financial burden on local and national governments,

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https://doi.org/10.1016/j.ijdrr.2022.103215
Received 20 February 2022; Received in revised form 1 July 2022; Accepted 29 July 2022
Available online 11 August 2022

typically allocating more than 25% of the disaster response expenses for managing the generated debris (United States Federal Emergency Management Agency (FEMA) 2007). Further, the potential contamination of the debris and the decaying nature of organic debris components pose serious human health and environmental safety threats [2]; United States Environmental Protection Agency (USEPA) 2019). In the long term, disaster debris can delay the rebuilding and recovery of impacted urban areas [6,7], in turn causing adverse economic and psychological impacts on disaster-affected communities [8,9].

The public health, environmental, social, and economic risks posed by disaster debris can be alleviated through proper planning and management practices. Detailed proactive plans and established frameworks for post-disaster debris clean-up operations contribute to building community resilience against future disaster events [10,11]. Developing such plans and decision-support systems, however, requires proper understanding of how different components of the disaster debris removal system work during the debris collection and clean-up operations. One such component is temporary debris management sites (TDMSs). Given the often large quantities of debris resulting from a disaster event, affected communities are unlikely to be able to immediately manage, treat, recycle, or dispose of the generated debris [12]. TDMSs provide a buffer for storing, sorting, and processing substantial amounts of debris before further treatment or disposal [13,14], and are hence considered critical for rapid and effective debris management operations [15].

Identifying suitable locations for TDMSs is a complex process that entails the assessment of geographic criteria to meet environmental, social, ownership, and logistical constraints. Besides geographic requirements, a significant, yet often unaccounted for, factor when assessing the suitability of a TDMS location is its impact on the dynamics of the post-disaster debris removal operations. Within this regard, a TDMS should be located close enough to debris source locations to enable optimized debris collection routing and expedite the debris collection process while also having access to major roadways and arterials. However, post-disaster conditions, particularly in terms of debris sources and infrastructure serviceability, are hard to predict. Such a high degree of uncertainty adds to the complexity of the already intricate TDMS location identification process.

Considering the immense cost and time implications that TDMSs locations have on post-disaster debris removal operations, there is a need for a framework that can effectively locate TDMSs based on all of the factors enumerated above. This study aims to address this need by proposing an integrated framework for identifying and selecting optimal locations of TDMSs that consider debris collection logistics planning in conjunction with TDMSs location suitability criteria. The proposed framework employs GIS analysis and simulation-based optimization, namely agent-based modeling (ABM). ABM enables modeling the complex behavior of each component of the system and monitoring the resulting overall performance in different scenarios. Through such a dynamic planning and simulation platform, debris management operations can be optimized based on current post-disaster conditions, particularly in terms of road blockages and system bottlenecks. Further, the proposed framework would enable planners and decision-makers to visualize the dynamics of the debris removal operations, allowing them to readily detect conflicts and suboptimal performance for more effective and efficient management of the disaster debris.

The remainder of the paper is organized as follows. Section 2 reviews the existing literature in the area of TDMSs location and debris allocation and highlights the present gaps within the context of the need for considering its subsequent impact on debris collection. Section 3 presents the framework proposed in this study. This will be followed by a demonstration of its application in Sections 4 and 5 using a case study of debris collection operations for Liberty County, Florida, for Hurricane Michael. Finally, Section 6 presents the conclusions of the study.

## 2. Literature review

Several geographical conditions on the location of TDMSs have been set by local governments and federal agencies [16] and cited in the literature. The aim of these conditions is to minimize the adverse impacts of debris management operations at TDMSs on the environment and the surrounding community. For example, a TDMS should not be located in environmentally restricted areas, including floodplains, wetlands, and seismic fault zones, as well as in areas where they can negatively affect ecological system components (e.g., groundwater) [12]. In addition, candidate TDMSs locations should maintain enough distance from schools, residential areas, businesses, and cultural landmarks to avoid any potential danger or safety risks [13]. Further, it is preferred that TDMSs be located on public over private land to reduce capital costs [13].

Several studies tried to identify ideal TDMSs locations by assessing a number of geographical factors using land suitability analysis [17]. used binomial cluster analysis to perform parcel-based TDMS land suitability analysis during the pre-disaster phase, where GIS was employed to map the characteristics of each parcel corresponding to the studied locational constraints. Such constraints mainly included geographic, ownership, and sizing criteria [13]. also utilized GIS to perform pre-disaster TDMS land suitability analysis, where each of the studied geographical criterion was mapped as a GIS layer. Subsequently, the authors used the Model Builder tool in ArcGIS to assess the mapped criteria, while standardizing their units and making them comparable by using Boolean logic [13]. While these studies assess geographic constraints to identify candidate locations for TDMSs, they do not consider post-disaster debris removal operations as part of the decision-making problem. With the innate uncertainty associated with disaster events, the impacted area, the debris source locations, and the infrastructure serviceability cannot be predicted with a high degree of accuracy. This implies that candidate TDMSs locations, identified by only geographic constraints during the pre-disaster phase, may end up being either inaccessible due to unpredictable post-disaster conditions or suboptimal with regards to expediting the debris removal operations. To address the first shortcoming [18,19], proposed a TDMS selection framework to be used during the response phase, during which post-disaster conditions are known and disaster debris can be estimated. While assessing the suitability of different TDMSs locations, both studies employed Analytical Network Process (ANP), along with fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), to rank candidate locations based on geographic land suitability criteria. Subsequently, when TDMSs locations were selected, allocation of the debris among these locations was optimized through fuzzy possibilistic programming in a way that minimizes either the debris transportation cost [18] or both the debris transportation cost and the TDMSs installation cost [19]. Although such a framework takes into consideration actual post-disaster conditions when selecting TDMSs locations, the selection process is limited to the consideration of geographic suitability criteria. The dynamics and performance of the debris removal operations are only considered later during debris allocation once TDMSs locations have been finalized. Also, considering post-disaster conditions, specifically the serviceability of the transportation network following a flooding event [20], proposed a GIS-based framework for selecting TDMSs. The selection process is based on 14 TDMSs suitability criteria, covering geographical factors and post-flooding vehicle accessibility constraints considering flood depth and road width [20]. While the proposed framework accounts for the post-flood conditions of the transportation system when selecting TDMSs, it does not take into consideration the optimality of the selected TDMSs with respect to the debris removal operations (i.e., cost, time, and environmental implications).

Trying to consider both geographical constraints and operational considerations, a group of studies [11,21–26] proposed TDMSs selection and debris allocation frameworks. In all of these studies, except [11]; geographically suitable TDMSs candidates were assumed to be known, and a selection from them was carried out since typically a constraint is set on the maximum number of TDMSs to open [27]. While selecting optimal TDMSs locations and accordingly planning the disaster debris supply chain, the employed objectives mainly focused on minimizing the debris removal costs [21–26], the collection time [22,24,26], and the total hauling distance [11]. Only some studies concurrently aimed to minimize the negative environmental impacts of the debris removal operations [21,24,26] and the risk from hazardous waste exposure [25]. To achieve the aforementioned objectives, mixed-integer linear programming models have been proposed. In some of these models, the complexity of the problem rendered feasibility challenges in finding an exact solution. As such, finding sufficiently good solutions was accomplished using a variety of optimization approaches, including metaheuristics (e.g., Particle Swarm Optimization [PSO], Differential Evolution [DE]) [21], vertex substitution heuristic algorithm [11], and evolutionary elitist multi objective genetic algorithm (e.g., NSGA-II) [25]. In other cases, such as in Ref. [24]; the goal was to make it feasible for users unfamiliar with mathematical concepts to optimize the selection of TDMSs and allocation of the debris. To facilitate that, the authors embedded the proposed optimization model in a user-friendly spreadsheet-based decision-support tool for disaster debris management [24].

While the reviewed studies propose frameworks to optimize disaster debris removal operations based on single or multiple

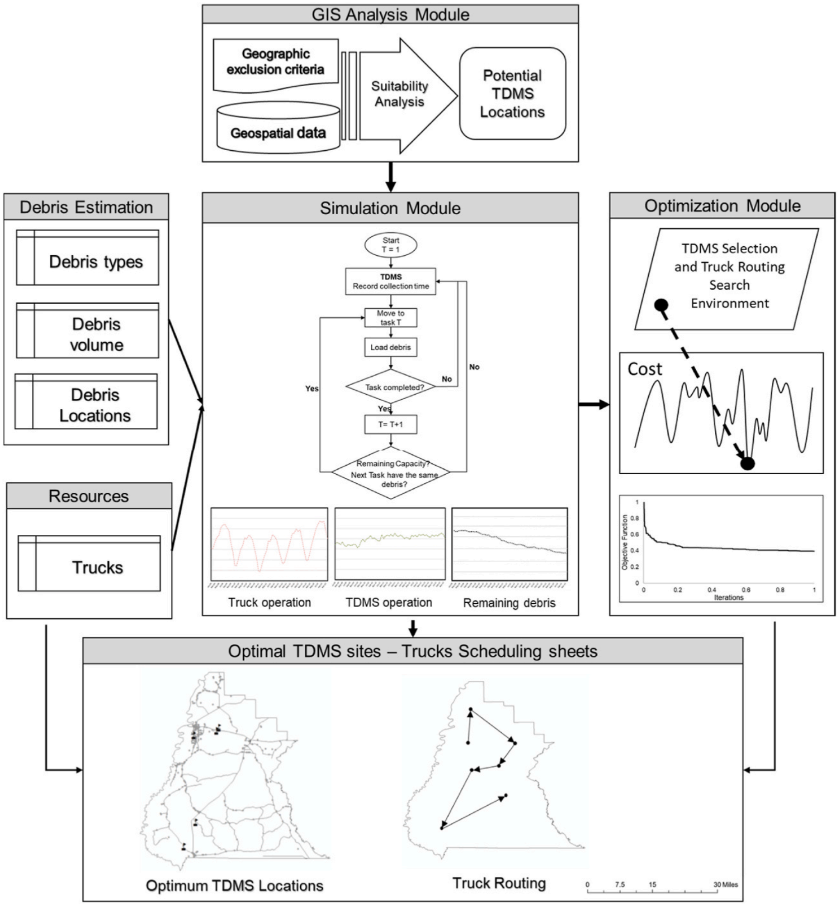



**Fig. 1.** The proposed framework for identification of the optimal locations for TDMSs.

objectives, none aimed to select TDMSs locations and plan debris clean-up operations in a way that timely collects the debris before its organic components decay. Such an objective would result in reduced public health and environmental risks, as well as maximizing debris recyclability. Further, the objective of prioritizing the collection of debris from heavily populated urban areas to minimize the social impact, in terms of not delaying the reconstruction and recovery efforts, was never previously employed in the literature. Additionally, although existing studies present novel mathematical models and decision-support tools for locating TDMSs and planning the debris clean-up process, none provide a practical method that facilitates the visualization of the debris removal operations during the optimization process. Such simulation and visualization are essential for decision-makers to better understand challenges and bottlenecks of the post-disaster debris collection operations.

To address the limitations in the literature, this study proposes a post-disaster TDMSs selection framework, which integrates geographic locational constraints and operational technical considerations to optimize debris clean-up, while accounting for health risks, recycling feasibility, and social impacts of the debris removal operations. Simulation-based optimization, through ABM, is used to enable practical dynamic modeling, visualization, and monitoring of the debris removal process. While simulation approaches have been previously utilized to support decision-making in solid waste management systems [28,29], they have not been employed in modeling disaster debris clean-up operations.

## 3. Methodology

The proposed framework aims to find the optimal locations for TDMSs considering geographical criteria as well as post-disaster debris collection operations. There are three key modules in the framework: (1) suitability analysis, (2) operation simulation, and (3) optimization (Fig. 1). The suitability analysis module finds candidate TDMSs locations that meet the environmental, social, and legal criteria for TDMSs. The operation simulation module simulates the disaster debris removal operations using estimated quantities, types, and locations of the generated debris, available debris removal resources (e.g., trucks), and the previously identified candidate TDMSs locations (i.e., the output of module 1). Finally, the optimization module determines the optimal TDMSs locations and generates optimal debris removal routing plans.

The proposed framework is not limited to any geographical area or disaster scenario as long as the required input information is provided by the user. However, the framework capabilities in determining optimal debris removal routing are limited to the resolution of the inputted debris information. For example, if the user provides the debris information at the census tract level, the framework would not be able to determine the debris collection priorities inside each census tract. Meanwhile, if such information is provided at the street-level, the framework would be able to prioritize debris collection tasks across different streets. The following subsections provide more extensive descriptions of each of the three modules of the proposed framework.

### 3.1. *Suitability analysis module*

Establishing inclusion and exclusion criteria is the first and most crucial step in the process of identifying candidate TDMSs locations. Such criteria, along with their locational constraints, were determined upon a review of the relevant literature and are listed in Table 1. TDMSs should be placed at a safe distance from wells, rivers, lakes, floodplains, wetlands, and environmentally sensitive regions [12]. Further, they should not be located in residential, institutional, commercial, and industrial areas (Cheng 2016). A suitable location for a TDMS should have adequate access to key highways, along with good ingress/egress, while not obstructing traffic flow along major transportation routes (Cheng 2016). When it comes to the site's ownership, public land is preferred over private land to host a TDMS since it costs less to rent. Following the identification of the geographic criteria for TDMSs locations, the geospatial data relevant to each criterion is collected and stored in the framework's data repository (Fig. 1).

Based on the identified TDMSs locational constraints, a restriction model was constructed using ArcGIS Model Builder tool to analyze the collected geospatial data and determine candidate TDMSs locations (Fig. 2a). Adopting a methodology similar to the ones proposed by Ref. [11] and Cheng et al. (2016), the restriction model generates buffer zones to specify the restricted areas. Subsequently, feasible TDMSs locations are identified by removing the restricted areas from the area of interest.

Following the identification of candidate TDMSs locations, ranking them based on their geographical characteristics enables the determination of the most suitable locations. Various methods have been used in the past to select the most suitable TDMSs locations [31]. ranked the identified feasible TDMSs based on total truck travel time [17]. performed such ranking based on the TDMSs geographical constraints (e.g., ownership, accessibility and relative distance to sensitive areas), where the least constrained TDMSs

**Table 1**
Summary of criteria and constraints considered.

| Criteria | Description | Constraint |
|---|---|---|
| Wetlands (Cheng 2016) | Lakes, reservoirs, streams, bays, springs, open water, wetland forests, vegetated and non-vegetated wetlands | Not in a 180 m buffer zone [30] |
| Agricultural lands and forests (Cheng 2016) | Cropland, tree crops, specialty farms, nurseries and vineyards, feeding operations, mixed forests, coniferous forests, tree plantations, hardwood forests | Not located in agricultural areas and forests (Cheng 2016) |
| Urban land use (Cheng 2016) | Residential, institutional, recreational, commercial, extractive | Not located in selected urban land use (Cheng 2016) |
| Transportation and utilities (Cheng 2016) | Transportation utilities and communication | Not in a 200 m buffer zone (Cheng 2016) |
| Industrial sites [11] | Industrial sites | Not in a 500 m buffer zone [11] |
| Flood zones [11] | 100-year flood plain | Not located in flood zones [30] |

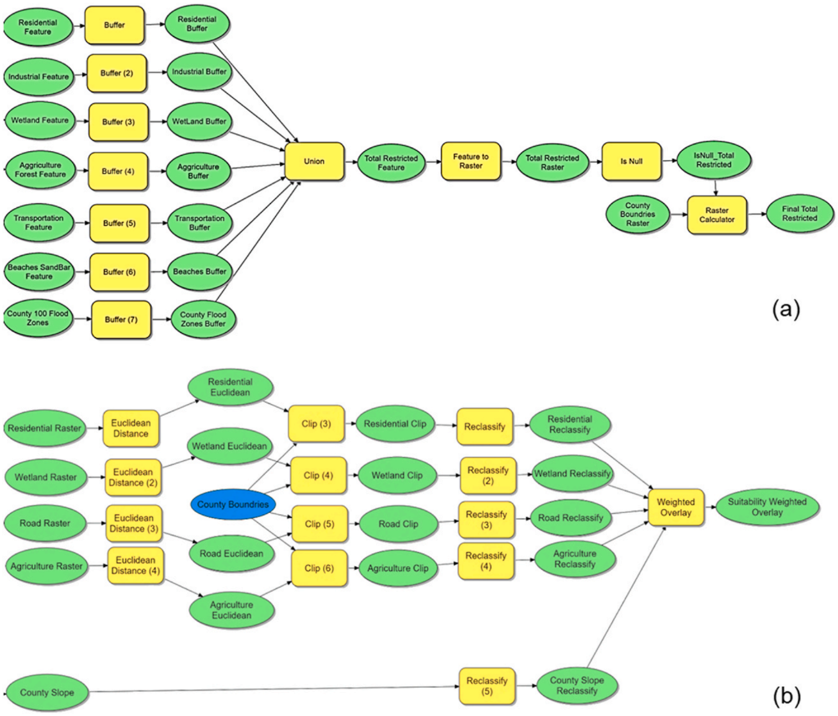



**Fig. 2.** Suitability analysis module: (a) Restriction model; (b) Suitability model.

locations were determined as the most suitable sites. Weighted overlay analysis of eligibility criteria is another approach utilized by researchers to rank feasible TDMSs according to their suitability [18,32]. In this approach, the score of each candidate TDMS is calculated against multiple ranking criteria. The weighted average of the score of each candidate TDMS is used to determine its corresponding suitability rank. In this research, the weighted overlay analysis approach proposed by Ref. [18] was adopted to rank the identified candidate TDMSs. In this regard, a suitability model was developed using ArcGIS Model Builder tool. The model uses the distance to urban buildings (residential, commercial, and institutional), wetlands, green lands (agricultural and forests), and transportation roads, as well as slope, as ranking criteria (Fig. 2b). Specifically, it calculates the Euclidean distance of county pixels to each type of land use. The resulting rasters are subsequently classified into five different classes (Classes 1 to 5) based on their calculated distance values [32]. Class 1 in each group represents the most suitable locations, while Class 5 represents the least suitable ones. The weighted overlay tool is then utilized to calculate the weighted average of all criteria for each class to combine different layers. The relative weights of the different criteria were adopted from Ref. [18]; yet they can be changed based on the judgment of decision-makers in accordance with the nature of the disaster and the regional characteristics [20]. The output of the suitability model are the identified feasible locations for TDMSs that are bigger than 2 ha, ranked based on their suitability.

### *3.2. Simulation module*

The simulation module simulates the post-disaster debris collection operations and allows decision-makers to visualize and monitor the process and identify its bottlenecks. Various simulation approaches have been employed to facilitate post-disaster planning and decision-making, the most common of which are discrete-event simulation (DES), system dynamics (SD), and agent-based modeling (ABM). DES is a simulation approach that models the operation of a system as a (discrete) sequence of events in time. In this approach, each event occurs at a specific point in time and represents a change in the system's state. Earthquake housing recovery operations [33] and disaster medical response operations [34] are examples of post-disaster planning problems supported by DES. SD is another modeling approach used to frame and understand complex, interdependent, and nonlinear systems [35]. SD considers the structure of a system and the relationship among its components to simulate a system's behavior over time using stocks, flows, internal feedback loops, table functions, and time delays. Researchers employed SD in various disaster management and planning efforts, including post-disaster hospital recovery [35] and disaster debris removal operations [11]. As for ABM, it is a modeling and computational framework that allows decision-makers to simulate system functionality by modeling the autonomous decision-making elements of the system, also known as "agents" [36]. Without any external direction, each agent individually assesses and responds to situations encountered during the simulation based on a predefined set of rules [37,38]. ABM has been widely utilized to simulate decision-making processes in various disaster risk reduction efforts, such as earthquake emergency response and rescue missions [39] and sustainable disaster recovery [40]. When selecting the most suitable modeling paradigm between DES, SD, and ABM, the characteristics of the studied system [41] and the level of abstraction required in the simulation [42] should be considered. Since the disaster debris collection process is dynamic and complex, and its simulation requires the micro-modeling of each actor/resource involved in the process to facilitate planning and decision-making, ABM was selected to be adopted in this research. The ABM approach allows decision-makers to simulate the behavior of the different players involved in the debris collection operations, while developing a detailed model of the operation. Moreover, it enables practitioners to visualize the entire debris collection process using animations, which facilitates understanding the process dynamics and the detection of its deficiencies.

Simulating the debris hauling operations using ABM is done via the object-oriented programming simulation software AnyLogic 8.7.8. Shapefiles of the road network corresponding to the geographical area understudy are first imported to AnyLogic GIS environment. These files are used to map the road network within the simulation model using GIS space markup properties of AnyLogic. Once the road network is generated, three types of agents (i.e., debris, trucks, and TDMSs) are populated and imported into AnyLogic GIS environment. Table 2 summarizes the parameters and variables corresponding to each of the three agents.

TDMSs agents are modeled as stationary warehouses. Their locations are selected from the list of candidate sites that was generated by the suitability module. The capacity $C$ of each TDMS is determined according to Equation (1) [22,43], where $A$ is the floor area of the site, $H$ is the height of the stored debris (5 m), and $R$ is the ratio of the debris storage area to the total floor area of the site (60%).

$$C = A \times H \times R \tag{1}$$

Within each TDMS, it is assumed that debris handling begins as soon as the debris is delivered to the site. This includes debris sorting, volume reduction (e.g., chipping/grinding), and transport to subsequent material recovery facilities or final disposal sites to open up space within the TDMS. As the details of such internal operations are outside of the scope of this study, the debris handling rate is simply defined as a function of the site capacity. It should be noted that if the TDMS reaches its maximum capacity, a loaded truck arriving at the TDMS would need to wait until enough room for the incoming debris becomes available (i.e., an equal amount of existing debris at the TDMS is processed and transferred to subsequent debris management pathways). As such, despite that the internal operations of TDMSs are not included in the simulation model, their overall effect on the debris collection operation is reflected with the debris handling rate parameter. The TDMS debris handling rate parameter determines the speed of debris sorting, processing, and transport for final disposal, which specifies the remaining capacity of the TDMS.

Debris agents represent the debris removed and transported by debris hauling trucks. Each debris agent is characterized by its geographic location, type, and volume. Researchers have proposed various methodologies to estimate debris volume in pre-disaster conditions [44]. Moreover, emergency management organizations have released various pre-disaster debris estimation tools, such as the Hazards US Multi-Hazard (HAZUS-MH) software developed by Ref. [45]. However, estimates developed by these tools are subject to errors and might not match the actual debris generated in post-disaster situations. The accuracy of the results generated by the proposed framework is enhanced when detailed and accurate post-disaster debris information is inputted into the model. In this regard, neural network-based methodologies and image processing approaches can be employed to identify the damaged areas and estimate the location, quantity, and type of the debris generated using post-disaster ground and aerial surveys [46].

Truck agents are modeled in the simulation as vehicles that can move along the road network. Each truck agent is characterized by a specific carrying capacity, which represents the maximum amount of debris that can be loaded into the truck. Further, each truck is assigned a unique list of debris collection tasks. Fig. 3a illustrates the truck agent movement logic. At the beginning of the simulation, all trucks are located at the TDMS. Each truck then starts collecting debris according to its assigned tasks. Upon loading the debris, the

**Table 2**
Simulation model parameters and variables.

| Agent | Parameter | Variables |
|---|---|---|
| TDMS | • ID<br>• Latitude<br>• Longitude<br>• Area<br>• Capacity<br>• Debris handling rate<br>• Distance to transportation network<br>• Distance to wetlands<br>• Distance to agricultural lands and forests<br>• Distance to industrial sites<br>• Distance to flood zones | • Vegetative debris received<br>• Non-vegetative debris received<br>• Debris in urban areas<br>• Debris outside urban areas<br>• Remaining capacity<br>• Processed debris |
| Debris | • ID<br>• Latitude<br>• Longitude<br>• Type<br>• Volume | • Remaining volume |
| Truck | • ID<br>• Task list<br>• Capacity<br>• Speed<br>• Loading time<br>• Unloading time | • Debris task<br>• Collected debris type<br>• Collected debris location<br>• Loaded debris volume<br>• Remaining capacity<br>• Penalty |

truck agent examines if it reached its carrying capacity. If that condition is met, the truck goes to the nearest TDMS to unload the debris; otherwise, it proceeds to the next assigned task if it has the same debris type as the currently loaded debris. In any case, each debris collection task needs to be completed before the following task is initiated. This implies that if the quantity of debris to be collected in a single task is more than the truck agent carrying capacity, the truck would have to complete that task in stages before proceeding to the next one. The simulation model captures the information about the incoming debris type, volume, and collection time once each truck enters a TDMS.

The loading and unloading process of each truck agent is modeled with truck waiting time. The waiting time refers to when the truck stops moving while it is either collecting debris in the roadway or delivering it at the TDMS. The truck waiting time in the roadway depends on the truck capacity, the loader operators' performance, and the loader bucket capacity. When delivering the collected debris to the TDMS, each truck is first weighed, paperwork for debris delivery is filled, and the debris in the truck is unloaded. The truck waiting time at the TDMS might vary considering the traffic inside the TDMS. The behavior and movement logic of the truck agents is simulated using AnyLogic statecharts (Fig. 3b).

As an illustrative example of the movement of truck agents, consider a simple network comprised of three debris nodes (Fig. 4a), along with three trucks, each assigned with a set of debris collection tasks (Fig. 4b). In this example, the capacity of each truck agent is 10 (CY) (i.e., 7.65 $m^3$). Since the amount of debris in each location (i.e., node) is more than the carrying capacity of each truck, multiple tasks are required to collect the debris from each node. Truck 03, for instance, is assigned Tasks 2, 5, and 6. Fig. 4c explains how this truck moves in the network and collects the debris. It starts with Task 2 at node 1 then moves to node 2 to perform Task 5, since it still has some remaining capacity. Once fully loaded, Truck 03 moves to the closest TDMS to deliver the collected debris. Subsequently, it returns to node 2 to complete Task 5 and then proceeds to node 3 to perform Task 6.

### 3.3. Optimization module

The optimization module aims to find the near-optimal locations for a fixed number of TDMSs defined by the decision-maker, considering the geographical requirements of TDMSs and debris removal operations. As previously explained, TDMSs locations should meet several environmental requirements enforced by governing agencies. Also, the locations of TDMSs directly impact the debris removal operations. Locating TDMSs far from debris source locations increases trucks' travel time and, hence, total debris removal duration, which has subsequent negative social and economic impacts on the disaster-affected community. For each candidate TDMS, numerous truck routing options are available with different debris removal durations. Therefore, selecting the optimal TDMSs from identified candidate locations also requires optimizing the truck routing of the debris collection. In other words, the search environment of the optimization in this module would consist of various combinations of (1) the previously identified candidate TDMSs locations and (2) truck routing.

Optimizing truck routing is generally considered a Vehicle Routing Problem (VRP). A VRP is typically formulated as a mixed-integer programming model [47]. Minimizing the cost of providing service and/or minimizing the total travel distance (time) are the most common objectives used in such models. In this study, minimizing the total debris collection time is set as the primary objective (Equation (2)). The TDMSs geographical criteria are also integrated into the model's objective function through a linear transformation $f(.)$, which converts distance values to time units using the truck speed. In this regard, the objective function is set to

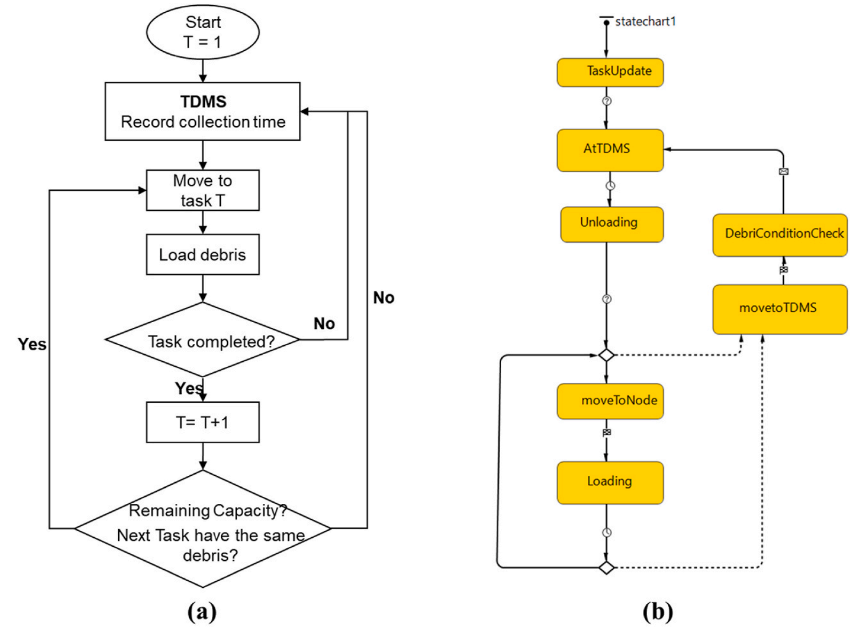



**Fig. 3.** Truck agent movement logic: (a) Movement flowchart; (b) Movement statechart.

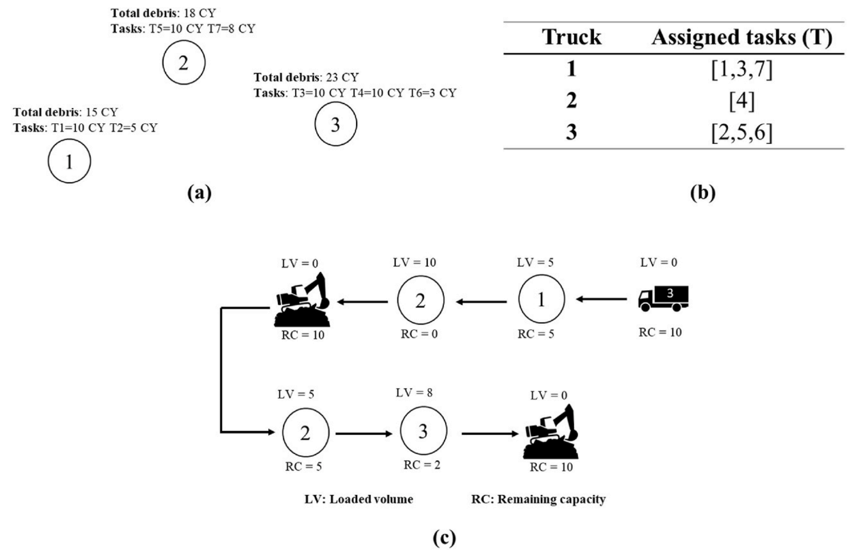



**Fig. 4.** Illustration example of the movement of truck agents: (a) Simple network; (b) List of tasks assigned to each truck; (c) Truck 3 movement in the network based on its assigned tasks.

minimize the distance of the TDMSs to the transportation network in order to minimize the length of access roads connecting the existing network to the facility while also maximizing its distance to wetland, agricultural lands, urban land use, industrial sites, and flood zones. TDMSs candidates are determined by the suitability analysis module. In other words, all candidates are outside of the restricted area and have suitable geographical characteristics for TDMSs. Therefore, the optimization module aims to identify the optimal TDMSs locations among suitable candidates.

$$\begin{aligned} &\text{Min } (\text{Total debris collection time} + f(\text{Distance to transportation network}) - f(\text{Distance to wetlands}) \\ &- f(\text{Distance to agricultural lands and forests }) - f(\text{Distance to urban land use}) - f(\text{Distance to industrial sites}) \\ &- f(\text{Distance to flood zones}) + \text{Penalty}) \end{aligned} \tag{2}$$

In addition to debris collection time and TDMSs geographic criteria, the model's objective function encompasses a penalty component. The aim is to allow decision-makers to prioritize the collection of certain debris tasks to minimize the adverse impacts of uncollected debris. The collection of hazardous/organic debris, for example, can be selected to be expedited in order to decrease its associated health and safety risks on the disaster-impacted community. Moreover, decision-makers may choose to prioritize collecting the debris from urban areas to accelerate the community's recovery. To enable such debris prioritization, this study uses the penalty approach to prioritize debris collection tasks according to decision-makers' preferences, adopted from Ref. [48]. In this approach, the objective function is penalized if priority tasks are delayed. The penalty is determined based on the waiting period for performing each debris removing task, evaluated using a quadratic function (Equation (3)). The penalty increases rapidly as the waiting period $T$ of a debris collection task increases beyond time $e_i$ (Fig. 5). Specifically, the algorithm penalizes cases where debris is delivered to the TDMS after an assigned time constraint. The time constraint can also be defined, for example, based on the changing property of the materials (e.g., organic waste) over time [3]. The coefficient $a_i$ is used to distinguish high priority tasks (Fig. 5a) from other debris collection tasks (Fig. 5b). In this regard, tasks that are prioritized will be assigned a higher value of $a_i$.

$$Penalty = a_i \times (T - e_i)^2 \tag{3}$$

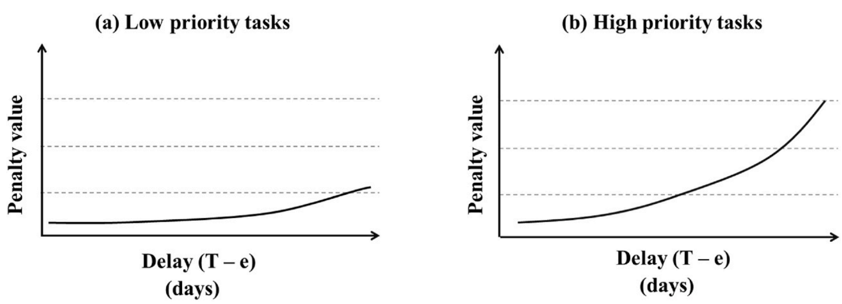



**Fig. 5.** Changes in the penalty function for priority tasks and non-priority tasks: (a) Low priority tasks; (b) High priority tasks.

VRPs are generally considered NP-hard problems, where exact optimization algorithms cannot find the global optimum promptly [49]. As such, metaheuristic algorithms are commonly used to intelligently explore the search space and find near-optimal solutions within reasonable computational time, such as simulated annealing [50], genetic algorithm [51], and Tabu search [52]. In this study, the optimization model is developed using the AnyLogic software's Custom Experiment feature and solved using the AnyLogic optimization engine. The latter is based on the OptQuest Optimization Engine, which finds near-optimal solutions using metaheuristics. At each iteration, the AnyLogic optimization engine runs the simulation model to calculate the objective functions. It assesses one alternative solution per iteration by modifying the design variables (i.e., TDMSs locations and the list of tasks allocated to each truck), while keeping the best-identified solution. As a result of the optimization process, the near-optimal locations of TDMSs and the corresponding truck routing schedule are identified.

## 4. TDMSs selection and debris logistics planning: a case study of Liberty County, Florida, in response to Hurricane Michael

Hurricane Michael was the first Category 5 hurricane that made landfall in the contiguous United States since Hurricane Andrew in 1992. It was estimated that Hurricane Michael caused over $25 billion in damages and generated over 5 million cubic yards of debris [53]. Hurricane Michael caused severe damages in several counties in the Florida Panhandle, including Bay and Liberty Counties. This section implements the proposed framework to select optimal locations for TDMSs in Liberty County, Florida, while minimizing the social impacts of the generated debris.

According to the proposed framework, three types of information are required to identify optimal locations for TDMSs during the post-disaster recovery phase: (1) geospatial information, (2) debris estimates, and (3) available resources. The geospatial information corresponding to this case study was gathered from a variety of sources. Specifically, the land use and cover data were obtained from the Florida Department of Environmental Protection (FDEP) Open Data Portal, the road network data was collected from the Florida Department of Transportation (FDOT) GIS data repository, the elevation data was acquired from the United States Geological Survey (USGS), and the flood plains data was obtained from FEMA. As for debris and resources information, they were acquired from the primary debris hauling contractors who participated in Hurricane Michael recovery operations in Liberty County. The collected data covered the debris source location, type, volume, and hauling information, such as truck capacity and destination location. With regards to each of the truck speed and waiting (i.e., loading and unloading) time parameters, a set of possible values was considered in the simulation. Table 3 summarizes the test scenario debris removal information.

The debris source locations along the roadways of Liberty County are plotted in Fig. 6a. In total, 47,400 debris tickets were issued to collect approximately 525,700 CY (401,926 $m^3$) of vegetative debris, C&D debris, and ash debris, as well as 34,000 units of leaners and hangers from the right-of-way of Liberty County. Moreover, 150 trucks with an average capacity of 50 CY (38 $m^3$) were used to collect the debris in approximately five months. Fig. 6a also depicts the location of the real-world TDMSs. These TDMSs were used to store and manage the generated debris from Hurricane Michael.

To simplify the number of debris source locations in the roadways, the debris in each road segment was aggregated into a single point. Each road between two consecutive intersections was defined as a single road segment. In cases where the segment length was greater than 2 miles (3.2 km), the segment was divided into multiple sections. The resulting average length of road segments where debris was located was 0.65 miles (1 km). The maximum length of the road segments (i.e., 2 miles) was defined based on the average amount of debris on the roadways and the capacity of debris hauling crews. There is about 526,000 CY (402,156 $m^3$) of debris scattered in ~330 miles (499 km) of roadways. This implies that each road segment, with an average length of 0.65 miles, contains ~1000 CY (765 $m^3$) of debris that can be collected by a single debris collection crew in four passes (each crew has a debris collection capacity of 250 CY (191 $m^3$)). The maximum length of the road segments can be adjusted based on decision-makers' preferences and the amount of debris on the roadways. It should be noted that reducing the maximum road segment length threshold will not result in significant

**Table 3**
Test scenario parameters.

| Attributes | Value |
|---|---|
| Debris hauling tickets | 47,400 units |
| **Debris types:** | |
| Vegetative debris | 502,000 CY[a] (383,807 $m^3$[b]) |
| Construction and demolition (C&D) debris | 6700 CY (5123 $m^3$) |
| Ash debris | 17,000 CY (12,997 $m^3$) |
| Leaners and hangers | 34,000 units |
| **Debris removing resources:** | |
| Number of debris removing trucks | 150 units |
| Trucks capacity | 50 CY (38 $m^3$) |
| Truck speed | [22, 25, 28] mph[c] ([35, 40, 45] kph[d]) |
| Truck loading time | [5, 6, 7] minutes |
| Truck unloading time | [8, 9, 10] minutes |
| Number of TDMSs | 4 units |

[a] CY = cubic yard.
[b] $m^3$ = cubic meter.
[c] mph = mile per hour.
[d] kph = kelometre per hour.

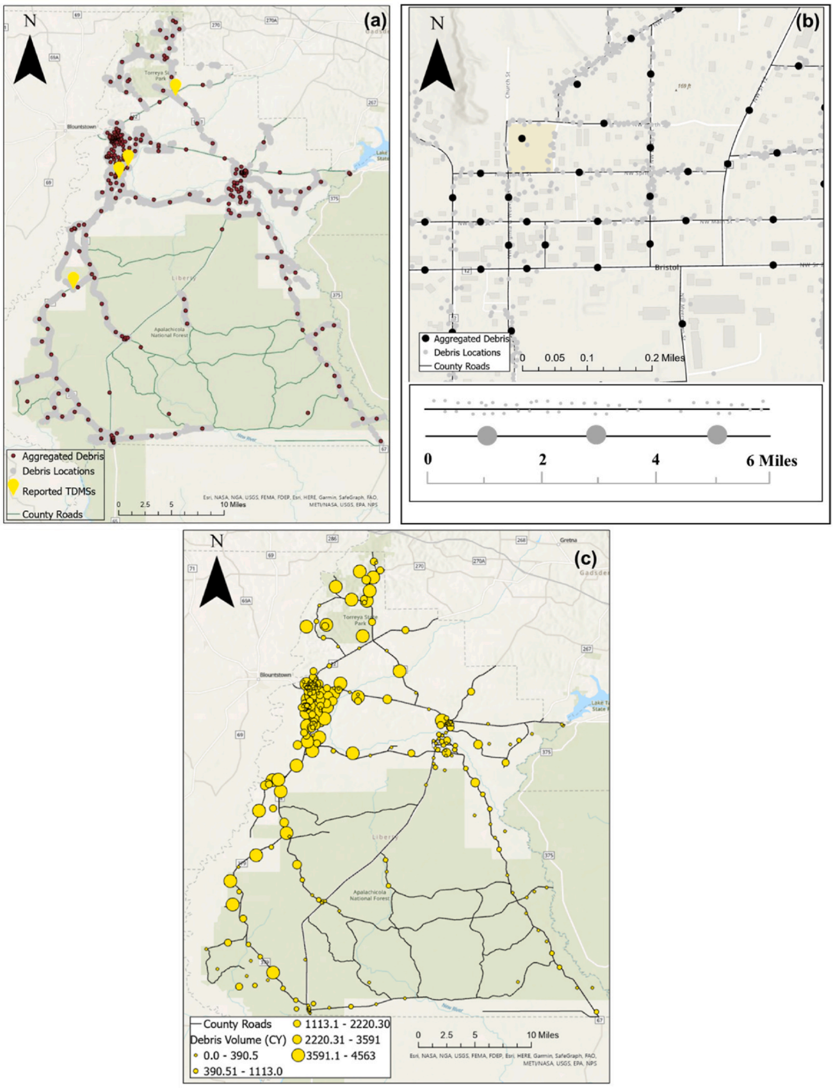



**Fig. 6.** Debris source locations and volume distribution in Liberty County, Florida, after Hurricane Michael: (a) Debris locations and original TDMSs; (b) Detailed illustration of the debris aggregation process in Blountstown; (c) Distribution of the debris volume throughout the network.

changes in the total debris hauling distance since the simulation model allows trucks to move to the next tasks and collect more debris if they have some capacity remaining. However, lowering this threshold would increase the number of debris hauling tasks and, in turn, the model complexity, hence reducing the efficiency of the optimization model. The aggregated debris source locations are plotted in Fig. 6a. Fig. 6b presents a more detailed map of Blountstown illustrating the debris aggregation process. The distribution of the debris volume throughout the network is presented in Fig. 6c.

Identifying eligible places that meet the geographical requirements, listed in Table 1, is the first step toward identifying near-optimal locations for TDMSs. The restricted areas were identified using the restriction model presented in Fig. 2a, and their suitability was determined based on their slope and distance from urban buildings, wetlands, green spaces, and transportation roads (Fig. 2b). Fig. 7 displays the candidate TDMSs zones as well as debris locations. The score of each TDMS candidate from the suitability analysis was used to denote its suitability as low, average, or high. The majority of the candidate locations were ranked as 'average' in the analysis, while few locations in southern Liberty County were rated as ideal for TDMSs (i.e., ranked as 'high'). Despite their relatively far distance to populated areas (i.e., red box in Fig. 7), they may be suitable for collecting debris from the county's southern roadways. In total, 45 locations were identified suitable to host TDMSs.

In the second module of the framework, a model was developed to simulate the post-disaster debris collection operations. Each debris source location was considered a single debris collection task and assigned to a debris collection crew consisting of five trucks as suggested by Ref. [54]. Thirty debris collection crews (i.e., 150 trucks) were assumed to be available for debris collection operations. Moreover, the capacity of each truck was assumed to be 50 CY (38 $m^3$). During the simulation, the trucks in each crew collectively work to remove the debris from roadways based on their assigned tasks. Collected debris is transported to the four TDMSs reported by the

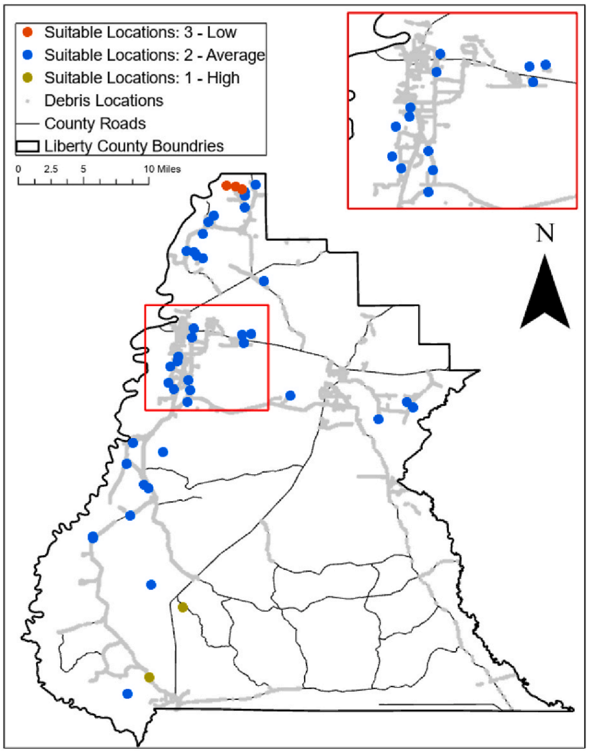



**Fig. 7.** Suitable locations for TDMSs in Liberty County, Florida.

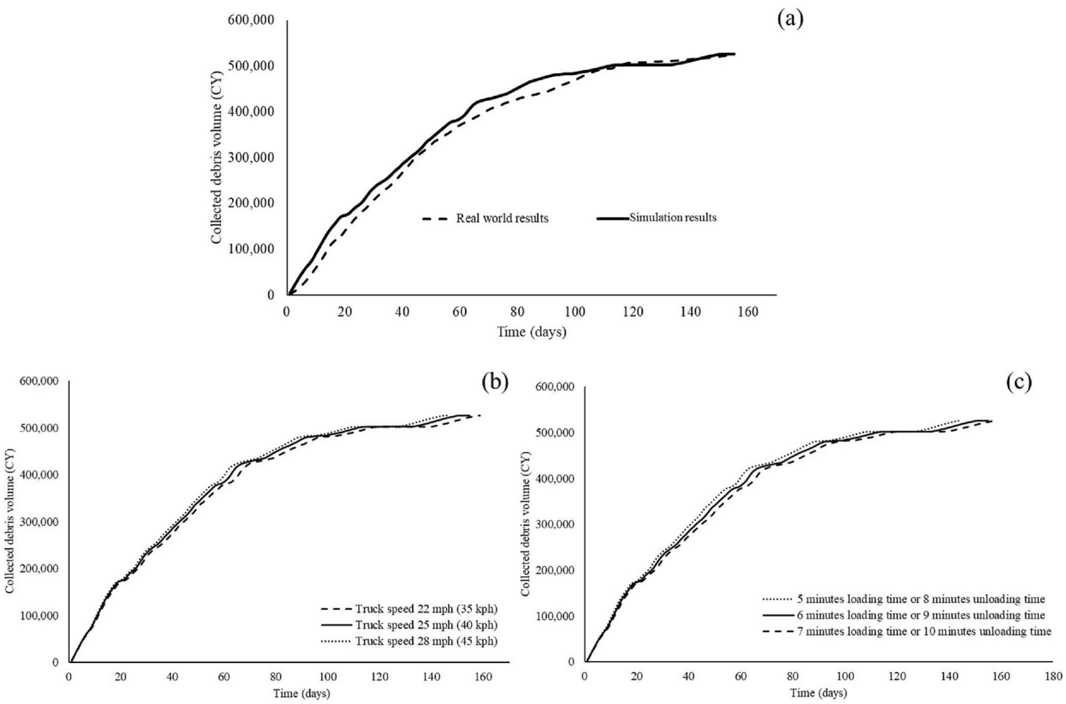



**Fig. 8.** (a) Comparison between debris removal simulation results and real-world operations in Liberty County, Florida; (b) Uncertainty analysis results for truck speed parameter; (c) Uncertainty analysis results for truck waiting time parameter.

primary debris hauling contractors. The time unit of the simulation model was set to "hours" to capture details of the truck movements within the road network. Moreover, the virtual time mode of the AnyLogic environment was utilized to maximize the simulation speed during the optimization process.

A calibration process was conducted to determine the values of the truck agents' speed, loading, and unloading time parameters from their corresponding sets of possible values, which were presented in Table 3. Within this regard, the truck speed was set to 25 mph, and the truck loading time and unloading time were set to 6 and 9 min, respectively. With these calibrated values, the simulation model yielded results that well captured the overall progression of the actual debris collection process (i.e., in terms of cumulative debris collected from roadways over time) (Fig. 8a). Such comparison, which is usually referred to as a behavior reproduction test [35, 55,56], verified that the developed model well captures the regularity of the real-world debris operations.

To further investigate the impact of changing the truck agents' speed and waiting (i.e., loading and unloading) time parameters on the simulation results, uncertainty analysis was performed, as presented in Fig. 8b and c, respectively. The analysis results indicate that variations in these parameters have a negligible effect on the simulated debris collection operations at the beginning of the simulation (i.e., the first 25%). However, as the simulation progresses, the disparity among the results increases. At the end of the simulation, the total simulation duration changes by 3.7% and 4% as a result of changing truck speed by 3 mph (12% change) and changing the truck waiting time by 1 min (16% change), respectively.

As previously explained, the proposed framework allows decision-makers to prioritize the collection of any kind of debris based on their emergency/recovery preferences. In this case study, the collection of vegetative debris and other debris, which are both located in urban areas, were selected to be prioritized to demonstrate the framework's capabilities. Vegetative debris constitutes most of the debris generated in Liberty County due to the abundance of green lands. In fact, piles of vegetative debris may become fire hazards during the dry season and attract insects, rats, and other rodents [57]. Further, due to various environmental stressors such as temperature and humidity, vegetative debris readily decays and loses its recyclable value over time. As such, in this case study, decision-makers were assumed to prioritize the collection of vegetative debris to maximize its recyclable value and minimize its potentially adverse impacts on surrounding communities. Additionally, debris within urban areas was considered as a priority to be collected, thereby expediting the recovery of the community and its return to normalcy.

Using the third module of the framework (i.e., the optimization module), near-optimal solutions for TDMSs locations were found to minimize the debris collection duration while prioritizing the collection of vegetative debris and debris within urban communities. In this module, the optimization's number of iterations should be adjusted to allow the optimization engine to investigate the search space sufficiently. In this regard, the optimization was conducted using various iteration numbers [8000; 9000; 10,000; 11,000] to

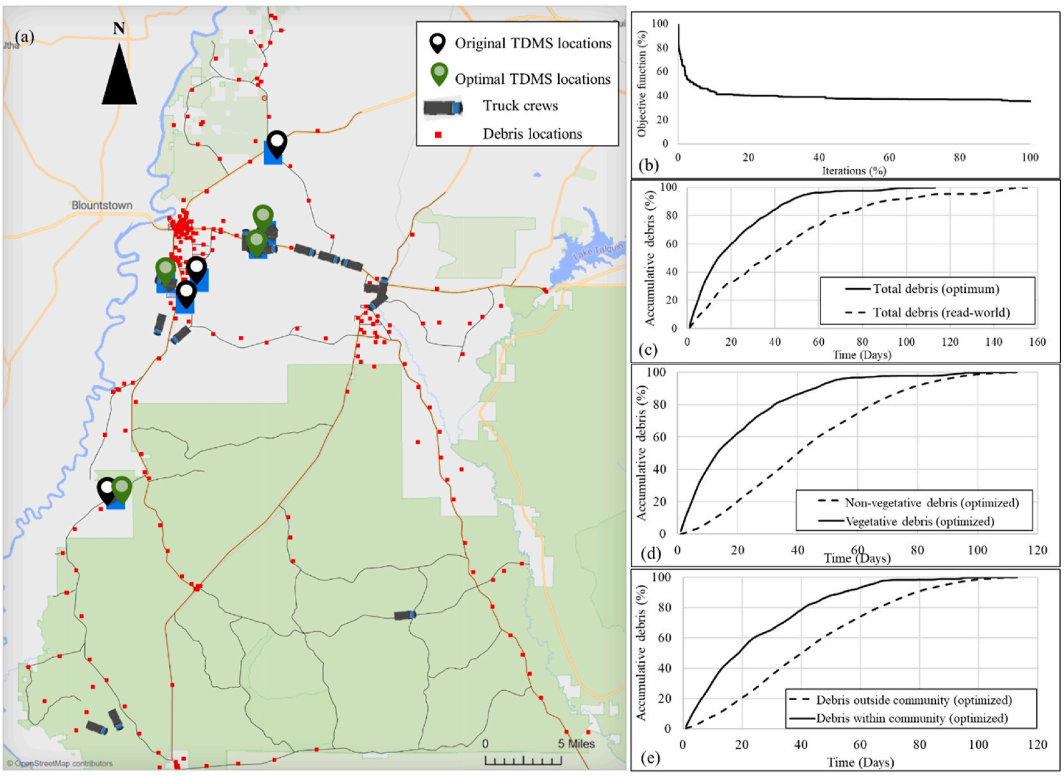



**Fig. 9.** Results of the optimization module: (a) Snapshot of the simulation model along with optimal TDMSs locations; (b) Normalized objective function with respect to the normalized number of iterations; (c) Normalized accumulative debris delivered to TDMSs; (d) Normalized accumulative vegetative and non-vegetative debris delivered to TDMSs; (e) Normalized accumulative debris within and outside urban communities delivered to TDMSs.

evaluate the effect of increasing the number of iterations. Results showed that the improvement of the objective function was insignificant beyond 10,000 iterations; the number of iterations was thereby set to 10,000. For simplification purposes, in this case study, the time constraint *e* in Equation (3) was set to zero while it may depend on various factors such as temperature, humidity, and changing properties of the material [3]. Fig. 9b illustrates how the normalized value of the objective function varies across different iterations. During early iterations, the value of the objective function drops fast as the algorithm searches globally within the search environment. However, as the algorithm searches locally and closer to the near-optimal solutions, the objective function's decreasing rate diminishes. Results show that the optimization module can successfully explore the search environment and find better solutions as it iterates.

Fig. 9a shows a snapshot of the simulation model during a simulation run. It depicts the near-optimal TDMS locations as slightly different from the initial TDMSs, since the former was selected in a way that would reduce the total operation duration. All four sites were graded "two" (i.e., average) based on the suitability analysis. Three of the locations were chosen to be closer to urban areas in order to speed up debris collection from these areas. The fourth TDMS was selected to manage debris located in the county's southern half.

Fig. 9c compares the total debris collection time for the real-world conditions (i.e., baseline) with the near-optimal solution. Results show that by applying the proposed framework for TDMSs selection and debris logistics planning, the total debris collection time decreased from ~156 to ~112 days. Fig. 9d and e depict the optimized progress of delivering debris to TDMSs by debris type (i.e., vegetative vs. non-vegetative) and debris location (within vs. outside community), respectively. The optimization results show that the collection of vegetative debris is prioritized over other types of debris (Fig. 9d). In particular, the vegetative debris is collected within 60 days, which is about 50% of the total debris collection duration (~112 days) due to the much faster collection rate. Similarly, the debris located within the community is collected within ~70 days, which is about 60% of the time spent collecting the debris outside urban areas (Fig. 9e). These results illustrate the effectiveness of the optimization module in planning the debris collection process in accordance with the prioritized debris types and source locations.

## 5. Managerial insights

Post-disaster recovery operations are often constrained by their available resources due to the enormity of the magnitude and extent of the disaster-resultant damage. In this section, some critical managerial insights are discussed to assist decision-makers in making more informed decisions regarding the required resources for the debris removal operations. In particular, this section analyzes multiple planning scenarios to evaluate the impact of varying resource availability on the duration of post-disaster debris removal operations versus their resulting cost, thereby enabling the development of cost-effective plans.

A sensitivity analysis was conducted for the number of trucks and available TDMSs using a total of 27 test scenarios (Table 4). More specifically, the number of trucks was increased from 50 trucks to 210 trucks with an increment of 20 trucks; and the number of available TDMSs was varied between three, four, and five. The optimization module was utilized in each scenario to identify near-optimal solutions for TDMSs locations and truck routing. The simulation module was used to evaluate the duration and cost of the debris removal operations. The latter consist of (1) the cost of collecting and transporting debris to TDMSs, (2) the cost of handling the debris within TDMSs, and (3) the cost of operating TDMSs. The debris transportation cost component was calculated based on the distance traveled by each truck agent multiplied by a unit transportation cost of $16/mile*ton ($10/km*ton), as suggested by Ref. [26]. Similarly, the debris handling cost was calculated based on the amount of debris handled at the TDMS multiplied by a unit handling total cost (i.e., processing and disposal) of $166/ton, as suggested by Ref. [26]. As for the cost of operating a TDMS, it was computed based on its floor area, with an estimated unit cost of $2000/acre/month [11].

The impact of varying the number of trucks and available TDMSs on the duration of the debris removal operations is illustrated in Fig. 10. Results of the sensitivity analysis show that as we increase the number of trucks from 50 to 210, the total debris collection duration is reduced by approximately 60%, regardless of the number of available TDMSs (i.e., three, four, or five) (Fig. 10a). Similarly, the collection durations of vegetative debris and debris within urban areas are reduced by almost 80% as the number of available trucks increases (Fig. 10b and c). Such enhanced rapidity in the collection and removal of disaster debris can positively impact the psychological recovery of the disaster-affected community [58] and the debris recyclability [12]. The impact of increasing the number of available TDMSs on the total duration of the debris removal operations is shown in Fig. 10d. The average values of operation duration for different truck numbers were calculated to study this effect. The results of the sensitivity analysis show an inverse relationship between the two (Fig. 10d). Opening more TDMSs results in more distributed facilities within the network and hence shrinks the area covered by each facility. Therefore, the travel distance for each truck to deliver the debris decreases, resulting in a reduction in the total operation duration. Such inverse relationship, however, was not apparent in Fig. 10c, where increasing the number of TDMSs had a negligible effect on the collection duration of debris within urban areas. The reason is that the optimization model does not select the locations for TDMSs in a way that minimizes the time to collect debris specifically from urban areas; the model optimizes TDMSs locations and collection operations to minimize the overall collection time as shown in Fig. 10d. In other words, the area covered by the extra facilities (i.e., four and five TDMSs test scenarios) selected by the optimization module is not

**Table 4**
Test scenarios for sensitivity analysis of debris removal resources.

| Number of TDMSs | Number of Trucks | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **3** | 50 | 70 | 90 | 110 | 130 | 150 | 170 | 190 | 210 |
| **4** | 50 | 70 | 90 | 110 | 130 | 150 | 170 | 190 | 210 |
| **5** | 50 | 70 | 90 | 110 | 130 | 150 | 170 | 190 | 210 |

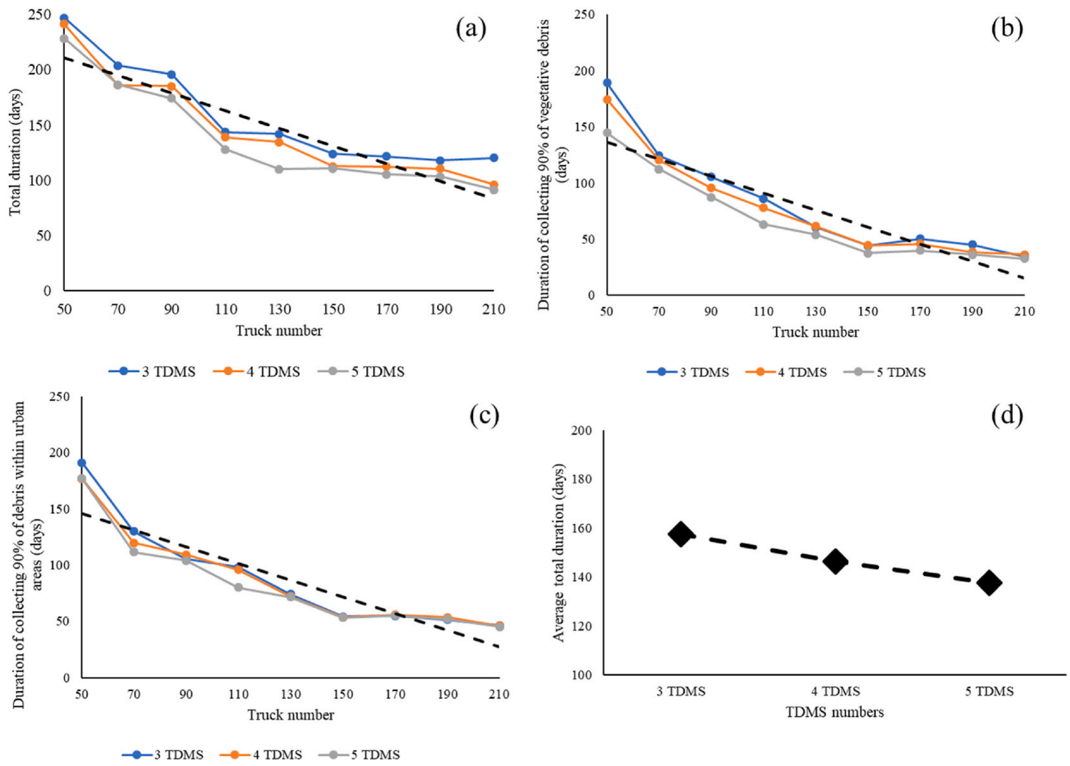



**Fig. 10.** The effect of increasing resources on (a) total operation duration, (b) duration of collecting vegetative debris, and (c) duration of collecting debris within urban areas; (d) Effect of increasing the number of TDMSs on the average total operation duration.

urban; hence, the added TDMSs did not contribute to quickly transferring and storing the debris from urban areas.

Fig. 11 depicts the effect of increasing resources on the total cost of the debris removal operations, as well as on its different components (i.e., transport cost, handling cost, and TDMSs operating cost). The overall trends in Fig. 11a suggest that as more trucks are used, the total operation cost decreases. A similar observation was reported by Ref. [11]. It should be noted that the inconsistency of such a trend across all test scenarios in Fig. 11a can be attributed to the general setup of the optimization problem. To be more specific, minimizing the total operation cost is not part of the objective function of the optimization algorithm, which was instead set to minimize the total duration of the debris collection operation. Further, fluctuations in the observed trends between different scenarios are expected due to the innate complexity of VRPs and the large number of variables existing in each scenario [47].

With regards to specific cost components, results indicate that increasing the number of trucks can have different effects. For example, increasing the number of trucks reduces the debris processed and hence its cost, due to the reduction in the total duration of the debris removal operations (Fig. 11b). Similarly, having more trucks reduces the TDMSs operating cost as they become operational for a shorter duration (Fig. 11d). As for the debris transport cost, it shows negligible variations when adding more truck resources (Fig. 11c). The reason is that the total debris removal tasks become distributed over more trucks, resulting in each truck performing fewer tasks. Additionally, each truck becomes operational for a shorter duration due to the reduced total operation duration. As for the impact of varying the number of TDMSs available, adding more TDMSs results in an increase in the total operation cost (Fig. 11a). With more TDMSs, the debris handling capacity increases and thus the debris handling costs (Fig. 11b). Additional TDMSs also mean increased total floor area, which translates to higher TDMSs operating costs (Fig. 11d). Further, as explained previously, adding extra TDMSs would reduce the area covered by each facility, resulting in a reduction in truck travel distances and hence debris transport cost (Fig. 11c).

As demonstrated in this section, the cost of the debris removal operations is largely impacted by its duration and the available resources. To further evaluate the cost and time implications of changing the number of available resources, cost-per-benefit ratio was utilized as an integrated cost-time measure, where the benefit was defined as the inverse of the total operation duration. In other words, the benefit gained would increase as the total operation duration decreases. Fig. 12 shows the normalized cost-per-benefit ratio variations among the test scenarios investigated in this section. According to Fig. 12, the cost-effectiveness increases as the number of trucks increases for each of the three investigated TDMSs scenarios; however, the rate of improvement diminishes as the number of trucks increases. For example, the cost-effectiveness improves by 63% when increasing the number of trucks from 50 to 130; however, it only improves by 13% when increasing the number of trucks from 130 to 210. Further, while increasing the number of trucks seems to positively affect the cost-per-benefit ratio, adding more than four TDMSs would reduce the cost efficiency of the debris removal operations. Therefore, balancing infrastructure capacity and resources is critical to increasing the efficiency of the debris removal operations.

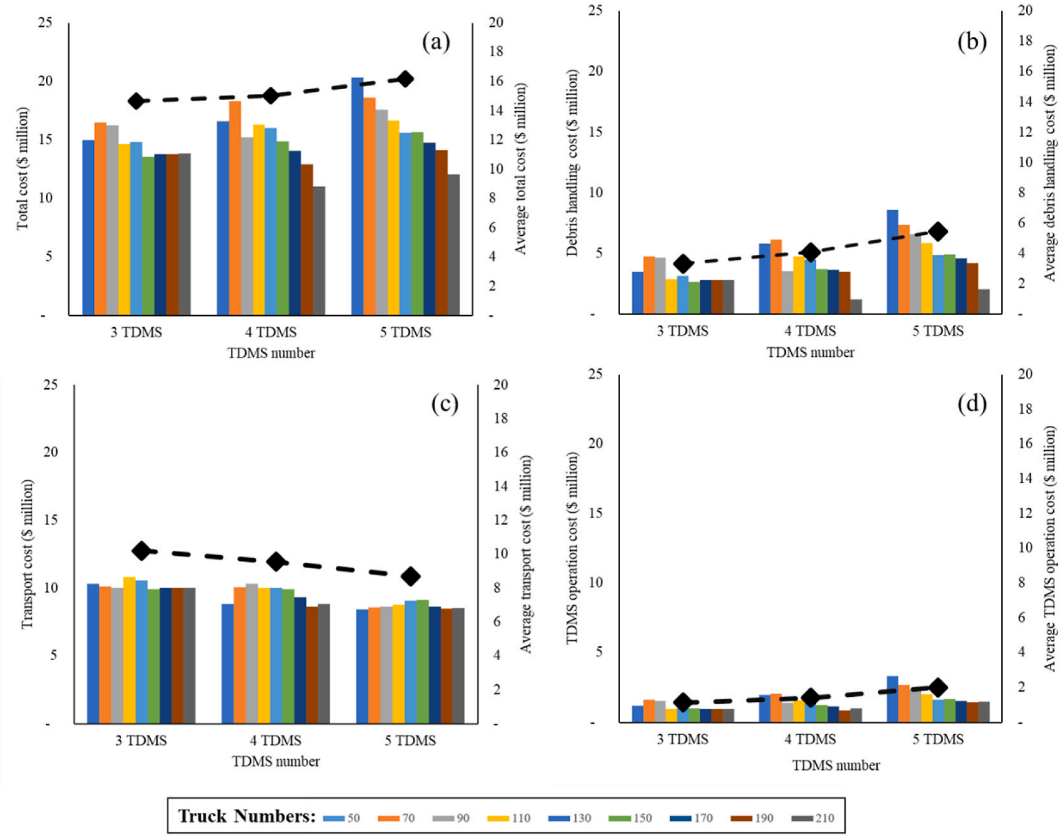
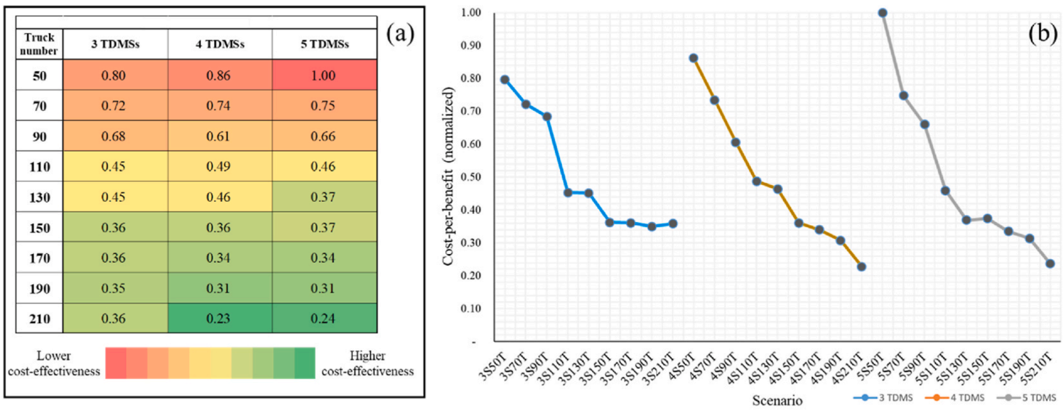



**Fig. 11.** The effect of increasing resources on (a) total operation cost, (b) debris handling cost, (c) debris transport cost, and (d) TDMSs operating cost.




| Truck number | 3 TDMSs | 4 TDMSs | 5 TDMSs |
|---|---|---|---|
| 50 | 0.80 | 0.86 | 1.00 |
| 70 | 0.72 | 0.74 | 0.75 |
| 90 | 0.68 | 0.61 | 0.66 |
| 110 | 0.45 | 0.49 | 0.46 |
| 130 | 0.45 | 0.46 | 0.37 |
| 150 | 0.36 | 0.36 | 0.37 |
| 170 | 0.36 | 0.34 | 0.34 |
| 190 | 0.35 | 0.31 | 0.31 |
| 210 | 0.36 | 0.23 | 0.24 |

**Fig. 12.** Variation in the cost-per-benefit ratio across different test scenarios.

## 6. Conclusions

TDMSs locations are critical design parameters of the disaster debris management system, significantly impacting the logistics of the debris collection operations. Without considering its subsequent impact on the debris collection logistics, most prior studies primarily rely on geographical factors when locating TDMSs. While limited studies address both locating TDMSs and planning the debris clean-up operations together, none provide a systematic approach that allows decision-makers to plan and prioritize the debris collection process in a way that minimizes the social and economic impacts of the disaster debris. Additionally, existing studies do not provide a visualization framework that enables decision-makers to better understand the debris collection process dynamics, challenges, and bottlenecks. This study addresses the current knowledge gaps by proposing an integrated simulation-based framework for identifying optimal TDMSs locations, taking into account both geographical factors and debris collection logistics planning. The proposed framework enables decision-makers to set debris removal priorities based on the debris type and source location. Further, the developed simulation model provides a visualization tool that can be used by decision-makers to identify system flaws and investigate different operational scenarios for process improvement.

A real-world case study of debris removal planning for Liberty County, Florida, for Hurricane Michael was used to demonstrate the proposed framework. The optimal TDMSs locations were determined in a way that satisfies relevant geographic suitability criteria and minimizes the truck routing time for debris collection. A sensitivity analysis was also conducted to guide debris resource planning and management. It was found that adding more trucks would reduce the duration and cost of the debris removal operations. Opening more TDMSs, on the other hand, would decrease the duration of debris clean-up but would increase its total cost, mainly due to the increased cost of operating the TDMSs.

The proposed framework is flexible and can be adapted to facilitate decision-making regarding disaster debris management and planning in other geographical areas and for other disaster scenarios (i.e., by adjusting the framework's input parameters [e.g., geographical characteristics, debris data, and available resources]). While this study sufficiently demonstrates its proposed integrated framework through the case study of debris management of Liberty County, there is still room for the proposed framework to be expanded and improved. For example, the proposed framework assumes that the entire disaster debris location, type, and volume is known and fixed at the beginning of the recovery phase. However, in reality, that assumption might not always be true. In other words, some debris might be relocated to the curbside from other public lands after initiating the recovery phase. The impact of non-stationary debris on debris collection logistics can be further studied in future research work. Additionally, developing a detailed simulation model of TDMSs' internal operations would provide a more detailed and accurate evaluation of the amount of processed debris and truck waiting periods. For example, in this study, it is assumed that trucks spend a fixed amount of time delivering the debris. However, as the number of trucks increases, the waiting time might increase due to traffic and congestion inside the TDMS.

Future research is also needed to evaluate the changing nature of disaster debris based on the material properties and governing environmental conditions. Such evaluation would be beneficial in determining time thresholds within which debris should be collected to avoid any adverse health impacts on its surrounding community, as well as to facilitate the implementation of sustainable debris management practices (e.g., recycling & reuse). Moreover, future studies are recommended to further investigate social aspects of post-disaster debris collection operations. The proposed framework aims to minimize the social impact of disaster debris by minimizing the community recovery duration and the impact of hazardous debris on the community's health. However, there might be other social aspects (e.g., neighborhood tolerance and disturbance, social disparities, etc.) that could potentially impact the post-disaster debris collection operation.

## 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.

## Data availability

The authors do not have permission to share data.

## Acknowledgments

This study is partially supported by the U.S. National Science Foundation under award CBET-2014330. Any opinions, findings, and conclusions expressed in this article are those of the authors and do not necessarily reflect the views of the U.S. National Science Foundation.

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